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Open problems in transportation engineering with connected and autonomous vehicles

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Abstract

In recent decades, technologies that can lead to fully automated driving have had a rapid development. In this framework, 'road transport automation' can potentially result in significant changes to the operation of road systems throughout the world. It is impossible to foresee how long it will take to realize such potential changes, because there are many uncertainties about both the technologies to deploy, and the policy environment where they should be deployed. 'Full automation' is the future of road transport, but the transition from manual to fully autonomous vehicles is especially dependent on the interactions between humans and automation, but also between automated vehicles and manual vehicles, and between automated vehicles and infrastructure.

In the above context, this paper, after introducing some open problems related to automated vehicles, focuses on a particular one, consisting of the simplified evaluation of the equilibrium points achievable by a mixed flow with different percentages of automated vehicles. The aim of the considered problem is to provide a first general estimation of the performance of an existing network in various scenarios, characterized by different percentages of autonomous vehicles and mobility demand. More in detail, a simplified kinematic supply model is introduced to assess the link flow/cost performances, aiming at estimating the potential congestion reduction. An application to a real word network is described, and the relevant results are reported and discussed.

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Keywords: autonomus vehicles; link flow/cost relation; traffic assignement

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1. Introduction

In recent years, the development of almost completely automated vehicles and the performed test of their prototypes on common roads has put into evidence that a significant change in transportation systems is going to occur. In this framework, different papers (Eckart and Vairavamoorthy, 2013; Levin and Boyles, 2015; Hoogendoorn et al., 2015) addressed some impact forecasts on pollution, energy saving, mode choice, and safety. Hence, beyond the continuous technology development, it seems interesting to focus on the forecast functionalities of autonomous vehicles, and investigate the problems and the opportunities related to this class of vehicles in terms of traffic performances.

In this context, to understand the better present condition and the near future perspective, it is possible to look at the functional classification among vehicles proposed in SAE J3016 Information Report ‘Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems’ (SAE, 2014):

Class 1 – human driver monitors the driving environment

- *Level 0:* the full-time performance by the human driver of all aspects of the dynamic driving task, even when enhanced by warning or intervention systems.
- *Level 1*: the driving mode-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment, and with the expectation that the human driver performs all remaining aspects of the dynamic driving task.
- *Level 2*: the driving mode-specific execution by one or more driver assistance systems of both steering and acceleration/deceleration using information about the driving environment, and with the expectation that the human driver performs all remaining aspects of the dynamic driving task.

Class 2 – automated driving system monitors the driving environment (hereafter addressed as ‘autonomous vehicles’)

- *Level 3:* the driving mode-specific performance by an automated driving system of all aspects of the dynamic driving task with the expectation that the human driver will respond appropriately to a request to intervene.
- *Level 4*: the driving mode-specific performance by an automated driving system of all aspects of the dynamic driving task, even if a human driver does not respond appropriately to a request to intervene.
- *Level 5*: the full-time performance by an automated driving system of all aspects of the dynamic driving task under all roadway and environmental conditions that can be managed by a human driver.

Given this classification, it results evident that at least the functionalities of the first class (SAE Levels 0-3) are already reached by many circulating vehicles. At the same time, it is apparent that the movement towards the scenario with only Level 5 vehicles circulating in the network can only be gradual, and totally prone to the solution of many different considerable problems mainly resulting from the interactions between human behaviour and automation, automated vehicles and infrastructure, automated vehicles and other traffic flow components.

In this framework, a central task consists of understanding and managing the transition among stages, when vehicles of all the six relevant classes are together in the networks. In particular, beyond the evident safety problems, fundamental questions are related to traffic network equilibria, where it would be interesting to understand, for instance:

- if the dynamic process that leads to an equilibrium with fixed or elastic demand (Payre et al., 2014), characterized by the different interacting dynamics, one for each class of vehicles, provides the same solutions that can be reached with traditional vehicles, maybe with different transient trajectories. Moreover, assuming that users can shift among vehicles with functionalities of classes due to different support capabilities of the road infrastructure, is the equilibrium stable? (Talebpour and Mahmassani, 2015)
- if there are particular functional specifications that vehicles, or infrastructure, must fulfill to better guarantee the effectiveness of a transportation network (Hoogendoorn et al., 2014; Kesting et al., 2007).
- which problems rise if autonomous transit modes are considered.
- how far the network equilibria are from the System Optimum, and if it is possible to drive the system towards it.

