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The economics of automated public transport: Effects on operator cost, travel time, fare and subsidy

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ABSTRACT

It is currently unknown in which city environments, automated vehicles could be deployed at reasonable speeds, given safety concerns. We analytically and numerically assess the impact of automation for optimal vehicle size, service frequency, fare, subsidy and degree of economies of scale, by developing a model that is applied for electric vehicles, with data from Chile and Germany, taken as illustrative examples of developed and developing countries. Automation scenarios include cases with partial driving cost savings and reduced running speed for automated vehicles. We find that a potential reduction in vehicle operating cost due to automation benefits operators, through a reduction of operator costs, and also benefits public transport users, through a reduction on waiting times and on the optimal fare per trip. The optimal subsidy per trip is also reduced. The benefits of vehicle automation are greater in countries where drivers' salaries are larger.

1. Introduction

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 driver wages within the cost structure of urban bus transport does not seem to have changed much over the years. Depending on bus type, driver cost accounts for between 40 and 70 per cent of total bus operator cost in Singapore (Ongel et al., 2019) and Australia (own calculation based on ATC, 2006). In Japan, driver salaries account for 53% and 70% of total operating costs of buses and taxis, respectively (Abe, 2019). In developing countries, where wages are relatively lower, driver cost is less significant but still sizeable, e.g., around 1/3 of total bus operator cost in Santiago de Chile (Librium, 2013). Therefore, it is expected that vehicle automation, where deployment is possible, could have profound impacts on the public transport industry and service in the next decades.

In this context, automated vehicles have the potential to eliminate one of the main elements that cause economies of scale in public transport: drivers' wages. The cost advantage of placing many travellers in large vehicles, such as buses or trams, will be reduced; thus, shared mobility services with smaller vehicles are expected to play a larger role in a future of highly or fully automated vehicles. Some empirical estimations of the dramatic effects of automation on reducing the costs of motorised shared mobility have been made. For example, in Zurich automation is estimated to reduce the cost of taxi trips by 85% (Bösch et al., 2018) and in Singapore, total operator costs of an electric 6-m long shuttle bus are reduced by 70% if automated, as compared to its human-driven equivalent (Ongel et al., 2019). More conservative estimations are provided by Wadud (2017) for the United Kingdom, who, after assuming that with automation a 40% of current driver costs will still be needed, estimates cost savings of 30% for the taxi industry and between 15% and 23% for the truck industry.[1]

Given the large initial cost of the technology to provide full automation capabilities to vehicles, automation is expected to be firstly adopted in ride-hailing, shared mobility and commercial services, rather than for individual ownership and use (Wadud, 2017; Sterling, 2018). This issue has several key implications for the future of mobility, as current research shows that the energy consumption and environmental effects of the future deployment of automated vehicles crucially depend on whether the use of automated vehicles will be individual or mostly shared (Wadud et al., 2016).

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[1] Keeping a cost equivalent to the 40% of manpower is justified as to support loading and unloading of goods at origins and destinations in the case of trucks, and for additional back-office infrastructure and equipment to enhance security in the case of taxis (Wadud, 2017).

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Pilot programmes with small scale public transport services have been operating in the past 3–4 years in the form of automated shuttle buses in several countries, such as Switzerland, France, The Netherlands, Sweden and Finland (for a review, see Ainsalu et al., 2018). The first full size 12-m automated buses are scheduled to start trials in 2019 in Singapore[2] and 2020 in Sweden[3] and Scotland,[4] in all cases being electric vehicles. Parallel to the progress of pilots with automated vehicles for shared use, there is a current debate among experts and researchers on whether fully automated vehicles will ever operate at acceptable levels in urban environments (Kyriakidis et al., 2019). Presently, there is a larger consensus that highly automated vehicles will be able to operate under certain conditions, such as segregated roads and low-speed environments (Kyriakidis et al., 2019).

Beyond operating cost savings, automation is expected to impact public transport in various ways. Several automation technologies will be introduced in public transport services, such as collision avoidance, lane-keeping, bus platooning, bus precision docking (i.e., having a narrow and stable gap between the vehicle and the platform at bus stops), cooperative adaptive cruise control (CACC) and automated emergency braking (Lazarus et al., 2018; Lutin, 2018). The expected benefits of such innovations include a reduction of collisions, injuries and liability costs, improved services for people with reduced mobility and an increase in transport capacity, especially in dedicated infrastructure, such as bus lanes and segregated corridors (Lazarus et al., 2018). Lutin (2018) predicts a great reduction in cost and improvement in service in the US paratransit industry, which caters for persons with reduced mobility, due to automation, even though a fully automated service for mobility-impaired passengers poses further challenges as, e.g., robotic assistance will be required for boarding and alighting.

Three works closely related to the current paper are Abe (2019), Zhang et al. (2019) and Fielbaum (2019). In Abe (2019), the total cost savings due to automation are estimated for the taxi, bus and rail industry in Japan, including operator cost and travel time for users. The author assumes a waiting time, which is exogenously set and is used for both human-driven and automated vehicles; therefore, the effect of automation on optimal supply levels for a public transport service (e.g., service frequency) is not considered. On the other hand, Zhang et al. (2019) optimise a fleet of fully-automated and semi-automated buses on a hub-and-branch network. By semi-automated buses, the authors consider vehicles forming connected platoons in which only the leading bus has a driver. Bus frequency and size are optimised to minimise total operator plus user cost. Results show that automated services have a larger optimal bus frequency and a smaller vehicle size if the cost savings due to automation compensate for any reduction in speed from automated vehicles. Cost savings of semi-automated vehicles are less prominent than those of fully automated vehicles. Zhang et al. (2019) assume that the linear relationship between bus size and operator cost found by Jansson (1980) still holds with automated vehicles and their numerical application uses data from diesel buses from the previous decade (2000s) in Australia. Finally, Fielbaum (2019) optimise a network composed of a trunk system and feeder lines, in which different configurations of truck systems are compared, following Fielbaum et al. (2016). The author adapts the cost data of automated vehicles estimated in Bösch et al. (2018) to the case of Santiago and finds that automated vehicles provide more "direct" lines, with fewer transfers than human-driven public transport, due to the saving in operator costs. In Fielbaum (2019), only the case of full driving cost saving due to automation and the same running time of automated and human-driven vehicles is considered.

