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An Explorative Study

Madadi, Bahman; van Nes, Rob; Snelder, Maaike; van Arem, Bart

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Network Design and Impacts of Automated Driving: An Explorative Study

Bahman Madadi, Corresponding Author
Delft University of Technology
Faculty of Civil Engineering and Geosciences
Department of Transport & Planning
Stevinweg 1, 2628 CN Delft, NL
Tel: +31 (0)15 27 84030; Email: b.madadi@tudelft.nl

Rob van Nes
Delft University of Technology
Faculty of Civil Engineering and Geosciences
Department of Transport & Planning
Stevinweg 1, 2628 CN Delft, NL
Tel: +31 (0)15 27 84033; Email: r.vannes@tudelft.nl

Maaike Snelder
TNO and Delft University of Technology
Van Mourik Broekmanweg 6, P.O. Box 49, 2600 AA Delft, NL
Tel: +31 (0)15 27 84981; Email: maaike.snelder@tno.nl

Bart van Arem
Delft University of Technology
Faculty of Civil Engineering and Geosciences
Department of Transport & Planning
Stevinweg 1, 2628 CN Delft, NL
Tel: +31 (0)15 27 86342; Email: b.vanarem@tudelft.nl

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ABSTRACT

This study introduces a network configuration 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 that automated driving will be allowed on a selection of roads. For the remaining roads, manual driving (although supported by assisting driving automation systems) is compulsory. A static Multi-Class Stochastic User Equilibrium traffic assignment based on the Path-Size logit and a Monte Carlo-Labeling combination approach for route set generation is adapted to model the behavioral differences of vehicles in mixed traffic. Two user-classes are distinguished: vehicles with automation levels 0-2 and vehicles with automation levels 3-4 having a different Passenger Car Unit value 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, the rest of the vehicles do not suffer deterioration in their travel conditions 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. Finally, a steady decline in total travel cost is observed with increase in market penetration rate of higher automation levels.

Keywords: Automated Driving Impacts, Network Design Problem, Multi-User Class Route Choice, Monte Carlo Labeling, Stochastic User Equilibrium, Path-Sized logit

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 *(1)*, there are five levels of vehicle automation; at level 1 and 2, the driving automation system provides the driver with longitudinal and lateral control (i.e. Adaptive Cruse 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 (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. Level 4 ADS is expected to handle the fail-safe situation autonomously, however the operating design domain would still be limited. This means that level 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 *(2)*.

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); however, it might take quite a long time before this situation is achieved. In the transition period there will be a mix of different levels of automation, including level 0, i.e. non automated vehicles. For AD levels 3 and 4 we envision that automated driving will be allowed on a selection of the roads and that for the remaining roads manual driving is 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 requirements with respect to the design of the roads and the intersections to facilitate safe and efficient automated driving. There is therefore a need for a network design approach to decide which roads should be selected to facilitate level 3-4 AD. This relates to the well-known Network Design Problem (NDP) in transport literature *(3)*.

The aim of this paper is to present a method to estimate impacts of different network configurations for level 3-4 automated vehicles on travel time, distance and cost in urban regions having mixed traffic. Network configuration refers to the selection of links on which level 3-4 AD is facilitated. Furthermore, we provide insights and model requirements for transport authorities in order to prepare for AVs in urban regions and guide future scenarios to the more desirable outcomes.

In this paper we distinguish two classes of vehicles: conventional vehicles (CVs) and automated vehicles (AVs). We consider AVs to be level 3-4 automated vehicles and CVs to be level 0-2. Level 1-2 automated vehicles are classified as CVs here since they have the same operating design domain as level 0 and assisting driving automation systems at these levels have marginal impacts on the traffic compared to level 3-4.

Therefore, we propose a static Multi-User Class (MUC) Stochastic User Equilibrium (SUE) traffic assignment with two user-classes: CVs and AVs having a lower Passenger Car Unit (PCU) value to account for the lower driving time headways, a lower Value of Time (VoT) and a higher fuel efficiency which will be referred to as value of driving (VoD) in the rest of this paper. Only limited parts of the network are chosen to be allowed for AD, therefore each class faces a different network. Consequently, considered route sets and route choice preferences are different. Thus we adapt a Monte Carlo-Labeling combination method for a priori route set generation to include favorable routes for AVs in their considered route sets.