In the above classification, the technological problems related to the ICT infrastructure are neglected, although it is clear that, in the transition phase, the higher levels of automation are achievable only when the infrastructure enables them. Moreover, other issues regard the effects of automation on users' awareness of the situation, as well as drivers' behaviours in varying traffic conditions (Jamson et al., 2013), in critical situations (Merat et al., 2014), towards safety in general (Hoogendoorn et al., 2015), or even security (Petit and Shladover, 2015).

By the way, in this paper the attention is focused on the last of the above questions, aiming at modelling the interactions among the vehicles making up a mixed road traffic flow, i.e., manually driven, connected, and automated vehicles, so as to determine a simplified approach to estimate the whole network performance. The considered approach is based on a macroscopic approach (Bose and Iannou, 2003) by deriving, via a simplified kinematic approach, the relation between the stream flow and the average stream speed, and provides a static approximation of the average traffic flows and the deriving network performances. In doing so, the fast dynamics of autonomous vehicles are neglected, although the considered approach results to be sufficient for estimating a global performance of the whole traffic network, and especially the performance trend with increasing mobility demand. To this aim, the System Optimum (SO) assignment for different scenarios is evaluated as a benchmark for the equilibria reached in some scenarios with different percentages of autonomous vehicles.

The paper is organised as follows: first, the considered problem is described, together with the simplified macroscopic modelling approach. Then, after introducing the assignment framework, the application to a simplified realistic case study is reported and discussed.

2. The considered problem

This section introduces the general framework of the problem of understanding the effect of autonomous vehicles in urban transport networks. To this purpose, a multiclass assignment problem is defined and solved for two possible choice criteria for 'No – Partially Autonomous (NPA) vehicles (SAE Levels 0–3)' and 'Highly – Fully Autonomous (HFA) vehicles' (SAE Levels 4–5):

In doing so:

1. a simplified macroscopic supply model is considered, assuming that different classes of vehicles are uniformly distributed on the links;
2. HFA vehicles are considered as 'users' whose choice process is almost deterministic. Such an assumption relies on the fact that it is reasonable to assume that, on one side, the path choice algorithms of such vehicles are a-priori known and can take the advantage of knowing exactly the state of the network. Nevertheless, since 'human deciders' are assumed to be always allowed to intervene in the path decision process, and also to take into account unidentified dynamics that generate model uncertainties, the path choice of a HFA vehicle is still modelled via Gumbel stochastic variables with small variance parameter $\theta_{HFA}^2 \ll \theta_{NPA}^2$, being θ_{NPA}^2 the variance parameter of human deciders;
3. both the classes of vehicles are assumed to choose among the different paths only with a generalized cost criterion, that is, minimizing the travel time and cost.

Further minor assumptions are:

- for each O/D pair only the first K alternative paths are considered. Therefore, the link – path incidence matrix is $\Delta \in \mathbb{R}^{na,K\cdot np}$, where na is the number of links of the network, and np is the number of O/D pairs with non-null demand;
- a Cross-Nested Logit Model (Vovsha et al., 1998) is used for modeling the decision process of human deciders, whereas autonomous vehicles are assumed not to be influenced by the perception of overlapping of paths, knowing the path costs exactly;
- the O/D matrixes $OD_{HFA} = [d_{HFA}(o,d)]_{\forall o,\forall d}$ and $OD_{NPA} = [d_{NPA}(o,d)]_{\forall o,\forall d}$ are assumed to be known and constant.

2.1. The supply model

In the considered model, the traffic network is represented by a graph $G = \{N, L, t\}$ where $N = \{i\}_{i=1}^{n}$ is the set of n nodes, $L = \{(h, l)\}_{h,l \in N}$ is the set of links, $t: L \rightarrow \mathbb{R}$ is a function assigning a weight to each link.

