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Automated vehicles (AV) dedicated networks and their effects on the traveling of conventional vehicle drivers

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Abstract

AV subnetworks is a way to deal with automated traffic and its technological need that will likely increase during the AVs deployment period. This strategy carries many benefits, yet some inconveniences are worth to mention. One of them relies on the fact that the design of AV subnetworks is often in practice focused on mitigating congestion in the peak-hours. However, designing for the most congested hour can be quite delicate when such a strategy is fixed throughout the day. The remaining part of the day involves different mobility patterns and shifting trips patterns throughout the day, i.e., different Origin-Destination pairs. When such O-D pairs are inside these AV subnetworks, CV owners cannot drive, and therefore a new mode of transport is necessary. This paper focuses on the lower-level decision problem, i.e., the traffic distribution during the transition period while AVs are being deployed in urban areas and AV subnetworks are expanding. A nonlinear mathematical programming model is presented to perform the trip distribution, where walking appears as an alternative. The main objective of this paper is to study the impacts of AV subnetworks from a CV owners' perspective. A novel formulation guarantees that CV trips starting inside AV subnetworks throughout the day aren't ignored – this means an alternative mode of transport, in this case, walking. This paper evaluates throughout the day when such situations would likely occur in a case study of the city of Delft, in the Netherlands, in two scenarios with AV subnetworks. The experiments revealed that walking is somehow inevitable when AVs reach 75% of the vehicle fleet – increasing travel costs up to 26.0% and 43.8%.

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This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0) Peer-review under responsibility of the scientific committee of the 23rd Euro Working Group on Transportation Meeting *Keywords:* automated vehicles; AV subnetworks; road network design; walking.

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1. Introduction

AV subnetworks are a way to deal with automated traffic and its technological need that will evolve during AVs deployment period. AVs are here considered to be at least level 4 (SAE, 2018), which means that inside dedicated roads, they drive automatically, segregated from human-driven vehicles – also called conventional vehicles (CVs). Such strategy of assigning part of the network to AVs carries benefits such as planning the public investment, improve traffic management for higher efficiency, and compliance with road safety to mitigate the number of urban conflicts. Such road network design problem (RNDP) must be carefully planned with concerns to the urban space that affects travel behavior and road traffic. Regardless of the strategy involved in the planning of progressive AV subnetworks; at some point, CVs trips might not be satisfied, whether because AVs demand wider AV subnetworks, or CVs cannot circulate, shifting to another mode of transport. Traffic management and planning often in practice consider the peak-hour of the morning or the afternoon, because congestion is worsened in these hours. However, considering the whole daily trips demand is mandatory for AV subnetworks since they are fixed throughout the day.

The main objective of this paper is to debate when the design for peak-hours, commonly used for this type of RNDPs, can create situations where the segregation of the network no longer allows the circulation of some CVs owners and walking becomes the only alternative. This paper concerns the lower-level decision of the RNDP-AVs, i.e., the traffic distribution during a transition period where AVs are progressively being deployed in urban areas, and AV subnetworks are expanding accordingly. This paper is an extension of a previous article (Conceição et al., 2020). A nonlinear mathematical programming model performs the trip distribution, and walking appears as a (very expensive) alternative. The results of a case study, the city of Delft, in the Netherlands, are discussed for the whole day with shifting demand, on two scenarios created with distinct planning strategies (Conceição et al., 2020).

The paper is organized as follows. Section 2 presents the background with the literature review. Section 3 proposes the formulation that performs the traffic assignment in the network that has AV subnetworks evolving with AVs penetration rate. Section 4 presents the results of the case study. Finally, Section 5 draws conclusions.