Based on this analysis and an explorative literature study, we present a research agenda for the development of a network design method that incorporates the key mechanisms of AD.

BACKGROUND

One of the major envisioned advantages of AD is the possibility of Cooperative Adaptive Cruise Control (CACC). Shladover et al. *(4)* provide clear definitions and operating concepts of CACC. Main benefits of Adaptive Cruise Control (ACC), i.e. improving traffic flow and fuel consumption, 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 seconds (current average for manual driving) to approximately 0.6 seconds *(5)* which would increase lane capacity. Some studies based on highway traffic simulations conclude that autonomous ACC does not have a significant effect on capacity *(6)*, *(7)*. Based on on-road-experiments, it is demonstrated in *(8)* that autonomous ACC platooning could lead to instability in the platoons. Although, with reduced time headways, at 100% penetration rate of CACC-equipped vehicles, it is possible to increase highway lane capacity from 2200 v/h to about 4000 v/h *(7)*. Using microscopic MIXIC traffic simulation model on a highway bottleneck, van Arem et al. *(9)* 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.

A potential means for improving the performance of CACC platoons as well as extending the operational domain for level 3 and level 4 ADS is dedicated lanes for CACC-equipped vehicles. Van Arem et al. *(9)* 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. It is intuitive that the presence of a dedicated lane with low penetration rate (i.e. insufficient demand for that lane) leads to underutilization of the lane.

Milakis et al. *(10)* provide a comprehensive literature review on various impacts of AD including cooperative and autonomous ACC as well as impacts of dedicated CACC lanes on traffic flow dynamics. However, most of the studies considering ACC and CACC focus on specific stretches of highways and network-wide studies that consider AD concepts within the NDP and provide impact assessments for design methods based on macroscopic traffic assignment models are rare with the exception of *(11)* and *(12)*.

Chen et al. *(11)* 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 multiple classes representing CVs and AVs. The objective is to minimize social costs with respect to market penetration rate of AVs. A set of links for deploying dedicated lanes is considered in order to represent practical restrictions but no selection criterion is used. The study relies on a general definition of AVs and does not relate the AVs to specific automation levels, operating design domains, and clear operational rules. Yet, it represents a possible network configuration for AD, and a network-wide assessment of its impacts using a macroscopic static traffic assignment model with multi-class equilibrium which opens up a new dialogue in the literature.

Another possible network configuration is presented in *(12)* where Chen et al. consider the problem of optimal AV zones in transport networks. An AV zone includes links that are adjusted for AVs, and into which, regular vehicles are not allowed to enter. So, different classes of vehicles

encounter different network topologies. As for routing, they consider a deterministic mixed routing model where within the AV zone, system optimal routing is applied and outside the AV zone, users try to minimize their individual travel cost (i.e. user optimal routing). A potential problem with zoning is that there may be no feasible route for CVs between some origin-destination pairs. Therefore, the objective function includes construction cost, total travel time, and a penalty for loss of welfare as a result of lost accessibility. With this formulation, the problem becomes similar to cordon design for cordon congestion pricing for which there are solution algorithms in the literature (see, for instance *(13)*). However, for applying this method in practice, some extensions are necessary; AVs should be defined in more detail. Operational domain of different automation levels significantly differ and different network topologies may be required for different levels. Moreover, extensions to this representation of the network and considerations for the hierarchy in the network are required in order to model complex real life networks. Nevertheless, the innovative network configuration and mixed routing method presented in *(12)* provide a strong theoretical basis for further developments in this area.

An important remark regarding *(11)* and *(12)* is that despite their theoretical merit, the effectiveness of these designs in practice depends on accurate prediction of market penetration rate of AVs. Predicting demand decades into the future includes a high margin of error (if possible at all). Furthermore, it is argued in *(9)* that the dedicated lane for AVs will only be effective with high market penetration rates of AVs (>60%). Moreover, possibility of underutilization of AV lanes with low AV penetration rates and sever congestion in the lanes with higher AV penetration rates as well as practical issues with handling dedicated lanes make them unattractive for transport authorities. The underutilization or over-congestion issues can exist in dedicated zones as well. In general, exclusive lanes, links, and zones can only be effective for a specific level of demand.