Since the traffic network is assumed to be in general congested, the travel time on each generic link (h, l) depends on the total traffic flow $f_{h,l} = f_{h,l}^{HFA} + f_{h,l}^{NPA}$, being $f_{h,l}^{HFA}$ the HFA traffic flow and $f_{h,l}^{NPA}$ the NPA traffic flow, and on the percentage of HFA vehicles with respect to the $f_{h,l}$, hereafter indicated as $p_{h,l} = f_{h,l}^{HFA} / f_{h,l}$. It is worth noting that, in the following, for the sake of clearness, the subscript (h, l) will be dropped.

Then, the analytical model of the travel time can be determined considering the inter-vehicle spacing among vehicles to be the weighted sum

$$s_{mix} = p s_a + (1 - p) s_m \tag{1}$$

based on the NPA spacing s_m and the HFA spacing s_a.

Then, considering that the traffic density can be in general expressed as the inverse of the spacing, that is, $k = 1/s$, it is possible to write the average mix density

$$\frac{1}{k_{mix}} = p s_a + (1 - p) s_m \tag{2}$$

Therefore, since the average traffic stream speed is constrained to the speed of the slowest vehicles, then $v_{mix} = v_a = v_m$, dividing both hands of Eq. (2) by v_{mix} , it is possible to obtain the inverse of the stream flow as

$$\frac{1}{q_{mix}} = \frac{1}{v_{mix} k_{mix}} = \frac{p s_a + (1 - p) s_m}{v_{mix}} \tag{3}$$

Moreover, in congested links where vehicles interact with each other, the inter-vehicle spacing can be written as

$$s_m = \left(\frac{v_{mix}^2}{2 a_m} + t_r v_{mix} + \lambda \right) \tag{4}$$

and

$$s_a = \left(\frac{v_{mix}^2}{2 a_a} + \lambda \right) \tag{5}$$

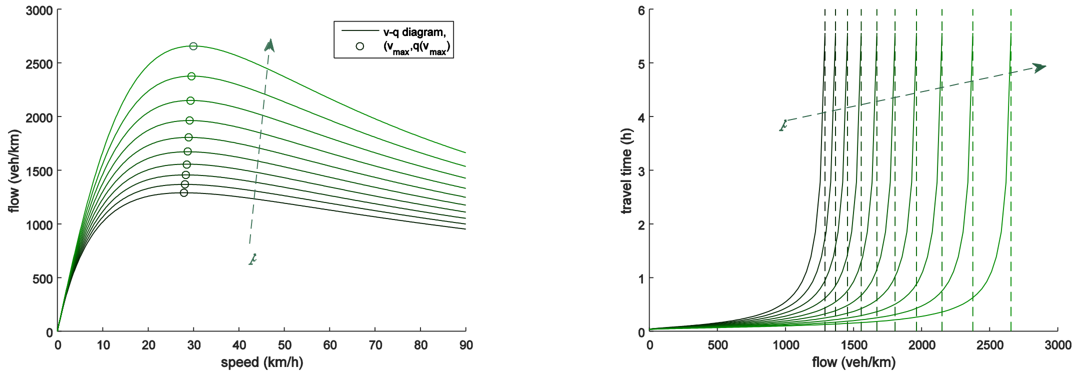
for manual and automated vehicles, respectively, being λ the average vehicle length, and a_m (resp., a_a) the maximum deceleration of the manual (resp., autonomous) vehicles. In Eq. (5) it is assumed that the reaction time of autonomous vehicles is negligible with respect to that of the manual ones.

Hence, it is possible to rewrite Eq. (3) as

$$\frac{1}{q_{mix}(v_{mix}, p)} = p \left(\frac{v_{mix}}{2a} + \frac{\lambda}{v_{mix}} \right) + (1 - p) \left(\frac{v_{mix}}{2a} + \frac{\lambda}{v_{mix}} + t_r \right) \tag{6}$$

which allows to determine the mixed traffic flow in function of the traffic speed $q_{mix}(v_{mix}, p)$ as

$$q_{mix}(v_{mix}, p) = \frac{1}{p \left(\frac{v_{mix}}{2a} + \frac{\lambda}{v_{mix}} \right) + (1 - p) \left(\frac{v_{mix}}{2a} + \frac{\lambda}{v_{mix}} + t_r \right)} \tag{7}$$



(a) (b)

Fig. 1. Stream average speed/flow and stream flow/travel time relations for different values of autonomous vehicle percentages.