We see that the current understanding of the economics of automated public transport is limited in a number of ways. None of the previous authors analyses the effects of vehicle automation on optimal pricing and subsidy decisions of public transport provision. In this paper, the effect of automation on public mobility services is addressed with a supply optimisation model that takes into account both user and operator costs (Mohring, 1972). Thus, we extend earlier cost models for automated vehicles that focus on operator costs only (e.g., Stephens et al., 2016; Bösch et al., 2018; Ongel et al., 2019), with the inclusion of users' costs in the form of waiting and in-vehicle times. We go beyond the works of Fielbaum (2019) and Zhang et al. (2019) by analysing the effects of vehicle automation, not only on optimal vehicle size and service frequency but also on optimal fare and subsidy. The degree of scale economies with and without automation is also calculated. Unlike Zhang et al. (2019), we use updated data from the operation of electric vehicles, given that all current public transport pilots of automated vehicles utilise electric vehicles and this is the technology expected to prevail (over internal combustion motor vehicles) at least in the near future.

Unlike Fielbaum (2019) and Zhang et al. (2019), we make our own estimation of capital and operating costs of automated and human-driven vehicles from scratch (see Appendix), which proves to be relevant as we are able to numerically assess if assumptions made by previous authors, concerning the effect of automation on the marginal cost of increasing vehicle size, hold. We analyse alternative scenarios of deployment of automated vehicles, considering the cases in which not all driving costs are saved due to automation, and that running speed of automated vehicles might be lower than that of human-driven vehicles, due to safety concerns in cities (Zhang et al., 2019 also analyse this case). Furthermore, this is the first article to compare the effect of automation on the optimal design of a public transport service in developed and developing countries – for which Germany and Chile are chosen for illustration – specifically concerning differences in drivers' salaries and values of time. We are able to show that, given a reasonable set of assumptions on operating and capital costs of human-driven and automated electric vehicles, Jansson's linear relationship between vehicle capacity and cost (Jansson, 1980) holds with human-driven and automated electric vehicles, for a range of vehicle types from cars to articulated buses.

We focus on fixed-route services. The service frequency (i.e., the inverse of the headway between vehicles) and the vehicle size are optimised to minimise total costs. Therefore, the choice of vehicle types, such that standard car, van, minibus and standard bus, is endogenous in the model, which is solved for increasing levels of demand. We also determine the effects of automation on the optimal (first best) fare, subsidy and on the degree of economies of scale of public transport provision. The increased capital cost of vehicles due to automation will be accounted for together with the reduction in operating cost due to automation. Sensitivity analyses on key parameters are performed to understand the main determinants of optimal shared or public transport supply levels.

In terms of results, the contributions of this paper are the following. It is shown that automation will increase the demand threshold that justifies the adoption of bigger vehicles, and that the size of the effect of automation on reducing vehicle size and increasing frequency depends on the country where automation is applied and on the final conditions regarding cost savings and running speed with automated vehicles. Second, combinations of running speed and cost saving with automation, that determine if there is an effect of automation on optimal frequency and vehicle size, are numerically established, which serve as a frontier for observable automation effects on supply outputs. Third, the relative cost saving due to automation is larger in Germany than in Chile, but in both countries, large savings are expected if full automation eventually materialises. Scenarios in which not all driving cost are saved and running speeds of automated vehicles are low can significantly

[2] https://www.bloomberg.com/news/articles/2019-03-05/volvo-to-start-trialing-autonomous-full-sized-buses-in-singapore, accessed March 08th, 2019

[3] https://www.electrive.com/2019/02/21/scania-to-test-autonomous-e-buses-in-sweden/, accessed March 08th, 2019

[4] https://www.sustainable-bus.com/news/autonomous-bus-fleet-pilot-in-scotland-from-2020-by-stagecoach-and-adl/, accessed March 08th, 2019

reduce expected cost gains. Fourth, we show analytically and numerically that the reduction in vehicle operating cost due to automation benefits two parties: (i) operators, through a reduction of operator costs and (ii) public transport users, through a reduction on waiting times and on the fare to be paid for the service. Moreover, there is a reduction in the optimal subsidy per trip to be allocated to the public transport system. The size of these savings in some cases is straightforwardly estimated and in others depends on the parameters of the problem. Automation reduces the degree of economies of scale in public transport. Numerically, we find that for automation to have a noticeable effect on reducing optimal fares, a fraction larger than 50% of the current driving cost must be saved.

The rest of the paper is organised as follows. Section 2 summarises current research on cost effects of vehicle automation and the use of electric vehicles for public transport. In Section 3, the supply optimisation model is presented, together with the derivation of optimal price and subsidy rules, which are used as a base to theoretically analyse the effect of automation on optimal supply and pricing outputs. Section 4 presents the estimation of relevant cost and operation parameters for the cities of Munich in Germany and Santiago in Chile, and the effect of automation on operator cost parameters is assessed. The full optimisation model is solved and applied in Section 5. Section 6 concludes.