Large infrastructure investments should not be made based on uncertain predictions. For the highly uncertain transition period with mixed traffic, an appropriate network configuration should be robust against changes in market penetration rate and other factors related to development path of AD (e.g. changes in road capacity and VoT). This study offers a more realistic network configuration compared to dedicated lanes and AV zones for the transition period. We advocate no-regret measures for infrastructure planning. We select certain parts of the network mainly consisting roads with flow function and distributors to allow for AD. Adjustments for 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 segregating inhomogeneous traffic. For an overview of possible adjustments the reader is referred to *(14)–(17)*. AD in limited access roads, minimum or no confrontation with vulnerable road users, and off-grade or clear on-grade intersections would guarantee safety for all road users. Regardless of market penetration rate of AVs and development path of AD in the future, such adjustments are beneficial for all road users.

Therefore, the problem becomes choosing links to adjust in order to construct a subnetwork to allow AD in mixed traffic. This study presents a qualitative scheme for choosing links and a quantitative method for assessing the impacts of this configuration as well as measured impacts for a case study. Quantitative (optimized) methods for choosing links and possible improvements on the model are mentioned in the discussion section and left for future work.

AD-ENABLED NETWORK DESIGN METHOD

In this section, the concept of AD subnetwork is introduced. Design concepts, construction of the network, assignment model details, mathematical formulations, and the solution algorithm for the assignment

problem are discussed in the following parts.

Constructing the AD Subnetwork

In order to envisage a network configuration for AD, it is essential to specify a feasible realm of operation for level 3-4 ADS. 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.

Automating parts of the process of extracting the feasible links from the network data is crucial since it is cumbersome to have observations for each single link in large urban regions. Road categorization can serve this purpose; 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. Road network observations in Delft, the Netherland 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.

The definitions of road functions used in this study are based on the Sustainable Safety vision presented in *(18)*. There is no clear correspondence between road functions and other common road categories. Still, another categorization is presented in the case study and the results are demonstrated and discussed. Figure 1 depicts the constructed AD subnetwork for the case of Delft which is discussed in details in the following sections.

Operational Concepts and Assumptions

It is assumed in this study that level 3-4 ADS-equipped vehicles form CACC platoons using V2V communication (whenever possible) in automated mode within the AD subnetwork. These vehicles are referred to as AVs and the concept is referred to as automated driving (AD) in the rest of this paper. The rest of the vehicles (levels 0-2) are referred to as CVs and the assumption, which is consistent with the literature and the current state-of-the-art, is that they 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. For clear definitions of CACC and AD concepts the reader is referred to *(4)* and *(1)*, respectively.

AVs always start manually and proceed in manual driving mode till reaching AD subnetwork (green parts in Figure 1). Then the ADS notifies the driver of the possibility of AD and the driver opts for AD, in which case he/she chooses the destination. 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, especially in case of a failure in level 3 ADS. In the case of level 4, ADS is expected to handle system failures without driver intervention, however he/she needs to be ready to take back control when exiting AD subnetwork.

It is assumed that outside the AD subnetwork (blue parts in Figure 1) all vehicles drive manually. Inside the subnetwork, CVs drive manually and AVs use AD. All vehicles are allowed everywhere in the network but AD is only possible inside the AD subnetwork for AVs.