2. Background on the RNDP-AVs

On the topic of AV subnetworks, Z. Chen et al. (2017) proposed a bi-level framework for the optimal design of AV zones in a general transportation network, solved through a simulated annealing algorithm. Madadi et al. (2019) proposed a framework for AV subnetworks through a modified static multiuser class stochastic user equilibrium with a path-size logit model with Monte-Carlo labeling for a priori route-set generation. In our first approach (Conceição et al., 2017), a mixed integer programming (MIP) model was formulated with a linear travel time function; the MIP is not aware of the length of the trips but the link flows instead. Also, the traffic efficiency coefficient, i.e., the capacity benefit given by AVs traffic, is constant (25%) regardless of the AVs penetration rate in both regular and dedicated roads. Recently, our second approach (Conceição et al., 2020), the RNDP-AVs model is formulated on a single-level formulation to evaluate such a combinatorial problem. The multi-class traffic equilibrium assignment does not have route choice algorithms or path flow constraints, but a user-equilibrium traffic assignment instead. The decision upon AV subnetworks simultaneously analyzes the increasing comfort and traffic efficiency as AVs' penetration rate evolves. The formulation guarantees that all travelers reach their destination while covering all links characteristics, i.e., individual link performance (travel time) functions. Besides, it also evaluates road investment for V2I connectivity to transform a regular road (mixed traffic) into a dedicated road for AVs (automated traffic-only). This paper also debates the design of progressive AV subnetworks on whether adding incrementally or limiting the planning to the solution that is optimal in the long-term.

The traffic assignment problem, in which this paper relies on, is the lower-level problem of the RNDP-AVs model: highly combinatorial, involving demand (trips) and supply (network). Forcing the traffic distribution on reaching the equilibrium is complex and hard to express it on mathematical programming (non-linearity). In theory, there are two types of traffic assignment: the user-equilibrium (UE) and the social equilibrium (Sheffi, 1985). The UE, also known to be ruled by the Wardrop principle (Wardrop, 1952), assumes that traffic arranges itself within congested networks so that no individual trip maker can reduce its path costs by switching routes. The social-equilibrium minimizes the total travel cost of all travelers, and vehicles are assumed to choose their paths in order to benefit the whole social system (Newell, 1980). In this paper, the UE is replicated amongst each class of vehicle.

3. Methodology: a nonlinear programming model

We present a new model formulated in nonlinear mathematical programming to perform the trip distribution throughout the day and the transition period (different AV penetration rates) where walking appears as a very expensive alternative to detour AV subnetworks. A UE among AVs and CVs is performed. The following model is an extension of a previous formulation (Conceição et al., 2020). The main difference from the previous is the use of the penalty variables to perform a different mode of transport; in this paper, the "walking variables." This framework evaluates whether walking is cost-efficient as an alternative to driving when a detour is far expensive or even when a detour is not possible (CV owners start their trips inside the AV subnetwork). The trips start either by AVs or CVs. When a CV reaches the borders of an AV subnetwork, the driver will park and walk henceforward. AVs travel more efficiently than CVs, allowing an increase in road capacity. Another assumption is added: "every street has sidewalks for pedestrians and CV parking is available".