2. Electric vehicles and automation in public transport

2.1. Cost-relevant effects of automation in public transport

The estimation of the effects on costs, travel time, traffic safety and energy consumption introduced by the adoption of automated vehicles is an area of research that has received a steep increase of attention in the past few years. As identified by Wadud et al. (2016), there are several forms in which vehicle automation will either reduce or increase total energy consumption, including the introduction of eco-driving and eco-routing, platooning at motorways, an expected increase in the number of vehicle-kilometres travelled (VKT), vehicle rightsizing and lightweighting and changes in speed limits. In this paper, we focus on the mechanisms that introduce cost changes that need to be assumed by the fleet operators in an urban environment. These are (i) the increase in vehicle cost due to the introduction of automation equipment, and (ii) savings in operating costs due to not needing drivers to operate vehicles. In a sensitivity analysis performed at the end of Section 5, the case of reduced running cost due to a more balanced circulation of automated vehicles will also be introduced.

As noted by Abe (2019), remote monitoring systems of fleets of automated vehicles could be made by humans or by computers; in the former case, even full vehicle automation does not mean a complete elimination of human-related costs for operation, as trained personnel may be required for monitoring and even taking control of the vehicle in case of an emergency. Moreover, additional hardware and software that vehicles need to have fully automated capabilities include high accuracy automatic location systems, video cameras, ultrasonic sensors, high-resolution maps, central processing units, devices to communicate with other vehicles (vehicle-to-vehicle V2V communication) and with the infrastructure (vehicle-to-infrastructure V2I communication) and odometry sensors (BCG, 2015; Wadud, 2017; Ainsalu et al., 2018). In the case of shared shuttles and buses, screens for human-machine interaction (HMI) with passengers (indoor screens) and pedestrians (outdoor screens) can also be included (Ongel et al., 2019), together with an increased need of cleaning (Bösch et al., 2018), if some passengers misbehave due to not having a driver in control.

Currently, there are a few estimations of the additional capital costs of vehicles due to full automation capabilities, either for cars only (IHS, 2014; BCG, 2015; Stephens et al., 2016; Bansal and Kockelman, 2017), for small buses (Ongel et al., 2019) or for different types and sizes of vehicles, including commercial services and private use (Wadud, 2017; Bösch et al., 2018). As the technology matures, assembly costs go down and the scale of production increases, it is estimated that prices for automation capabilities will consistently decrease over the years, at an estimated annual rate with a lower bound around 5% and an upper bound around 10% (BCG, 2015; Bansal and Kockelman, 2017). This effect explains the trend in existing cost premiums estimated in the literature to have full automation capabilities, as summarised in Fig. 1.

Regarding larger vehicles, such as trucks and buses, there are very few estimations in the literature, based on assumptions extrapolated from the car cost estimations. For example, given the larger size of trucks, Wadud (2017) estimates the extra cost of automated trucks to lie between 13,700 and 21,840 USD by 2020. As percentage of the purchase cost, Wadud (2017) estimates, by 2020, the extra cost of automated trucks to be between 37% for single-unit trucks and 24% for large trailers in his baseline scenario, being 47% and 32% the price marks ups in a "pessimistic" scenario of increased automation cost, respectively. On average, Wadud (2017) estimates that automation produces a purchase price increase of 57% in cars and 29% in trucks.

Regarding public transport, on their cost estimations for different automated services, Bösch et al. (2018) and Abe (2019) assume that the extra cost due to automation is not significant as compared to the purchase price of a bus; consequently, a zero cost increase is assumed for buses. Fielbaum (2019), by following Bösch et al. (2018), makes the same assumption. The only current estimation for a price mark up for automation in public transport was found in Ongel et al. (2019) who estimate, for a 6-m electric minibus, that the price mark up for full automation today is around 36%, but it is expected to fall to 7% by 2030.

To the extra cost due to technology, Litman (2018) claims that, for the maintenance of the technologies and usage fees of navigation and security services, "hundreds of dollars of annual fees" should be added to the purchase cost. However, these costs are at least partially offset if more considerate automatic driving reduces the need for maintenance of common vehicle components (Bösch et al., 2018). Regarding having a more balanced driving style as a benefit of automation, different estimations on running cost savings have been provided in the literature with savings in fuel cost assumed to be, e.g., 5% by Wadud (2017) and 10% by Bösch et al. (2018).

2.2. The use of electric vehicles for public transport

Based on the current tendency of automated vehicles that are being used for public transport, for the numerical application of our model, we assume that automated vehicles are electric, and therefore, need to be compared against human-driven electric vehicles. Presently, we are observing a fast-paced transition towards electric buses for urban public transport services, with China being the leader in both production and use of electric buses. By the end of 2017, an estimated 385,000 electric buses were operating around the world, 99% of them in China, while in Europe the largest fleets are found in the United Kingdom, Germany and the Netherlands, with around 300 vehicles each (Bloomberg, 2018).[5] In early 2019, 200 new electric buses were deployed in Santiago, Chile. The purchase price of electric vehicles varies amply depending on the size of the battery and manufacturer (Chinese vehicles are typically much cheaper than European ones). Grütter (2014) shows that by 2012, prices of electric buses were roughly double in Europe and North America, compared to China. Current data shows that the price difference might be even larger. Without including shipping costs, current price ranges for electric vehicles manufactured in China are USD

[5] Main drivers for the adoption of electric buses include high levels of local air pollution, savings in operational costs and maintenance and less noise, whilst barriers for the adoption of electric buses include high upfront costs, reduced flexibility (e.g., inability to operate 24 h, dependence on recharging infrastructure and availability), concerns about energy supply reliability, lack of operational experience and the certainty that the cost of technology will decline in the coming years (Bloomberg, 2018).

