Autonomous public transport: more frequent services, smaller vehicles, reduced fare and reduced subsidy

Alejandro Tirachini ([a,b]), Constantinos Antoniou ([b])

([a]) Transport Engineering Division, Civil Engineering Department, Universidad de Chile.
([b]) Chair of Transportation Systems Engineering, Department of Civil, Geo and Environmental Engineering, Technische Universität München, Germany.
Alejandro.tirachini@gmail.com
c.antoniou@tum.de

Abstract

Driverless vehicles will eliminate one of the main elements that cause economics of scale in public transport: drivers' wages. Therefore, the cost advantage of placing many travellers in large buses will be reduced; thus mobility services with smaller vehicles are expected to play a larger role in the future. In this paper, the effect of automation on shared or public mobility services is addressed with a supply optimisation model that takes into account both users and operator costs. We extend current cost models for autonomous vehicles that focus on operator costs only. Vehicle frequency and size are optimised to minimise total (user plus operator) costs; optimal fare and subsidy is also derived. The model can be solved for increasing levels of demand. We show that the benefits of the reduction in vehicle operating cost due to automation benefit three parties: (i) operators, through a reduction of operator costs; (ii) public transport users, through a reduction on waiting times and on the fare to be paid for the service, and (iii) the public sector, through a reduction on the optimal subsidy to be allocated to the public transport system. The size of these savings in some cases are straightforwardly estimated and in others depends on the parameters of the problem.

Keywords: autonomous vehicles, public transport, shared mobility, total cost, first-best pricing

1. Introduction

Driverless vehicles will eliminate one of the main elements that cause economics of scale in public transport: drivers' wages. Therefore, the cost advantage of placing many travellers in large vehicles such as buses will be reduced; thus mobility services with smaller vehicles is expected to have a large role in a future of autonomous vehicles. Some empirical estimations of the dramatic effects of automation on reducing the costs of motorised shared mobility have been made. For example, Bösch et al. (2018) estimated that automation can reduce the cost of taxi trips by 85% in Zurich, Switzerland, mainly because of the savings in drivers' salary. In this paper, the effect of automation on public mobility services is addressed with a supply optimisation model that takes into account both users and operator costs. Thus, we extend current cost models for autonomous vehicles that focus on operator costs only (e.g., Bösch et al. 2018), to the inclusion of users costs in the form of access, waiting and in-vehicle times. Vehicle frequency, vehicle size and optimal fare and subsidy are obtained and analysed. It is expected that automation will increase the demand threshold that justifies the adoption of bigger vehicles, therefore smaller vehicles will be deployed in a wider range of scenarios as compared to the current situation.

2. The economics of public transport: total cost minimization

2.1 Optimal headway and vehicle size on a single line

Almost 40 years ago, J.O. Jansson showed that crew costs were by far the largest cost item of local bus companies in Sweden, accounting for 42% of the total operator cost, followed by bus capital costs, which represented 21% of the total costs (Jansson 1980). The large role of drivers wages within the cost structure of urban bus transport does not seem to have changed much over the years, as we will see in this study. Therefore, it is expected that vehicle automation will have profound impacts in the public transport industry and service in the next decades.

We model one hour of operation. Total cost of a public transport service is comprised of operator and user cost as follows:

$$C_{tot} = c\ B + P_a t_a + P_w t_w + P_v t_v \tag{1}$$

Where c is the cost per bus unit [€/veh-h], B is number of vehicles [veh], t_a, t_w and t_v are total access, waiting and in-vehicle times of users and P_a, P_w and P_v are the values of access, waiting and in-vehicle time savings. Vehicle cost c can be modelled as a linear function of vehicle capacity K (Jansson 1980, Tirachini and Hensher 2011):

$$c = c_0 + c_1 K \tag{2}$$

Fleet size B is the total cycle time t_c divided by the service headway h. Cycle time is composed of running time R (including acceleration and deceleration time at stops and intersection delays) plus passenger boarding and alighting time at stops. If q is total demand [trips/h] and t_b is the average boarding and alighting time per passenger, then cycle time is:

$$t_c = R + q\,h\,t_b \tag{3}$$

And therefore operator cost is:

$$C_{op} = (c_0 + c_1 K)(R + q\,h\,t_b)\frac{1}{h} \tag{4}$$

If a_1 is the ratio between the average waiting time and the service headway (if equally spaced buses and random passenger arrival at constant rate, $a_1 = 0.5$), a_2 is the ratio of the average trip length to the total route length, then user cost is:

$$C_u = P_w a_1 h\,q + P_v a_2\,(R + q\,h\,t_b)q \tag{5}$$

In (5), we did not include access time costs as the distance between stops is not an optimisation variable in this model. Finally, if θ is the ratio between the maximum passenger load of the route and the total passenger demand along the route, we can impose that vehicle capacity is directly obtained from vehicle headway as follows:

$$K = \theta\,q\,h \tag{6}$$

which means that vehicles are full on the point of maximum load. All in all, total cost has the following form:

$$C_{tot} = (c_0 + c_1\theta\,q\,h)(R + q\,h\,t_b)\frac{1}{h} + P_w a_1 h\,q + P_v a_2\,(R + q\,h\,t_b)q \tag{7}$$

By minimising (7) with respect to headway h, we obtain a version of the well-known square root formula for optimal vehicle headway:

$$h^* = \sqrt{\frac{c_0 R}{P_w a_1 q + t_b q^2 (c_1\theta + P_v a_2)}} \tag{8}$$

And optimal vehicle capacity is given by

$$K^* = \theta\,q\,h^* \tag{9}$$

Introducing (8) into (7), we obtain the minimum level of the total cost as follows:

$$C_{tot-min} = [C_{tot}]_{h=h^*} = 2\sqrt{c_0 R[P_w a_1 q + t_b q^2 (c_1\theta + P_v a_2)]} + q[c_0 t_b + R(c_1\theta + P_v a_2)] \tag{10}$$

2.2 Optimal pricing and subsidy

Optimal public transport pricing has been studied in first-best and second-best environments (Tirachini and Hensher 2012). The first-best public transport fare is set to maximise social welfare, defined as the sum of user and operator benefits, without any restriction. It has been shown that the optimal public transport fare P^* [€/pax] in a first-best environment is equal to the total marginal cost (including user and operator marginal costs) minus the average user cost (e.g., Else 1985):

$$P^* = \left[\frac{dC_{tot}}{dq} - \frac{C_u}{q}\right]_{h=h^*} \quad (11)$$

After introducing optimal headway (8) into total cost (7), we derive the first-best rule (10) in our model as follows:

$$P^* = \frac{\sqrt{c_0 R}\ t_b q(2c_1\theta + P_v a_2)}{\sqrt{P_w a_1 q + t_b q^2 (c_1\theta + P_v a_2)}} + c_0 t_b + c_1 \theta R \quad (12)$$

As shown by Mohring (1972), because reducing the service headway (increasing the service frequency) reduces waiting time for users (and to a lower extent it reduces in-vehicle time as well through a reduction on the time at bus stops), there are economies of scale in this framework, therefore it is optimal to provide a subsidy s^* [€/pax] on first-best grounds, derived as the difference between the average operator cost and the optimal fare,

$$s^* = \left[\frac{C_{op}}{q}\right]_{h=h^*} - P^* \quad (13)$$

which, in this model, turns out to be:

$$s^* = \frac{\sqrt{c_0 R}\, P_w a_1}{\sqrt{P_w a_1 q + t_b q^2 (c_1\theta + P_v a_2)}} \quad (14)$$