Sets:		
I = (1,	., <i>i</i> ,, <i>I</i>)	set of notes in the network, where I is the number of nodes.
$\boldsymbol{R} = \{\dots, (i, j), \dots\} \forall i, j \in I \cap i \neq j$		set of arcs of the road network where vehicles move
$\boldsymbol{P} = \{\dots, (o, d), \dots\} \forall o \in O \cap d \in D \cap o \neq d$		set of origin-destination pairs that represent the trips demand in the network.
$\boldsymbol{V} = \{AV, CV\}$		class of vehicles in the network: AV and CV
$\boldsymbol{H}=\{1,.$, <i>h</i> ,, 24}	hours of the day
Data:		
ρ	AVs penetration rate, i.e.,	percentage of AVs on the fleet (between 0 and 1).
		s the efficiency of automated traffic that benefits road capacity, in mixed traffic
		CVs to which an AV corresponds. Defined between 0 (an AV has no effect on
	traffic) and 1 (an AV is as	
		s the maximum efficiency of automated traffic in dedicated roads, also between 0
drivi	and 1.	
		driving in monetary units per hour.
		walking in monetary units per hour.
$\mathcal{T}_{-v h_i h_f}$	walking speed, expressed	-
$D_{od}^{v h_i h_f}$		$p \in D$, towards a destination node $d \in D$, from period $h_i \in H$ to period $h_f \in H$.
t_{ij}^{min}	minimum travel time in ro	
L_{ij}	length of each link (i, j) in	
C_{ij}		in vehicles per time period $\forall (i, j) \in R$.
Μ	Big number, e.g., 9999999	
x_{ij}	binary variable equal to 1	if road link (i, j) is assigned for AVs only driving, $\forall (i, j) \in R$.
Decision variables:		
h _i h _f W _{ijod}	discrete variable that indicates the flow of CV trips that are not allowed in AV zones and therefore represent the	
	walking in each link $(i, j) \in \mathbf{R}$, regarding each O-D pair $(o, d) \in \mathbf{P}$, from period $h_i \in \mathbf{H}$ to period $h_f \in \mathbf{H}$.	
$f_{ijod}^{\nu \ h_i h_f}$	$h_{ad}^{h_i h_f}$ discrete variable that corresponds to the flow of class $v \in V$ in each link $(i, j) \in R$, regarding each O-D pair $(o, d) \in R$	
, i jou	from period $h_i \in H$ to period $h_f \in H$.	
$z_{ijod}^{h_ih_f}$	continuous variable that distinguishes AVs benefits in mixed or automated traffic. It represents the flow of AVs when	
$(i,j) \in \mathbf{R}$ is dedicated for AVs only $(x_{ij} = 1)$, regarding each O-D pair $(o, d) \in \mathbf{P}$, from		-
	$h_f \in H$.	

The second component in the objective function previously presented in (Conceição et al., 2020) was modified to include the cost of the walking (travel time) trips – see (1). The objective function (1) is subject to the constraints expressed between (2) and (15). Constraints (11)-(14) are proposed in this paper. The remaining constraints are part of the previous formulation (Conceição et al., 2020).

$$\operatorname{Minimize}(\operatorname{Cost}) = VOT^{car} \sum_{(i,j)\in \mathbb{R}} \int_{0}^{f_{ij}^{h_i h_f}} t_{ij}^{h_i h_f} df + VOT^{walk} \sum_{(i,j)\in \mathbb{R}} \sum_{(o,d)\in \mathbb{P}} w_{ijod}^{h_i h_f} \frac{L_{ij}}{\tau}$$
(1)

$$\sum_{i \in I} f_{ojod}^{v \, h_i h_f} = D_{od}^{v \, h_i h_f}, \forall \ (o, d) \in \mathbf{P}, v \in \mathbf{V}, D_{od}^{v \, h_i h_f} > 0$$
⁽²⁾

$$\sum_{i=1}^{v} f_{jdod}^{v \ h_i h_f} = D_{od}^{v \ h_i h_f}, \forall \ (o, d) \in \mathbf{P}, v \in \mathbf{V}, D_{od}^{v \ h_i h_f} > 0$$
(3)

$$\sum_{i \in I}^{v \ h_i h_f} f_{ijod}^{v \ h_i h_f} = \sum_{i \in I}^{v \ h_i h_f} f_{jiod}^{v \ h_i h_f}, \forall (o, d) \in \mathbf{P}, i \in I, v \in \mathbf{V}, D_{od}^{v \ h_i h_f} > 0, i \neq o, d$$
(4)

$$\int_{ij}^{h_i h_f} = \sum_{\substack{(o,d) \in P}} \left[\left(\alpha_{automated} * z_{ijod}^{h_i h_f} + \alpha_{mixed} * \left(f_{ijod}^{AV h_i h_f} - z_{ijod}^{h_i h_f} \right) \right] + \left(f_{ijod}^{CV h_i h_f} \right) \right] \forall i, j \in I$$
(5)