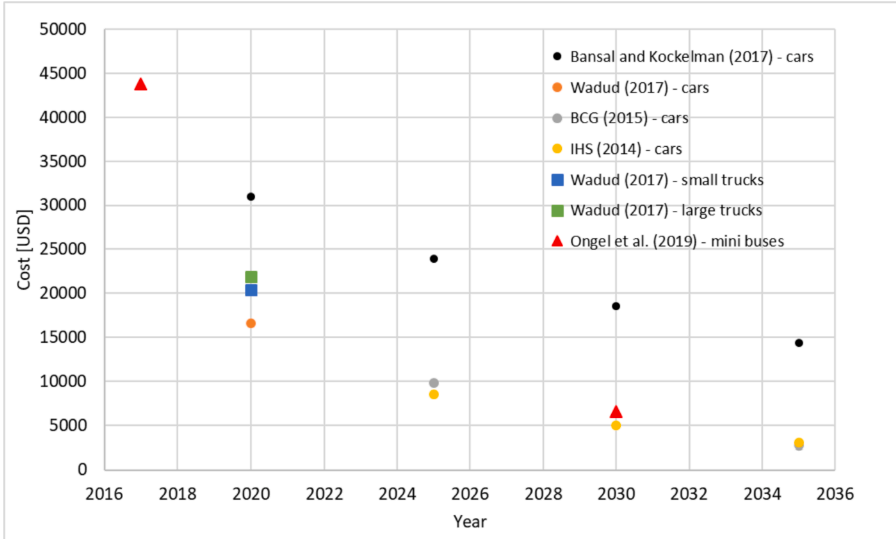

Fig. 1. Estimations of additional vehicle cost to have full automation capabilities. Own elaboration based on sources cited.

8000–30,000 for sedan cars, USD 60,000–70,000 for vans (6-m long), USD 70,000–100,000 for minibuses (8-m long), USD 120,000–250,000 for standard rigid buses (12-m long) and USD 420,000–800,000 for articulated buses (18-m long).[6] On the other hand, a standard 12-m long electric bus from European manufacturers cost around USD 500,000 in 2018 (Bloomberg, 2018).

A large driver of the price of an electric bus is the battery cost. The average price of lithium-ion batteries sharply reduced from 1000 USD/kWh in 2010 to 209 USD/kWh in 2017 and is expected to reach around 100 USD/kWh by 2025 (Bloomberg, 2018). Current battery sizes in buses are between 70 and 350 kWh, depending on bus size (from 8 to 18 m) and desired autonomy range. Nominal energy consumption rates are between 0.7 and 1.3 kWh/km for 8-m and 12-m long buses.[7] This information will be used for the estimation of cost parameters, as explained in the Appendix.

3. The economics of public transport: total cost minimisation

3.1. Optimal headway and vehicle size on a single line

We model 1 h of operation. The 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 the 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, as estimated, e.g., for Sweden (Jansson, 1980) and Australia (Tirachini and Hensher, 2011):

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

Fleet size B is the total cycle time t_c times the bus service frequency f [vex/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:

$$t_c = R + t_b \frac{q}{f} \tag{3}$$

where q/f is the average number of passengers per vehicle. Therefore, the operator cost is:

$$C_{op} = (c_0 + c_1 K)\left(R + t_b \frac{q}{f}\right) f \tag{4}$$

If a_1 is the ratio between the average waiting time and the service headway and a_2 is the ratio of the average trip length to the total route length, then user cost is:

$$C_u = P_w a_1 \frac{q}{f} + P_v a_2 \left(R + t_b \frac{q}{f}\right) q \tag{5}$$

Some particular cases of bus operation and passenger behaviour can be analysed for their impact on the value of a_1. For the case of passengers arriving randomly at bus stops at a constant rate and equally spaced buses (regular headways), $a_1 = 0.5$; if poor bus headway control leads to bunching and buses arrive following a Poisson process, then $a_1 = 1$. On the other hand, if headways are large and a timetable of bus schedule is published, then passengers adjust their behaviour and arrive at bus stops a few minutes before scheduled bus arrival, therefore $a_1 < 0.5$. In (5), we did not include access time costs as the distance between stops is not an optimisation variable in this model (bus stop location is assumed fixed). 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 service frequency as follows:

$$K = \varphi\,\theta \frac{q}{f} \tag{6}$$

In (6), for the determination of vehicle size, parameter φ is introduced to have spare capacity to absorb random variations on demand, e.g., $\varphi = 1.1$ means that vehicles have a 10% extra capacity on top of the passenger occupancy at the point of maximum load along the route (Tirachini et al., 2010). All in all, total cost has the following form:

$$C_{tot} = \left(c_0 + c_1 \varphi \theta \frac{q}{f}\right)\left(R + t_b \frac{q}{f}\right) f + P_w a_1 \frac{q}{f} + P_v a_2 \left(R + t_b \frac{q}{f}\right) q \tag{7}$$

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

[6] As extracted from www.alibaba.com, accessed March 8th, 2019.
[7] Own estimation based on Bloomberg (2018).

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

and optimal vehicle capacity is given by

$$K^* = \varphi\,\theta \frac{q}{f^*} \tag{9}$$

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

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

Optimal frequency (equation (8)) follows the square root rule first introduced by Mohring (1972) and extended by Jansson (1980) and Jara-Díaz and Gschwender (2003), among others. It states that optimal service frequency increases as a function of demand q and of the value of waiting and in-vehicle times (P_w and P_v). Moreover, optimal frequency increases with the marginal cost of vehicle capacity (c_1 from expression 2) and decreases with the base parameter of the unit operator cost c_0. Both c_0 and c_1 are to be affected by automation, hence, understanding their role in the optimal design of bus services is particularly relevant. On the one hand, reducing driving costs due to automation directly reduces the value of c_0, consequently it increases optimal frequency. On the other hand, the cost of technology to have automation capabilities increases operator cost c, therefore it partially offsets the effect of a driving cost reduction through c_0, but it also pushes to increase frequency through c_1.