Table 1. Model parameters.

λ	8m
t_r	1 s
a_m	5 ms^{-2}
a_a	5 ms^{-2}

whose shape is reported in Fig. 1 for different percentages of HFA vehicles. The maxima of $q_{mix}(v_{mix}, p)$, indicated in Fig. 1, denote the maximum capacity for different values of p.

Finally, the travel time with respect to the stream flow for all the network links is computed as

$$t(q_{mix}, p) = \frac{L}{v_{mix}(q_{mix}, p)} \tag{8}$$

being $v_{mix}(q_{mix}, p)$ the average vehicle speed obtained by inverting Eq. (8) and L the length of a generic link.

Assuming the values in Tab. 1 for the model parameters, the shapes of the speed-flow and flow-cost functions of a generic arc of 1 km are reported in Fig. 1, where the functions are depicted for different values of percentage p. In particular, the maximum flow (i.e., the link capacity) versus the stream speed is indicated in Fig. 1.a. Such values correspond to the dashed lines in Fig. 1.b.

2.2. The assignment problem

As regards the considered assignment problem, whose logical scheme is depicted in Fig. 2, it consists of a two--classes assignment based on the Stochastic User Equilibrium (SUE) model. In doing so, the path choice process is represented by a Cross Nested Logit (Vovsha and Bekhor, 1998) in which, considering that autonomous (and in general connected vehicles) know and compare reliable travel times of the different alternatives, the relevant commonality factor is set to 0.

As regards the model details, at each iteration i, given the column $\Delta_{k,od}$ of the link-path incidence matrix of the k^{th} path connecting the pair o/d, the vector $\boldsymbol{c}(\boldsymbol{f}^{(i)})$ of the link costs depending on the link flows $\boldsymbol{f}^{(i-1)}$ computed at the $(i-1)^{th}$ iteration, and the commonality factor $CF_{k,od}$ for manual vehicles, the path systematic utilities

$$V^a_{k,od}\left(\boldsymbol{f}^{(i-1)}\right) = -\Delta^{\mathrm{T}}_{k,od}\boldsymbol{c}\left(\boldsymbol{f}^{(i-1)}\right), \forall k, \forall o, d \tag{9}$$

for autonomous vehicles, and

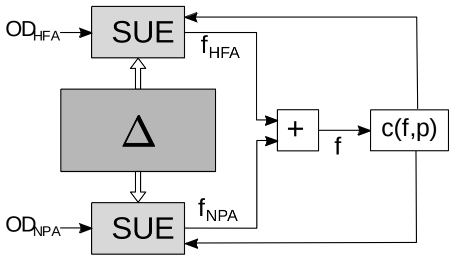


Fig. 2. Model logical scheme

$$V^{m}_{k,od}\left(\boldsymbol{f}^{(i-1)}\right) = -\Delta^{\mathrm{T}}_{k,od}\boldsymbol{c}\left(\boldsymbol{f}^{(i-1)}\right) - CF_{k,od}, \forall k, \forall o, d \tag{10}$$

for human deciders are determined. In turn, the two probability matrices P_m and P_a expressing, for each O/D pair and for each path, the relevant choice probability for manual and automated vehicles, respectively, are determined. The entries of these matrices are determined with the usual formulation in the Logit based models and by means of the systematic utilities computed by means of Eq. (9) and Eq. (10).

Then, the output of the SUE module consists of the total manual and automated path flows, namely $\boldsymbol{h}_a^{(i)}$ and $\boldsymbol{h}_m^{(i)}$, the total one $\boldsymbol{h}^{(i)} = \boldsymbol{h}_a^{(i)} + \boldsymbol{h}_m^{(i)}$, and the corresponding total link flows $\boldsymbol{f}^{(i)}$ which are used to determine link costs by the Link Cost /Mixed Flow.

The link cost identified by the Link Cost /Mixed Flow Function module represents the input, at the following iteration, of the Mixed Traffic Assignment module, making possible for it to update route flow and cost.

The outputs of the SUE assignment process are the equilibrium link flow $\boldsymbol{f}_{eq}$, the relevant equilibrium link cost $\boldsymbol{c}_{eq}$, and the total cost at the equilibrium $CT_{eq} = \boldsymbol{c}_{eq}^T\, \boldsymbol{f}_{eq}$.