2.3 The effect of vehicle automation

In this section, we analyse the effect of introducing driverless vehicles in our total cost framework. For driverless vehicles, we assume a unit operator cost for driverless vehicles, $\bar{c}$, as follows:

$$\bar{c} = \alpha\, c_0 + c_1 K \quad (15)$$

where α is the percentage reduction in vehicle unit cost due to not having to pay a driver, $0 < \alpha < 1$. There are a couple of relevant points to make about equation (15). First, we are assuming that vehicle automation, by saving the driver wage, reduces only the fixed component of unit operator cost (expression 2) and it does not affect the marginal cost of increasing vehicle capacity (c_1) with respect to a human driven vehicle. In Section 3 we show why this is a plausible assumption with current public transport service provision data. Second, we are assuming that there is cost reduction due to automation, i.e., $\alpha < 1$. However, at least during the first years of the introduction of autonomous shuttles and buses, these vehicles are expected to be more expensive than human-driven vehicles, until the point in which technology is mature enough that costs are driven down. In Section 3 we analyse this issue using empirical data and show that, for a wide range of scenarios, it is reasonable to assume $\alpha < 1$.

Another assumption that has to be made is if autonomous shared or public transport services will have longer or shorter travel times than conventional services. Even though it has been anticipated that in highways and environments without pedestrians and cyclists, travel times of autonomous vehicles can be reduced due to having shorter headways between vehicles and the possibility of circulating in platoons, in cities it is unclear that these advantages can be exploited, if vehicles share the space with e.g., children, pedestrians and cyclers. Vehicle maximum speed could be set low in order to avoid any major traffic safety risk[1]. Therefore, given the uncertainty of the potential speed gain due to technology and speed reduction due to future safety regulations, we assume in this section that travel time with autonomous vehicles remains the same as with conventional vehicles, R, assumption that can be easily relaxed in the numerical application of the paper, as a sensitivity analysis.

Therefore, if $\bar{h}$ and $\bar{K}$ are optimal headway and vehicle size for autonomous vehicles, introducing (15) into (8) and (9) we obtain:

$$\bar{h} = \sqrt{\alpha}\, h^*, \quad \bar{K} = \sqrt{\alpha}\, K^* \tag{16}$$

We find that, it is optimal to provide the service with smaller vehicles and shorter headways (more frequent services), reducing both service headway and vehicle size by a factor $\sqrt{\alpha}$, in a way that total transport capacity, obtained as K/h, is kept constant. Note that the reduction in headway and capacity is less than proportional as the reduction in unit operator cost, because $\sqrt{\alpha} > \alpha$ for $\alpha < 1$.

Concerning financial effects, we find that both the optimal fare and optimal subsidy are reduced. If $\bar{P}$ and $\bar{S}$ are the optimal fare and subsidy with autonomous public vehicles, from equations (12) and (14) we find that

$$\bar{S} = \sqrt{\alpha}\, S^*, \quad \bar{P} < P^* \quad but \quad \bar{P} \neq \sqrt{\alpha}\, P^* \tag{17}$$

That is, subsidy is reduced by a factor $\sqrt{\alpha}$, whereas the fare is also reduced but by a factor different from $\sqrt{\alpha}$, owing to the terms $c_0 t_b + c_1 \theta R$ in equation (12). Therefore, the effect of automation in optimal fare hast to be found numerically, as it depends on the parameters of the problem.

To summarise, we have shown that the benefits of the reduction in vehicle operating cost due to automation, in an optimal price and transport supply environment, benefit three parties: (i) operators, through a reduction of operator costs; (ii) public transport users, through a reduction on waiting times and on the fare to be paid for the service, and (iii) the public sector, through a reduction on the optimal subsidy to be allocated to the public transport system.

3. Input parameters: cost estimation

The model is applied using input data from Australia. Regarding operator cost, we consider it as having three components:

(a) Vehicle capital costs.
(b) Driver costs.
(c) Running costs, e.g., fuel or energy consumption, lubricants, tyres, maintenance.

[1] For example, in current experiences like the autonomous shuttle *Postauto* that runs since 2016 in Sion, Switzerland, maximum speed has been set at 20 km/h.

We use cost data from urban bus systems in Australia, taken from ATC (2006), updated to 2012[2]. Cost estimations, for four vehicles sizes, are presented in Table 1.