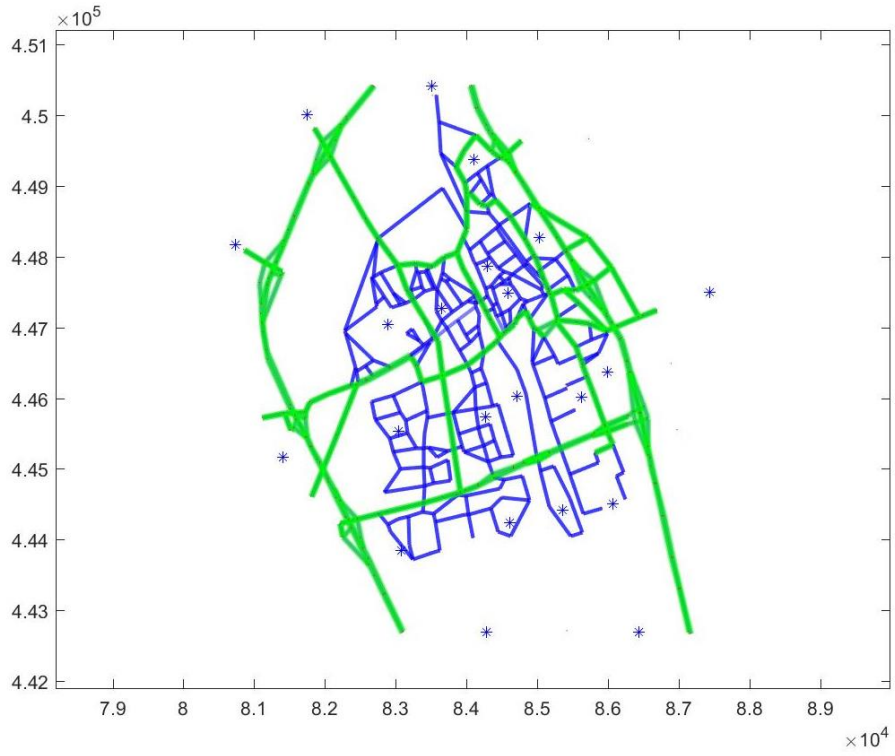


FIGURE 1 AD subnetwork: links that belong to the AD subnetwork are shown with (bright) green and the rest with (dark) blue. Stars represent zone centroids (origins and destinations) and axes represent x-y coordinates.

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 may cause some long and unusual routes that are (largely) within the AD subnetwork to become desirable for AVs due to their lower travel cost. 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 *(19)* is used with some adjustments to generate appropriate route sets for AVs. In addition to common labels, 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 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. Regular route sets used in this study for CVs are generated by setting mentioned multiplier to one.

Multi User-Class Route Choice and Mixed Network Equilibrium

A key requirement for modeling AVs' behavior is a multi-user class traffic assignment model. Higher levels of automation are expected to reduce VoT and VoD as well as to increase capacity via shorter distances between vehicles leading to lower driving time headways *(10)*. The lower headways can be modeled via using a lower PCU value for AVs. Furthermore, they can follow different routing principles, and even face different network topologies. Therefore, in order to accurately model the behavior of these vehicles, they should be considered as separate classes during the assignment.

Another expected change from AD is related to travel route choice. Since AVs are expected to have different generalized travel costs due to AD efficiency, face different network configurations, and possibly, have more accurate information regarding the state of the network, it is likely that they will follow different routing principles. Moreover, in centrally controlled traffic management scenarios, (see *(4)*) there might be a possibility to provide route guidance to AVs that can lead to system optimal routing. Some of these possibilities are explored in multiclass and mixed routing models. Chen et al. *(11)* use a multi-class network equilibrium routing model to consider different routing principles of AVs traveling within a network of dedicated lanes and regular vehicles in the rest of the network. The equilibrium routing model used therein was developed in *(20)*, where in the original problem two classes of travelers with and without advanced traveler information system (ATIS) are considered and a mixed stochastic and deterministic network equilibrium model is presented. Chen et al. *(12)* developed a mixed routing equilibrium model to include different routing principles within and outside the AV zone. There are several other mixed equilibrium models in the literature (see for instance *(21)–(23)*) where both the user-optimum and system-optimum route choice behaviors are considered. It should be noted that system optimal routing may only be possible with complex traffic management systems and major changes in laws and regulations. Implementation of such control systems in large urban regions is a challenging task.

It is assumed in this study that both CVs and AVs follow a user optimal route choice behavior. Based on this and the previous assumptions presented in this study, a MUC SUE assignment with two classes, namely AVs and CVs, having different VoT, VoD, and PCU values along with considering different cost functions for links belonging to different parts of the network and separate route set generations introduced earlier are deemed sufficient for modeling behavioral differences of CVs and AVs in AD subnetwork.

Fisk *(24)* presents the mathematical formulation of the single class SUE assignment as a minimization problem. An early extension of the problem to a MUC SUE is introduced in *(25)*. 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 introduced in the literature in order to overcome this issue. This is discussed in *(26)* where the performance of existing extensions to the MNL model are compared. The path-size logit (PSL) model presented in *(27)* is one of the extensions that can lead to more realistic flow predictions. In this study, a 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 presented in *(28)*. Mathematical formulation of this method is presented in the next subsection.