$$z_{ijod}^{h_i h_f} \ge f_{ijod}^{AV h_i h_f} - M * (1 - x_{ij}), \forall (i, j) \in \mathbf{R}, (o, d) \in \mathbf{P}, D_{od}^{AV h_i h_f} > 0$$
(6)

$$z_{ijod}^{h_i h_f} \le f_{ijod}^{AV h_i h_f}, \forall (i,j) \in \mathbf{R}, (o,d) \in \mathbf{P}, D_{od}^{AV h_i h_f} > 0$$

$$\tag{7}$$

$$z_{ijod}^{h_i h_f} \le C_{ij} * x_{ji}, \forall (i,j) \in \mathbf{R}, (o,d) \in \mathbf{P}, D_{od}^{AV h_i h_f} > 0$$

$$\tag{8}$$

$$w_{ijod}^{h_ih_f} \ge f_{ijod}^{CV \ h_ih_f} - M * (1 - x_{ij}), \forall (i, j) \in \mathbf{R}, (o, d) \in \mathbf{P}, D_{od}^{CV \ h_ih_f} > 0$$

$$(9)$$

$$w_{ijod}^{(n,i)} \leq f_{ijod}^{(n,i)}, \forall (i,j) \in \mathbf{R}, (o,d) \in \mathbf{P}, D_{od}^{(i,i)} > 0$$

$$(10)$$

$$w_{ijod}^{h_ih_f} \le w_{ijod}^{h_ih_f} + C_{ij} * x_{ij}, \forall i, j \in \mathbf{I}, (o, d) \in \mathbf{P}, i \neq o, d, D_{od}^{CV} h_i^{h_f} > 0$$

$$\sum w_{ijod}^{h_ih_f} \le \sum w_{ijod}^{h_ih_f}, \forall i \in \mathbf{I}, (o, d) \in \mathbf{P}, i \neq o, d, D_{od}^{CV} h_i^{h_f} > 0$$

$$(12)$$

$$\sum_{j \in I} j_{ioa} = \sum_{j \in I} i_{joa}$$
(12)

$$\sum_{ojod}^{n_in_f} \le D_{od}^{CV} * x_{oj}, \forall j \in I, (o,d) \in \mathbf{P}o \neq d, D_{od}^{CV} * n_in_f > 0$$

$$(13)$$

$$w_{idod}^{h_ih_f} \le \sum_{j \in I} w_{jiod}^{h_ih_f} + C_{id} * x_{id}, \forall i \in I, (o, d) \in \mathbf{P}, i \neq d, D_{od}^{CV \ h_ih_f} > 0$$

$$\tag{14}$$

$$f_{ij}^{h_ih_f}, f_{ijod}^{v \, h_ih_f}, w_{ijod}^{h_ih_f}, z_{ijod}^{h_ih_f} \in \mathbb{N}, \forall \ (i,j) \in \mathbf{R}, (o,d) \in \mathbf{P}, D_{od}^{AV \ h_ih_f} > 0$$
(15)