2.3. Performance benchmark

To understand the goodness of the network performances, the solution obtained via the System Optimum (SO) assignment is considered. Such a solution is provided by the well-known problem

$$\begin{aligned} &\boldsymbol{f}_{opt} = \arg\min \boldsymbol{c}(\boldsymbol{f})^T \boldsymbol{f} \\ &s.t. \\ &\boldsymbol{f} \in S_f \end{aligned} \tag{11}$$

where $S_f = \{\boldsymbol{f} | \boldsymbol{f} = \sum_{od} \boldsymbol{\Delta}_{od}\boldsymbol{h}_{od}, \boldsymbol{h}_{od} \geq 0, \mathbf{1}^T\boldsymbol{h}_{od} = d_{od}\}$ is the set of admissible flows.

Since the solution of the problem in Eq. (11) represents the ideal case in which the total cost is minimized, then the term $CT_{opt} = \boldsymbol{c}_{opt}^T\left(\boldsymbol{f}_{opt}\right)\boldsymbol{f}_{opt}$ can be used as a comparison term for the equilibrium total cost for different values of the autonomous vehicle percentage p.

It is reasonable to expect that the cost performances of the whole road transportation network improve with the percentage of autonomous vehicles, and the equilibrium and optimum total costs decrease.

3. An application example

As an application example, the portion of the Italian city of Genoa depicted in Fig. 3, covering an area of about 50 km^2, is considered. The relevant main transportation network can be represented by means of a graph with 57 nodes and 155 arcs (those in dashed lines represent the railway links), selected by taking into account the topology of the city. Such a network, which is relatively small, is considered without losing generality with the aim of keeping the implementation and the result analysis simple enough, in particular:

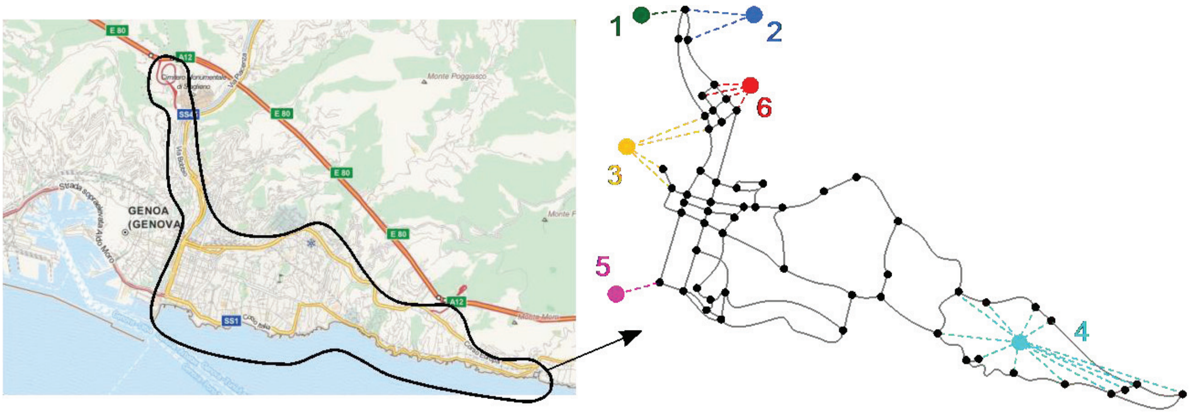


Fig. 3. Case study road transportation network graph and the relevant schematic graph.

Table 2. O/D matrix for the 'Morning peak scenario' (1 – Genova Est (Highway Gate), 2 – Alta Val Bisagno, 3 – Centro (City center), 4 – Levante (Eastern side), 5 – Ponente (Western side), 6 – Marassi, 7 – (Stadium)).

	1	2	3	4	5	6	7
1	-	10	350	80	10	100	10
2	10	-	200	50	10	50	-
3	50	10	-	30	10	50	-
4	-	10	350	-	-	150	-
5	-	5	150	30	-	100	-
6	-	5	350	50	120	-	-
7	-	-	-	-	-	-	-

1. for verifying the actual capacities of the links with those computed with $p = 0$ (verification details are not reported due to the lack of space, although it is worth saying that a set of 23 links have been considered, with 15% maximum error);
2. when comparing the results in different scenarios.