3.2. Optimal pricing and subsidy

Optimal public transport pricing has been studied in first-best and second-best environments (Small and Verhoef, 2007; 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. The maximisation of social welfare is consistent with the minimisation of operator plus users costs in a parametric demand model as the one presented in Section 3.1. 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; Tisato, 1998):

$$P^* = \left[\frac{dC_{tot}}{dq} - \frac{C_u}{q}\right]_{f=f^*} \tag{11}$$

After introducing optimal frequency (8) into total cost (7), we derive the first-best rule (12) in our model as follows:

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

As shown by Mohring (1972), because increasing the service frequency (reducing the service headway) 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,

$$s^* = \left[\frac{C_{op}}{q}\right]_{f=f^*} - P^* \tag{13}$$

which, in this model, turns out to be:

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

Optimal fare and subsidy are sensitive to the effect of vehicle automation on the operator cost structure, as equations (12) and (14) show the dependency of P^* and s^* of cost parameters c_0 and c_1. The size of these effects is analytically assessed in Section 3.3 and numerically assessed in Sections 4 and 5.

3.3. The effect of vehicle automation

In this section, we analyse the effect of introducing automated vehicles in our total cost framework. We assume that automation has chiefly two effects for operator cost: a reduction in operating cost due to not having to pay (at least a fraction of) drivers and an increase in capital cost due to the inclusion of automation technology in vehicles. For automated vehicles, we assume a unit operator cost, $\overline{c}$, as follows:

$$\overline{c} = \overline{c_0} + \overline{c_1} K = \alpha c_0 + \beta c_1 K \tag{15}$$

where $\alpha = \overline{c_0}/c_0$ is the relative change in the fixed or base parameter of the unit operator cost and $\beta = \overline{c_1}/c_1$ is the relative change in the marginal cost of providing increased vehicle capacity, per vehicle-hour. If the saving of driving cost is larger than the increased capital cost of vehicles, then $0 < \alpha < 1$. If the marginal cost of vehicle capacity increases with vehicle automation, then $\beta > 1$. In spite of the estimations of increased capital cost due to automation capabilities (see Fig. 1), previous studies on automated vehicles including buses, such as Bösch et al. (2018) and Abe (2019), have assumed no increased cost due to bus automation, which in our framework is equivalent to imposing $\beta = 1$. On the other hand, Zhang et al. (2019) assume an extra capital cost due to automation that increases only the fixed unit cost $\overline{c_0}$ in equation (15), and no effect is assumed on the marginal cost parameter $\overline{c_1}$, which again in our framework is equivalent to imposing $\beta = 1$. Furthermore, in a numerical application using data from Australian diesel buses, Zhang et al. (2019) suppose a 50% increase in capital cost due to automation, regardless of vehicle size. In Section 4 we will test the plausibility of the assumption $\beta = 1$ as done in the literature, by estimating parameters c_0, c_1, $\overline{c_0}$ and $\overline{c_1}$ for different scenarios with alternative assumptions regarding the effects of automation on the cost structure of public transport, using updated data from electric buses in Germany and Chile. We will show that, under our assumptions, α is clearly lower than 1 and that β is slightly larger than 1. Thus, assuming $\beta = 1$ as a first approximation to the problem is plausible.

Another relevant point to discuss is if automated public transport services will have longer or shorter travel times than conventional human-driven services. Even though it has been anticipated that in highways and environments without pedestrians and cyclists, travel times of automated 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 people on bicycles and scooters. Maximum speed could be set low to avoid any major traffic safety risk from automated vehicles. In current experiences with automated shuttle vehicles in Switzerland, Finland and Sweden, maximum running speed is set between 14 and 20 km/h. In Stockholm, the shuttle running in the district of Kista had a maximum speed of 12 km/h on its first four months, which was increased to 15 km/h afterwards (Pernestål et al., 2018). Such a tendency to start with very low speeds and incrementally increase it is to be expected, due to safety reasons and learning about the operating environments in which automated vehicles are to be deployed. However, at this stage, it is unknown in which type of urban settings, automated vehicles will be able to operate at a speed comparable to current human-driven vehicles. So, for modelling purposes, we can distinguish the following cases:

a) Equal average running speed of automated and human-driven vehicles: this scenario takes place if the reduction on travel times due to the technology of automation, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) connectivity, is fully matched by a reduction of running speed set on automated vehicles on traffic safety grounds.

b) Different speed (possibly lower) of automated vehicles in urban settings: This scenario resembles all current pilot programs of automated shuttle buses and may happen in the future in those areas in which, due to safety concerns, low speed limits are imposed on automated vehicles (Kyriakidis et al., 2019), in a way to more than compensate any potential reduction in travel time enabled by the technology of automation and V2V and V2I communications.

Let $\overline{R} = \gamma R$ be the running time of automated vehicles, expressed as a fraction γ of the running time with human-driven vehicles ($\gamma = 1$ in the case of equal running times). Therefore, if $\overline{f}$ and $\overline{K}$ are optimal frequency and vehicle size for automated vehicles and we further assume $\beta = 1$, introducing (15) into (8) and (9) we obtain:

$$\overline{f} = \frac{f^*}{\sqrt{\alpha\gamma}},\ \overline{K} = \sqrt{\alpha\gamma}K^* \tag{16}$$

In Sections 4 and 5, we show that $\alpha\gamma < 1$ for a range of alternative assumptions regarding increased cost of automation technology, drivers' salaries and difference in speed between automated and human-driven vehicles in cities. Therefore, *we* find that, if the objective is minimising the total cost of the public transport service, it is optimal to provide the service with smaller vehicles and larger frequencies (smaller headways between vehicles), increasing service frequency by a factor $1/\sqrt{\alpha\gamma}$ (equivalent to reducing headways by a factor $\sqrt{\alpha\gamma}$) and reducing vehicle size by a factor $\sqrt{\alpha\gamma}$, in a way that total transport capacity, obtained as *fK*, is kept constant. For the particular case of $\gamma = 1$, the increase in frequency and the reduction in vehicle size is less than proportional than the reduction in unit operator cost α, because $\sqrt{\alpha} > \alpha$ for $\alpha < 1$.