Constraints (2)-(4) assure that, for each O-D pair, both AVs and CVs flows ($v \in V$) are generated in the origin node $o \in \mathbf{0}$ (2), absorbed in the destination node $d \in \mathbf{D}$ (3), and there is a flow equilibrium in the intermediate nodes(4). Constraints (5) compute the total flow in each link $(i,j) \in \mathbf{R}$. The AVs flow involves a benefit that is computed through the auxiliary variable $z_{ijod}^{h_ih_f}$ - the benefit varies if traffic is mixed or automated through constraints (6)-(8). In dedicated roads, the variable assumes AV flow through constraints (6) and (7), whereas in regular roads, this variable is null by constraints (8). Constraints (9)-(14), define the walking flows. CV travelers can park and walk until destination when their driving path is blocked by a dedicated road, and if walking is more cost-efficient than detouring. Constraints (9) and (10) assure that for a dedicated link ($x_{ij} = 1$) the walking flow is identical to the CV flow. In the remaining roads, i.e., $x_{ij} = 0$, the range is bounded to be in the interval $[0; f_{ijod}^{CV}] \forall (i, j) \in \mathbf{R}, (o, d) \in \mathbf{P}$. Yet the lower limit of that interval is naturally chosen since this is a minimization problem. Constraints (11) assure that the walking flow of every link $(i, j) \in \mathbf{R}$ is limited to the preceding flow of link $(j, i) \in \mathbf{R}$ and extra walking flow might be added if that link is dedicated. Constraints (12) guarantee the continuity of the walking flow through the network: walking flow departing node $i \in I$ shall be higher than the walking flow arriving at that node, except in the origin and destination of every O-D pair. Constraints (13) assure that travelers shall start their trips with CVs if such trip origin is not entirely surrounded by AV subnetworks, yet they must start their trips on walking if the origin is inside an AV subnetwork. Constraints (14) absorb the walking flows from the preceding links in the links surrounding the destination node of every trip. Constraints (15) set the domain of the decision variables.

4. Application to the case study: the city of Delft, the Netherlands

The application (Conceição et al., 2020) was exemplified in a quasi-real case study: the city of Delft, in the Netherlands. The original travel database (MON 2007/2008) was provided by the Dutch government for transport research. 60300 trips were considered through 58 O-D pairs among 12 centroids (Correia and van Arem, 2016). Regarding the capacity increase in mixed traffic conditions, a second-degree curve was adapted from (Calvert et al., 2011). The AVs flow is discounted through a coefficient that has an inverse relationship with the capacity benefit:

 $\alpha_{mixed} = 1/Adjusted Capacity;$ whereas $\alpha_{automated} = 1/1.68 \approx 0.60$ (Conceição et al., 2020). The reference value of travel time spent inside CVs (*VOT*^{car}) in the Netherlands is considered to be 10 € per hour (Yap et al., 2016). The reference value of time while walking (*VOT*^{walk}) is considered 20% higher than while driving: 12 € per hour. The walking cost is higher than the driving cost, which is believed to represent the reality nowadays. The walking travel time was computed from the average pedestrian's speed on an empty sidewalk, of 5.0 ft/s equivalent to 5.48 km/h, i.e., a default walking free-flow speed (HCM, 2010). The scenarios evaluated under this framework were the ones created in the previous (Conceição et al., 2020). Three scenarios experimented: Scenario O, without AV subnetworks (for comparison purposes only); Scenario I was envisioned for 90% of AVs, which will happen somewhere between 2060-2080 (Nieuwenhuijsen et al., 2018) and AV subnetworks in the transition period were designed for long-term planning strategy that reversely removes dedicated roads from the last design stage; Scenario II was envisioned with a road investment added in the objective function and AV subnetworks in the transition period were design stage. Fig. 2 shows the progression of AV subnetworks in each scenario.



Fig. 1 - RNDP-AVs peak-hour design: AV subnetworks progression in Scenarios I-LTP and II-IP.

Fig. 2 resumes the results obtained in terms of daily costs on each scenario I and II. Each hourly traffic assignment was computed in a few seconds on every scenario. Both scenarios revealed sensitive results, with increased 26.0% and 43.8% travel costs when AVs are 75% of the vehicle fleet in comparison with scenario O. It seems that walking, as the alternative mode of transport, is inevitable and would only occur on those stages.



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Fig. 3 depicts walking in every hour occurring at each design stage. Walking is inevitable when AVs reach a penetration rate of 75% onwards. The worst-case (higher costs) is the scenario I, because AV subnetworks are widespread when no road investment is involved. Walking occurs throughout the day in the scenario I, almost every hour. This varies according to the shifting trips demand (O-D matrix) throughout the day. In scenario II, AV subnetworks are substantially smaller because the road investment already limited the creation of AV subnetworks, and therefore walking does not occur so often.