Evidently, a more detailed network can be easily analysed, being the static assignment algorithms well known and easy to implement.

Coming back to the case study, two scenarios with different mobility demand, characterized by the O/D matrices reported in Tab. 2 and Tab. 3, are analysed. The first one represents a typical morning rush hour, and is characterized by a trip demand directed to the 'City Centre' and 'Ponente' (western side of the city), where the administrative offices and the production activities, respectively, are localized. Such scenario is characterized by a high total demand.

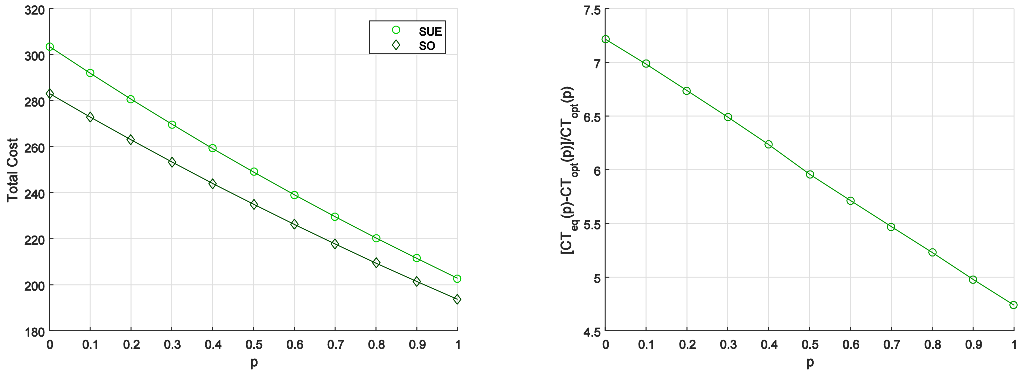
The second scenario represents a 'Soccer Sport Event', and is characterized by a trip demand directed to the stadium from the other zones. Such scenario is characterized by a medium total demand.

As regards the results, the SUE and SO total costs, namely CT_{eq} and CT_{opt}, are reported in Fig. 4.a and Fig. 5.a for different values of the autonomous vehicles percentages.

In both figures, it is possible to note that the equilibrium and optimum total costs decrease with the percentage p. In particular, although in a simplified case study, it is easy to observe that starting from $p \geq 0.2$, the total cost at the equilibrium is smaller that the optimum total cost with only manual vehicles ($p = 0$). Such results point out the formidable potentiality of autonomous vehicles: even with a small market penetration, the road network can achieve better performances than in the (ideal) optimal condition with only manual vehicles.

Table 3. O/D matrix for the 'Sport event' peak scenario (1 – Genova Est (Highway Gate), 2 – Alta Val Bisagno, 3 – Centro (City center), 4 – Levante (east side), 5 – Ponente (West side), 6 – Marassi, 7 – Stadium)).

	1	**2**	**3**	**4**	**5**	**6**	**7**
1	-	-	-	20	10	-	300
2	30	-	-	0	20	-	200
3	10	-	-	-	30	-	300
4	10	-	-	-	30	-	300
5	0	-	25	-	-	25	30
6	-	-	10	-	-	-	300
7	10	-	-	20	-	-	-



(a) (b)

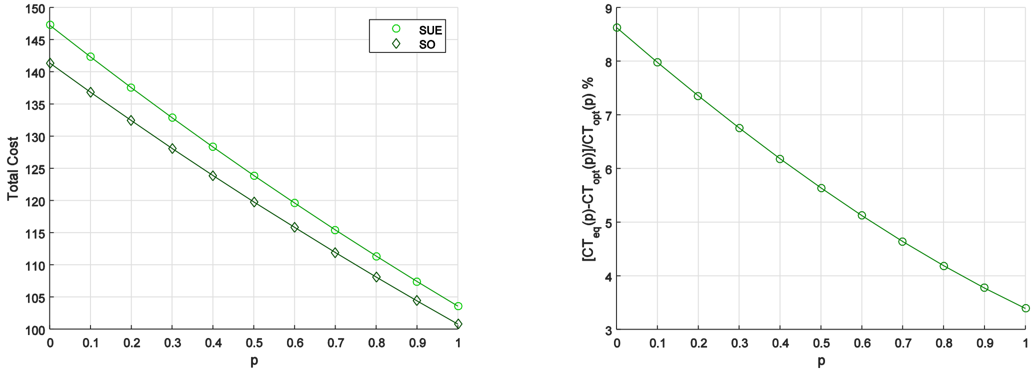
Fig. 4. Total cost for the 'Morning Peak Hour' scenario.