Concerning financial effects, we find that both the optimal fare and optimal subsidy per trip are reduced. For illustrative purposes, we show the case of $\beta = 1$. If $\overline{P}$ and $\overline{S}$ are the optimal fare and subsidy with automated public vehicles, from equations (12) and (14) we find that

$$\overline{s} = \sqrt{\alpha\gamma}s^*\ \mathit{but}\ \ \overline{P} \neq \sqrt{\alpha\gamma}P^* \tag{17}$$

Moreover, $\overline{P} < P^*$ if $\gamma = 1$. That is, the optimal subsidy per trip is reduced by a factor $\sqrt{\alpha\gamma}$, whereas the fare is reduced by a factor different from $\sqrt{\alpha\gamma}$, owing to the terms $c_0 t_b + c_1\theta R$ in equation (12). Therefore, the effect of automation in optimal fare must be found numerically, as it depends on the parameters of the problem.

To summarise, if $\alpha\gamma < 1$, we obtain that the reduction in vehicle operating cost due to automation, in an optimal price and transport supply environment, benefits two parties: operators, through a reduction of operator costs, and public transport users, through a reduction on waiting times and on the fare to be paid for the service (the latter effect only if travel time with automated vehicles is not too low). We also find a reduction in the optimal subsidy per trip to be allocated to the public transport system. The size of these savings in some cases is straightforwardly estimated ($\sqrt{\alpha\gamma}$) and in others depends on the parameters of the problem; therefore a numerical application needs to be implemented to quantify these effects, as done in Section 5.

4. Operator cost

4.1. Cost input parameters

The model is applied using input data from Munich in Germany and from Santiago in Chile. Regarding operator cost, we consider three components:

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

In the literature, it is usual to express (a) and (b) on a temporal basis (€/veh-h or €/veh-day) and running costs on a spatial basis (€/veh-km). In our setting, we assume all costs are expressed on a temporal basis (per hour); therefore, running costs must be converted to a temporal basis by using the average vehicle speeds. Parameter values for the cities of Munich and Santiago are shown in Tables 1 and 2. For operator cost calculations, five vehicle sizes are included based on current vehicle types including cars, vans and buses. The procedure to obtain the parameter values, data sources and assumptions for the estimations is explained in the Appendix.

For the case of the driver cost, monthly gross salaries of €2700 and €1194 are used for Munich and Santiago, respectively (see Appendix). For the case of Germany, we also include Berlin (monthly gross salary of €2300) for the estimation of cost parameters α and β, to assess the effect of differences in drivers' salaries within the country.

With automation, it is not clear that all human driving cost will be saved, as humans will still be needed for some activities related to automated vehicles. For example, the monitoring of fleets of automated vehicles could be remotely made by humans or by computers (Abe, 2019); in the former case, new employees need to be hired or former drivers need to be re-trained. Extra costs of cleaning are also expectable (Bösch et al., 2018). There might also be a preference from users to have employees inside vehicles to monitor operations and provide information (Dong et al., 2019). Wadud (2017) assumes that for a fleet of fully automated taxis, 40% of driver salaries will still be required, for back-office personnel and new safety devices in vehicles. In our framework, we accommodate the possibility of new costs by defining δ as the percentage of current human driving cost that is still required under automation. For instance, $\delta = 0$ means all human driving cost can be saved with automation and $\delta = 0.5$ means that 50% of salaries can be saved with a system of automated buses (Wadud, 2017, assumes $\delta = 0.6$ for the case of automated taxis). Numerically, it is found that α is a linear function of δ,

$$\alpha = \alpha_0 + \alpha_1\delta \tag{18}$$

where α_0 and α_1 are parameters to be estimated, as presented in Section 4.2; α_0 is the value of α when all driving cost is saved. All in all, Table 1 shows that for the case of Munich, total operator cost for human-driven vehicles goes from 18.9 [€/veh-h] for cars to 36.3 and 45.1 [€/veh-h] for standard and articulated buses, respectively, whilst for the case of automated vehicles with 50% of driving cost saving, total operator cost is 12.1 [€/veh-h] for cars and 23.9 and 41.5 [€/veh-h] for standard and articulated buses, respectively.

In Fig. 2, we show the ratio between driver cost and unit operator cost for increasing asset life values ranging from 4 to 8 years for cars and vans and from 8 to 15 years for buses, for the case of Munich (a lower useful lifetime is used for car-size vehicles compared to buses, as explained in the Appendix). We find that even though asset life has an influence on the relative weight of capital vs operating cost of public transport service provision, in all scenarios driver costs is a large fraction of the total unit operator cost: driver cost is in the range 78%–82% of total cost for cars, 73–78% for vans, 48–56% for minibuses, 38–44% for standard buses and 30–36% for articulated buses. The larger the useful life of vehicles, the larger will be the savings due to automation.

4.2. Estimation of parameters α and β

The total operator costs as estimated in Tables 1 and 2 for five alternative vehicles sizes, are used in linear regression models to estimate the value operator cost parameters c_0 and c_1 for human-driven and automated vehicles, in the latter case considering different levels of driving costs that can be saved due to automation (parameter δ). Then,

Table 1
Operator cost parameters, Munich.