Table 1: Vehicle types and costs items

Bus type	Length [m]	Nominal capacity [pax/veh]	Capital cost –purchase [€]	Capital cost –per hour [€/veh-h]	Driver cost [€/veh-h]	Running cost [€/veh-h]	Driver cost/ operator cost
Mini	8	40	104,929	3.7	30.1	9.1	70%
Standard	12	70	346,722	12.3	30.1	13.1	54%
Rigid long	15	90	364,970	12.9	30.1	14.5	52%
Articulated	18	120	547,456	19.4	30.1	16.5	46%

Annualised capital cost C_{annual} is obtained through (18), assuming a discount rate $r = 7\%$, a residual value $V_r = 5\%$ of the initial purchase price C_{cap}, and an asset life $n = 15\ years$.

$$C_{annual} = C_{cap}(1 - V_r)\frac{r}{1-\frac{1}{(1+r)^n}} \qquad (18)$$

Next, we need to estimate the amount of equivalent yearly hours of operation of a peak period. ATC (2006) estimates that 8.8% of the total bus-kilometres operated in a working day are on the morning peak hour, then a weekday is equivalent to 1/8.8% = 11.36 peak hours. Then, using the number of weekdays, weekends and the share of vehicle-kilometre of each type of day from ATC (2006) it is estimated that a year is equivalent to 2947 peak hours of operation. This value is used, together with expression (18), to estimate capital costs per veh-h as done in Table 1. Finally, Table 1 shows the proportion of the unit operator cost that corresponds to drivers costs, ranging from 70% for mini buses to 46% for large articulated buses.

ATC (2006) estimates an asset useful life of 10 years for 8 mini buses and of 20 years for bigger buses. We assumed an average asset useful life of 15 years for the calculations in Table 1. As this parameter depends on many factors, including road quality, intensity of vehicle use and level of maintenance, actual useful life of vehicles is variable. In Figure 1, we show the ratio between driver cost and unit operator cost for increasing asset life values ranging from 5 years to 20 years. Even though asset life has an influence on the relative weight of capital vs operating cost of bus service provision, we find that in all scenarios driver costs play the largest role in total unit operator cost, being in the range 64% - 71% for mini buses, 43% - 56% for standard buses and 34% - 48% for articulated buses. The larger the useful life of vehicles, the larger will be the savings due to automation.

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[2] We use an inflation rate of 2.5% and a 2012 exchange rate of 1 € = 1.24 AUD.

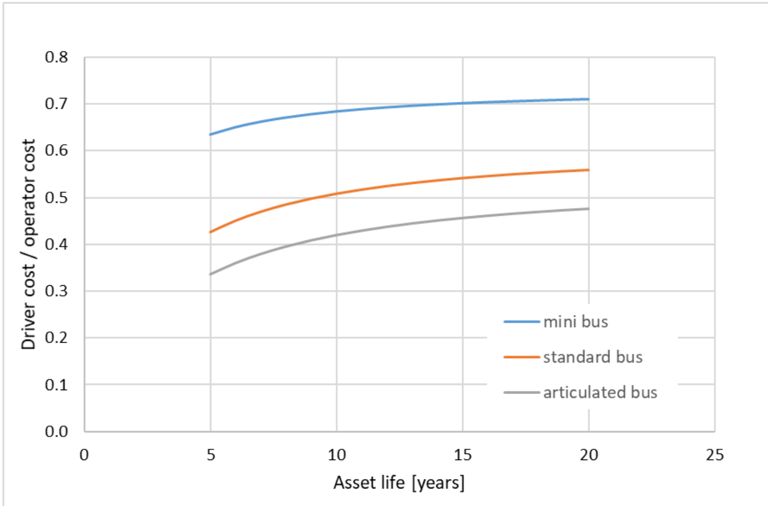

Figure 1: Driver cost as a proportion of the total operator cost

Regression models are estimated to calibrate operator cost functions for human driven vehicles (equation 2) and for autonomous vehicles (equation 15, estimated first without increasing capital cost). Results are shown in Table 2 for three different asset useful life periods.