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 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* $\left(\textit{assignment map}\right)$

α_a = *BPR function parameter for link a*

β_a = *BPR function parameter for link a*

Λ_a = *Capacity of link a*

$T_m^{w,r}$ = *Flow of route r between origin – destination pair w for class m*

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

$f_{m,a}$ = *Flow of class m in link a*

q_a = *Total flow of link a* $\left(\textit{PCU equivalent}\right)$

$c_m^{w,r}$ = *Travel cost of route r between origin – destination pair w for class m*

$\overline{f_{m,a}}$ = *Equilibrium flow of class m in link* a

$\overline{t_a}$ = *Equilibrium travel time of link a*

Equilibrium Assignment: Lower Level Optimization Problem

The PSL-based MUC SUE formulation of this problem is presented here as a mathematical programing problem.

MP:

Min

$$Z = \sum_m \frac{1}{\mu_m} \sum_{w \in W} \sum_{r \in R^w} T_m^{w,r} \ln T_m^{w,r} - \sum_m \frac{1}{\mu_m} \sum_{w \in W} \sum_{r \in R^w} T_m^{w,r} \ln PS_m^{w,r}$$

$$+ \sum_{m \in M} \sum_{a \in A} \int_0^{f_{m,a}} c_{m,a}(q_a) df_{m,a}$$

S.t.

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

$$q_a = \gamma_0 f_{0,a} + \gamma_1 f_{1,a} \quad , \forall a \in A_1 \tag{2}$$

$$\sum_{r \in R^w} T_m^{w,r} = D_m^w \quad , \forall w \in W, \forall m \in M \tag{3}$$

$$\sum_{w \in W} \sum_{r \in R^w} T_m^{w,r} \delta_{m,a}^{w,r} = f_{m,a} \quad , \forall a \in A, \forall m \in M \tag{4}$$

$$T_m^{w,r} \geq 0 \quad , \forall w \in W, \forall m \in M, \forall r \in R^w. \tag{5}$$

Where link travel time function is given as:

$$t_a(q_a) = t_a^0 [1 + \alpha_a (\frac{q_a}{\Lambda_a})^{\beta_a}].$$

And link cost at O-D level is:

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

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

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

The solution to the above MP formulation gives the probability:

$$P_m^{w,r} = \frac{\exp(-\mu c_m^{w,r} + \beta_m \ln PS_m^{w,r})}{\sum_{r \in R^w} \exp(-\mu c_m^{w,r} + \beta_m \ln PS_m^{w,r})} \quad \forall w \in W, \forall m \in M, \forall r \in R^w$$

Where:

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

And:

$$c_0^{w,r} = \sum_{a \in A} \delta_{0,a}^{w,r} T_0^{w,r} (\theta_0 l_a + \eta_0 t_a(q_a))$$

$$c_1^{w,r} = \sum_{a \in A_0} \delta_{1,a}^{w,r} T_1^{w,r} (\theta_0 l_a + \eta_0 t_a(q_a)) + \sum_{a \in A_1} \delta_{1,a}^{w,r} T_1^{w,r} (\theta_1 l_a + \eta_1 t_a(q_a))$$

Impacts: Upper Level Objectives

Impacts of CVs and AVs in AD subnetwork in equilibrium conditions are based on the following formulae.

Total travel Cost:

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

Total travel Time:

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

Total travel Distance:

$$TTD = \sum_{a \in A} l_a (\overline{f}_{0,a} + \overline{f}_{1,a})$$

Solution Algorithm

There are several solution algorithms in the literature for the MUC SUE problem. A review of these algorithms is provided in *(29)*. The problem with presented formulation in this paper can readily be solved using the solution method developed in *(30)* where the authors introduce a MUC extension of MSA algorithm.

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 data is available via *OmniTRANS* traffic modeling software in Delft tutorial project. It includes 1151 links, 494 nodes and 22 zones.

Passenger car travel demand from the base case in Delft tutorial case in *OmniTRANS* is used with 40% extra demand for each zone in order to observe more congestion in the network. Demand for AVs is considered via seven scenarios based on different market penetration rates of AVs.

Three different network configurations 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 Figure 1 as none-AD links ($A_0 = A, A_1 = \varnothing$).
- AD everywhere network: this is used to demonstrate the extreme impacts for comparisons and it includes all links in Figure 1 as AD links ($A_1 = A, A_0 = \varnothing$).
- AD subnetwork: this network is shown in Figure 1 ($A_0 \cup A_1 = A, A_0 \cap A_1 = \varnothing$). The subnetwork for AD covers 38% of the overall distance in the network.

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. In this case, 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, demand scenario, road type, and user class is investigated.