Parameter	Unit	Car	Van	Mini bus	Standard bus	Articulated bus
Vehicle length	[m]	4	5	8	12	18
Vehicle capacity	[pax/veh]	5	8	44	70	110
Vehicle price	[€/veh]	29490	43433	281234	419429	627696
Energy consumption	[KWh/km]	0.14	0.15	0.64	0.90	1.30
Cost of energy	[€/kwh]	0.23	0.23	0.23	0.23	0.23
Average speed	[km/h]	18.1	18.1	18.1	18.1	18.1
Energy cost	[€/veh-h]	0.6	0.6	2.6	3.7	5.3
Driver cost	[€/veh-h]	15.3	15.3	15.3	15.3	15.3
Vehicle capital cost	[€/veh-h]	1.4	2.1	7.7	11.5	17.2
Vehicle maintenance cost	[€/veh-h]	0.8	1.0	1.6	3.5	3.5
Charging infrastructure cost	[€/veh-h]	0.8	1.0	1.5	2.3	3.8
Increased capital cost automation	[%]	57	57	37	25	24
Capital cost automated vehicle	[€/veh-h]	2.3	3.3	10.5	14.3	21.3
Total cost human-driven vehicle	[€/veh-h]	18.9	20.0	28.7	36.3	45.1
Total cost automated vehicle, $\delta = 0$	[€/veh-h]	4.4	5.9	16.2	23.8	33.9
Total cost automated vehicle, $\delta = 0.5$	[€/veh-h]	12.1	13.6	23.9	31.5	41.5

Table 2
Operator cost parameters, Santiago.

Parameter	Unit	Car	Van	Mini bus	Standard bus	Articulated bus
Vehicle length	[m]	4	5	7.7	12	18
Vehicle capacity	[pax/veh]	5	8	50	90	140
Vehicle price	[€/veh]	29490	43433	189881	283186	423802
Energy consumption	[KWh/km]	0.14	0.15	0.64	0.90	1.30
Cost of energy	[€/kwh]	0.13	0.13	0.13	0.13	0.13
Average speed	[km/h]	19.3	19.3	19.3	19.3	19.3
Energy cost	[€/veh-h]	0.4	0.4	1.6	2.2	3.2
Driver cost	[€/veh-h]	6.2	6.2	6.2	6.2	6.2
Vehicle capital cost	[€/veh-h]	1.4	2.1	5.2	7.7	11.6
Vehicle maintenance cost	[€/veh-h]	0.8	1.0	1.6	3.5	3.5
Charging infrastructure cost	[€/veh-h]	0.8	1.0	1.6	2.5	4.0
Increased capital cost automation	[%]	57	57	37	25	24
Capital cost automated vehicle	[€/veh-h]	2.3	3.3	7.1	9.7	14.4
Total cost human-driven vehicle	[€/veh-h]	9.6	10.7	16.1	22.1	28.5
Total cost automated vehicle, $\delta = 0$	[€/veh-h]	4.3	5.7	11.8	17.9	25.1
Total cost automated vehicle, $\delta = 0.5$	[€/veh-h]	7.3	8.8	14.9	21.0	28.2

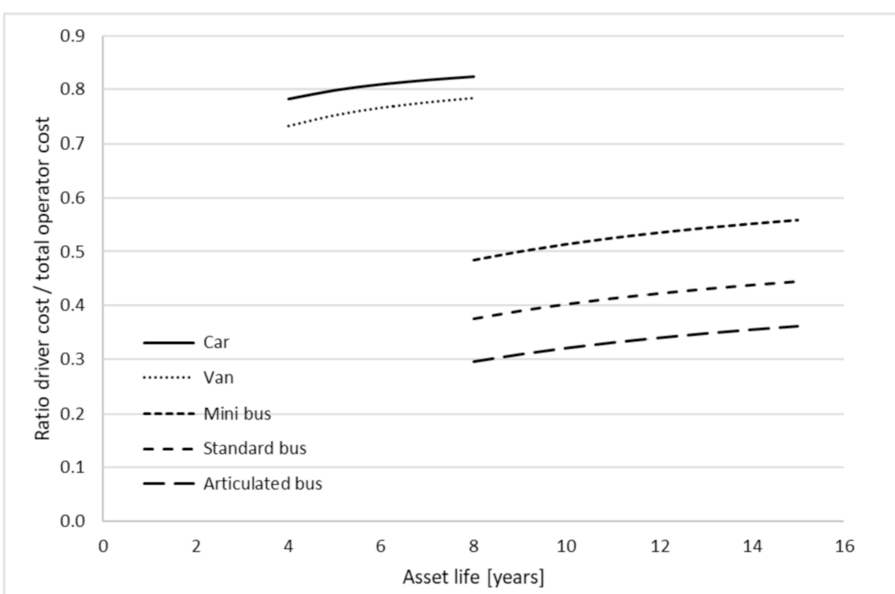

Fig. 2. Driver cost as a proportion of the total cost automated vehicles, Munich values.

the values of α and β are estimated as the ratios of the cost parameters c_o and c_1 with and without automation, as shown in equation (15). Furthermore, for the case of α, parameters α_0 and α_1 are estimated using

Table 3
Estimation of operator cost parameters ***α* and *β***.

Case	Munich		Berlin		Santiago	
	c_o [€/veh-h]	c_1 [€/veh-h-pax]	c_o [€/veh-h]	c_1 [€/veh-h-pax]	c_o [€/veh-h]	c_1 [€/veh-h-pax]
Human-driven	17.93	0.25	15.66	0.25	9.26	0.14
Automated (δ = 0)	3.56	0.28	3.66	0.28	4.09	0.15
Automated (δ = 0.5)	11.24	0.28	10.10	0.28	7.18	0.15
α_0	0.20		0.23		0.44	
α_1	0.86		0.82		0.66	
β	1.12		1.12		1.09	

(18).

In Table 3 we show the estimation of parameters α_0, α_1 and β for Munich, Berlin[8] and Santiago. First, regarding the value of the cost reduction parameter α, if automation saves the cost of driving completely (δ = 0), then α is 0.20, 0.23 and 0.44 in Munich, Berlin and Santiago, respectively. In other words, the larger the value of driver cost today, the larger the saving in the unit cost parameter of vehicles. In Chile, α is roughly double the value found in Germany, which reflects that the current driver wage in Chile is roughly half of that in Germany. The case in which part of the driving cost has to be maintained after automation depends on the percentage of the driving cost being needed. For example, when δ = 0.5, α is 0.63, 0.64 and 0.77 in Munich, Berlin and Santiago, respectively.