Table 2: Estimated parameters for operator cost functions

Parameter	Asset useful life period [years]		
	10	15	20
c_0 [€/veh-h]	32.42	33.26	33.65
c_1[€/veh-pax-h]	0.33	0.28	0.25
$\alpha\ c_0$[€/veh-h]	2.31	3.15	3.54
R^2	0.96	0.96	0.96
α	0.07	0.09	0.11
$\sqrt{\alpha}$	0.27	0.31	0.32

Using current operator cost values, we estimate that optimal headway, vehicle size and public transport subsidy is severely reduced, to values around 30% ($\sqrt{\alpha}$) of the equivalent figures with human driven vehicles, if ignoring any increase in cost of capital due to vehicle automation. So this estimation is thought to illustrate a distant future in which the technology of autonomous vehicles is mature enough to cost roughly the same of what a human driven vehicle costs today.

Alternatively, we can estimate how much the capital cost of vehicles should increase, in order to compensate the large savings accruable due to saving driver costs, as depicted in Figure 2. The cost of an autonomous mini bus should go up by a factor between 4.4 and 10, in order to compensate for the saving in driver costs, depending on asset useful life. Capital cost of bigger buses would have to at least be doubled (for 10 years or more of useful life), to have the same compensating effect in operator costs. Therefor, we estimate cost savings due to automation are definitively accruable in public transport, even if capital cost of vehicle increase in the short run.

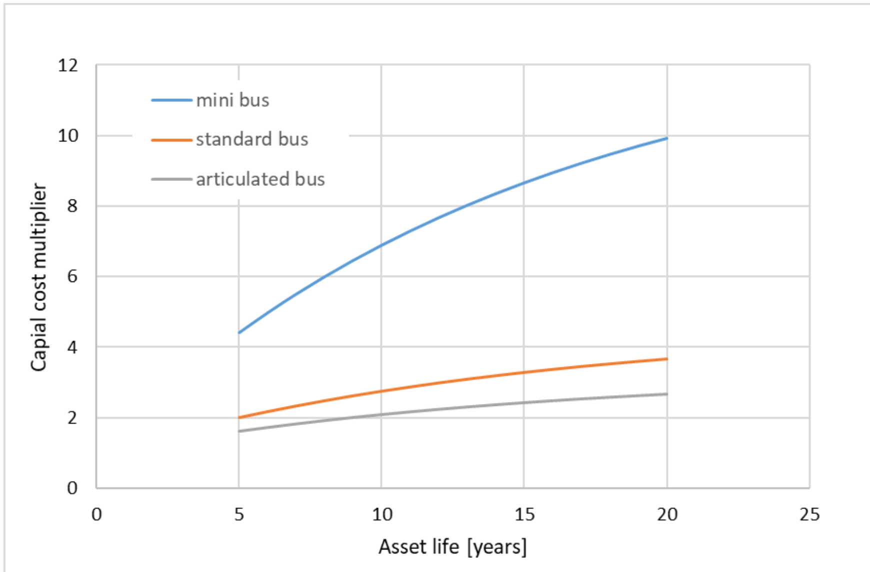

Figure 2: Capital cost multiplier necessary to compensate for driver cost saving due to automation

4. Full model application and outlook

Besides operator costs, other input parameters are necessary to operationalise the model. Values of time are taken from Tirachini (2014), $P_w = 12.1$ €$/h$ and $P_v = 8.1$ €$/h$. We assume regular headways between vehicles, therefore $a_1 = 0.5$. Taking the Military Road example from Sydney, as set in Tirachini et al. (2014), we use $a_2 = 0.2$ and $\theta = 0.42$, route length is $L = 6.88\ km$ and running time is $R = 0.4\ h$. For t_b, we assume vehicles with two doors and an off-board payment method, therefore $t_b = 1.8\ s$. Bus average (commercial) speed in the base situation is 16 km/h.

The full model from Section 2 will be solved to determine optimal headway, vehicle size, fare and subsidy under a range of scenarios regarding potential future effects of automation on capital vehicle costs. The increased capital cost of vehicles due to automation will be accounted for together with the reduction in (hourly) operating cost. Sensitivity analyses on key parameters will be performed to understand the main determinants of optimal public transport supply and pricing levels.

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