The AV parameters representing changes in PCU, VoT, and VoD for AD are chosen from *(31)* where Puylaert et al. consider a system dynamic approach to provide a quantitative assessment of AD impacts. The exact values are provided in Table 1. The parameters for the PSL model are similar to those used in *(32)* and the rest of the parameters 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.

RESULTS

As explained in the case study section, 7 demand scenarios for 3 network configurations are considered in this study and for each case statistics are measured separately for each road type and each user class. Furthermore, sensitivity analyses are performed for AD parameters used in the model. Due to lack of space, only a selection of the results is presented in this section and the rest are discussed in the next section. All numbers reported are indexed and the indexing is mostly with respect to the base case scenario. Further information regarding indexing is provided in relevant table captions.

Table 1 summarizes the changes in total travel time, cost and distance for all variants and scenarios compared to the base case. No AD and AD everywhere with 100% AV scenarios represent the two ends of the spectrum with no impacts and highest impacts, respectively. A significant and steady decrease in total travel cost, a minor decrease in total travel time, and a small increase in total travel distance is 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 2, 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 and 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.

TABLE 1 Indexed Travel Impacts for All Network Types and Demand Scenarios (indexing is based on the base case scenario)

Network Type		**No AD (Base Case)**	**AD Subnetwork**						**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

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 3. 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. Although with extreme values for VoT and VoD, some significant changes are observed in total travel cost, these are direct effects of the parameters on cost rather than the results of profound behavioral changes.

TABLE 2 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, so values in each row do not add up to 100)

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						
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	15.12	5.31	5.04	8.39	49.89
	AV	15.05	5.49	5.30	8.03	50.11
	Overall	30.17	10.80	10.33	16.42	100.00
Total Travel Distance	CV	24.90	6.54	4.28	4.45	49.94
	AV	24.78	6.80	4.50	4.22	50.06
	Overall	49.68	13.34	8.78	8.67	100.00
90% Penetration Rate in AD Subnetwork						
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	3.00	1.05	1.00	1.68	9.95
	AV	26.85	9.81	9.52	14.50	89.95
	Overall	29.85	10.86	10.52	16.18	99.88
Total Travel Distance	CV	4.98	1.31	0.86	0.89	9.99
	AV	44.61	12.24	8.10	7.60	90.12
	Overall	49.59	13.55	8.96	8.49	100.11

TABLE 3 Sensitivity Analysis Summary for 90% AV Market Penetration Rate Scenario in AD Subnetwork (indexing is based on values of the base case)

Parameter	Parameter Ratio (X_{AV}/X_{CV})	Vehicle Type	Total Travel Cost	Total Travel Time	Total Travel Distance
Passenger Car Unit (PCU)	**0.7**	CV	9.88	9.81	9.94
		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
		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
		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

DISCUSSION AND CONCLUSIONS

Predicting the future of AD and its impacts, especially for the mixed traffic condition, is a complex task subject to several uncertainties. In this study, different scenarios are used to gain insight into the impacts of one possible AD network configuration (AD subnetwork) and compare it to the extreme cases. 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 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 proportion of benefits obtainable from AD everywhere. Given that AD everywhere is only possible for level 5 AVs and that AD subnetwork introduced here is suitable for level 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 level 3-4 AVs.

According to the sensitivity analysis, it can be concluded that the parameters individually have limited impacts 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 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.

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 logic behind the shift; AD subnetwork is more efficient and desirable for AVs and is expected to attract more traffic. However, lower congestion and higher accessibility of main urban roads and regional roads compared to freeways make them more attractive, especially for AVs. Moreover, for some O-D pairs there is no feasible route including freeways but in most cases, there are routes including regional roads and main urban roads.

This study assesses the impacts of a specific AD subnetwork configuration with a certain congestion level in the network with several scenarios. Changes in general demand level (congestion level) and distance coverage of AD subnetwork, which is 38% of the total distance in this case, are left for future work. As for AD subnetwork coverage, it can be expected that higher coverages of the network lead to more significant changes.

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

- *Dynamic network loading:* these methods account for queueing and spill back in the network as well as the temporal aspect of the traffic leading to more accuracy and precision in predicting travel behavior compared to static traffic assignment.
- *Elastic demand:* AV demand and their 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.
- *Quantitative optimization methods:* the choice of links in this study is based on 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.
- *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 uncertainty.

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