Fig. 4 (a) illustrates the average degree of saturation experienced during the day. Scenario I, under long-term planning, is able to reduce the degree of saturation by 8.8% when AVs are 10% of the fleet, and when AVs reach 90%, the degree of saturation reduces 13.1%. Scenario II – when an investment is involved – it only reduces 4.0% when AVs are 10% of the fleet and 9.7% at the end of the transition period. In scenario II, the most significant contribution of AV subnetworks is during the transition period from 25% to 90% of AVs, achieving 7.0-13.1% of reduction. Fig. 4 (b) shows the length (in kilometers) of congested roads throughout the day, i.e., when traffic flow is near practical capacity, above a degree of saturation of 75%. Congested roads are not obvious to predict, given the shifting trips demand throughout the day. The peak depicted in the scenario I under long-term planning for a penetration rate of 10% may suggest that AV subnetworks should only start when AVs reach 25% of the vehicle fleet (in case that AVs level 4 do not need any investment to be able to read the roads). Overall, it is conclusive AV subnetworks mitigate the length of congested roads after that penetration rate (25% of AVs). Walking plays an essential role in reducing congestion in the latest design stages (75% of AVs onwards).



Fig. 4 - RNDP-AVs peak-hour design with walking as an alternative: (a) daily average DS (degree of saturation), (b) daily congested roads (km).

Fig. 5 (a) depicts the daily delay among AVs and CVs to scenario O where AV subnetworks do not exist. The results suggest that in scenario I under the long-term strategy, CV delay increases at the beginning of the transition period and decreases in the latest stages, starting at 50%. In scenario II, under an incremental strategy, CV delay is essentially reduced after 75%. Note for a penetration rate of 75 and 90%, the reduction of the delay is due to the existence of walking trips in this deployment stage. Looking at the AV outcomes, the delay is always reduced, no matter which stage of the transition period, except for a penetration rate of 1% where AV delay increases by 2% in both scenarios. Fig. 5 (b) illustrates the daily distance results of AVs and CVs in both scenarios. It seems that the use of AV subnetworks imply that CVs may have to travel longer in the latest stages of the transition period but note that there are fewer CVs in these stages. In scenario I, AVs also travel longer except when there is 1% of AVs. In terms of distance, scenario II is the one that presents the best results. CV distance increase by 5% and up to 7% at the end of the period, while AV distance is close to null throughout the transition period.



Fig. 5 - RNDP-AVs peak-hour design with walking as an alternative: (a) daily delay, (b) daily distance.

5. Conclusions and future work

This paper estimated the implications of the peak-hour design in the remaining hours of the day, and walking was created as the alternative for CVs when there was no other option left than walking, i.e., in cases where CV detour is not available or is more expensive than walking itself.

Through the application in the scenarios created for the case-study of Delft, such situation (walking) only happened for significant shares of AVs, 75% onwards - which is explained by the widespread of AV subnetworks in these stages. Travel costs can rise up to 26.0% and 43.8%, depending on the scenario – which is significant enough to reconsider the usual practical design for the peak hour in transport planning. Such a design will ignore different mobility patterns and shifting trip patterns. Nevertheless, it is also shown that AV subnetworks can decrease the daily average degree of saturation (a congestion traffic indicator) by 8.8% and 13.1%. It is also obvious that throughout the day, congested roads (with a degree of saturation over 75%) are essentially reduced when AVs surpass 50% of the vehicle fleet. CV delay is also reduced in the latest stages of the transition period, whereas AVs seem to benefit from the beginning. CV distance is mainly affected and worsened by AV penetration rates 75% onwards.

Nevertheless, the model was formulated with the introduction of some simplifications and assumptions - representing a simplistic scenario where walking is the only alternative. Further research shall include more accurate traffic efficiency parameters, but also public transportation as another alternative mode of transport – yet, it would involve both bus routes and schedules, transforming the whole RNDP into a massive combinatorial transit assignment problem.

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