Moreover, Fig. 4.b and Fig. 5.b show that, in both scenarios, the relative difference $[CT_{eq}(p) - CT_{opt}(p)]/CT_{opt}(p)$ decreases with p, indicating that, as the general congestion level improves, the paths chosen by users at the equilibrium tend to coincide with those minimizing the total cost. Finally, considering a fixed autonomous vehicle percentage $p = 1$, Fig. 6.a and Fig. 6.b show the amplification factor that can be applied to the trip demand in the two scenarios in Tab. 2 and Tab. 3, without exceeding the total cost $CT_{eq}(0)$. Such figures show that, for the 'Peak Hour' scenario with only automated vehicles, it is possible to multiply the trip demand by an amplification term of about 1.9 ($i = 3$) without exceeding the cost $CT_{eq}(0)$. Analogously, in the 'Sport Event' scenario, it is possible to multiply the trip demand by an amplification term of about 3.1 ($i = 7$) without exceeding the cost $CT_{eq}(0)$.

Again, these last results show the potentiality of road networks of managing a significant increase in traffic demand without an evident performance loss with respect to the present situation, identified by $p = 1$. Such a result shows that an average improvement of the network performance can be reached without any investment on the civil infrastructure in the considered area. To conclude, it is worth saying that the considered assignment process also provides the level of service of each link, allowing to determine which of them requires a more detailed analysis.

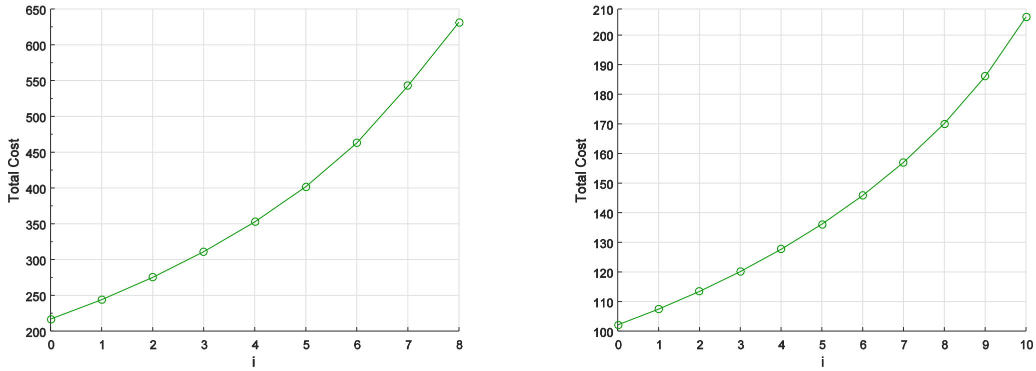
4. Conclusions and future developments

In this paper, some 'traffic' issues related to vehicles automation are analysed. Therefore, the attention is focused on the evaluation of the effects of the gradual penetration of autonomous vehicles among 'traditional' manual traffic flows. To do so, a simplified kinematic supply model has been determined and the relevant application to a real-world road network in the Italian city of Genoa has been developed via a mixed assignment problem. In this framework, the Stochastic User Equilibrium and the System Optimum states of the network have been determined and compared. The obtained results show that the introduction of automated vehicles in the traffic stream significantly enhances the road link performances, and therefore helps reducing the global network congestion.



(a) (b)

Fig. 5. Total cost for the ‘Sport Event’ scenario.



(a) (b)

Fig. 6. Total cost at the equilibrium with O/D matrices multiplied by factor amplification $= 1 + 0.3i$.

Work is in progress for enhancing the model by taking into account different path choice criteria for automated vehicles. For instance, a promising criterion could be based on the ‘propensity’ of automated vehicles to choose the path which guarantees the highest automation performance, so as to take the best advantages from the technological equipment of the infrastructure.

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