Interestingly, the value of β moves between 1.09 and 1.12, i.e., with the assumed increase in capital cost due to automation (see Tables 1 and 2), the marginal cost of vehicle capacity increases by 9%–12%. Therefore, we numerically estimate that β is larger than 1, but it is close to 1 as assumed by all previous studies on automation that include bus costs (Bösch et al., 2018; Abe, 2019; Zhang et al., 2019).

In all cases shown in Table 3, R^2 is 0.995 or larger. For illustration, Fig. 3 shows the cases of human-driven vehicles and automated vehicles with γ = 0 and γ = 0.5 for Munich.

In Table 4 we show values of α for different levels of driving cost to be maintained with automation, from γ = 0 (full driving cost saving) to γ = 0.75 (only 25% of the current driving cost to be saved). For each city, we also show the values of $\sqrt{\alpha}$ and $1/\sqrt{\alpha}$, which correspond to the reduction in optimal vehicle size and the increase in optimal frequency, respectively, for the case of automated vehicles, under the assumptions β = 1 (no increase in marginal cost of capacity due to automation) and $\gamma = 1$ (running time is equal with automated and human-driven vehicles), as shown in Section 3.3.

In the scenario of full cost saving, the value of α is 0.20 in Munich, 0.23 in Berlin and 0.44 in Santiago, optimal vehicle sizes are roughly halved in Germany and reduced to 2/3 of the optimal size of human-driven vehicles in Chile ($\sqrt{\alpha}$). Optimal frequency is consequently doubled in Germany and increased by 50% in Chile, with full automation and full driving cost saving, versus the case of human-driven vehicles ($1/\sqrt{\alpha}$). The larger the current driver cost (Munich), the larger is the reduction of vehicles sizes and the increase in optimal frequencies. If the driving cost savings due to automation are not full and a fraction of driving cost is still needed, we see that the smaller the driving cost saving due to automation, the smaller is the vehicle size reduction, as expected. Moreover, for values of δ larger than zero, we see that the vehicle size reduction due to automation gets closer between cities with smaller and larger driving wages. For example, for δ = 0.5, optimal vehicle size is reduced between 12% (Santiago) and 21% (Munich), and for δ = 0.75, the effect of automation is negligible in Santiago (optimal vehicle size is 3% smaller than that of human-driven vehicles).

5. Full model solution

5.1. Munich

For the Munich and Santiago case studies, we solve and analyse five scenarios, one of human-driven vehicles and four alternative scenarios of automated vehicles. The definition of scenarios is the following:

I. Human-driven vehicles.
II. Automated vehicles with full driving cost saving (δ = 0) and no change in running time with respect to human-driven vehicles ($\gamma = 1$).
III. Automated vehicles with driving cost saving accounting for 50% of human-driven vehicles (δ = 0.5) and no change in running time with respect to human-driven vehicles ($\gamma = 1$).
IV. Automated vehicles with full driving cost saving (δ = 0) and doubling of running time with respect to human-driven vehicles ($\gamma = 2$).
V. Automated vehicles with driving cost saving accounting for 50% of human-driven vehicles (δ = 0.5) and doubling of running time with respect to human-driven vehicles ($\gamma = 2$).

User cost parameters and route characteristics are shown in Table 5. Details on parameter imputation and sources of information are shown in the Appendix.

Fig. 4 depicts the optimal value of service frequency [veh/h], vehicle capacity [pax/veh], fare [€/trip] and subsidy [€/trip] for the five scenarios under study. Fig. 4 a shows the increase in optimal frequency with automation for scenarios II, III and IV. Frequency increases 2.2, 1.3 and 1.6 times, respectively, while optimal vehicle size (Fig. 4b) is reduced to 45%, 79% and 63% of the size with human-driven vehicles, respectively, along the demand range under analysis (from 100 to 4000 trips/h). With human-driven vehicles, minimum vehicle capacity is 8 pax/veh for 100 pax/h and a vehicle with capacity for 23 passengers is optimal with 1000 pax/h.

A vehicle with capacity for 12 passengers (similar to the current automated shuttles that are piloted in several cities), is optimal for 300 pax/h with human-driven vehicles, for 2500 pax/h for automated vehicles with full driving cost saving and no increase in running time, and for 900 pax/h if running time is doubled, but all driving cost is saved. In Scenario IV (only 50% of driving cost reduction), a 12-pax vehicle is optimal for 500 pax/h. Therefore, we conclude that automation increases the demand range for which smaller vehicles are optimal, and the larger the cost saving, the larger the demand for which small vehicles are optimal. Scenario V, however, presents a reduction of frequency and an increase in vehicle size, owing to the fact that the doubling of running time with automated vehicles more than compensates for the 50% reduction of driving cost that was assumed.

Regarding optimal fare (Fig. 4c), it is reduced in all scenarios in which there is no increase in running time (II and III). If full running cost reduction and no increase in running time is assumed, optimal fare is reduced to 69–85% of the original optimal fare with human-driven vehicles, which is larger than $\sqrt{\alpha} = 0.45$ for δ = 0 in Table 4, a result that is explained by the term $c_1\varphi\theta R$ in optimal fare (12). As the marginal cost of increasing vehicle capacity is not reduced with automation (actually c_1 is increased by 12% with automation), total fare reduction, in relative terms, is lower than $\sqrt{\alpha}$. In Scenario III, optimal fare is 91–99% of that of Scenario I, which shows that for automation to have a significant effect on reducing optimal fares, a large fraction (larger than 50%) of current driving cost must be saved. On the other side, Scenarios IV and V have increases in optimal fare, between 21% and 63% in Scenario IV and between 51% and 79% in Scenario V. Therefore, we find that saving half

[8] For Berlin, the only difference in operator cost with respect to Munich is the drivers' salary.

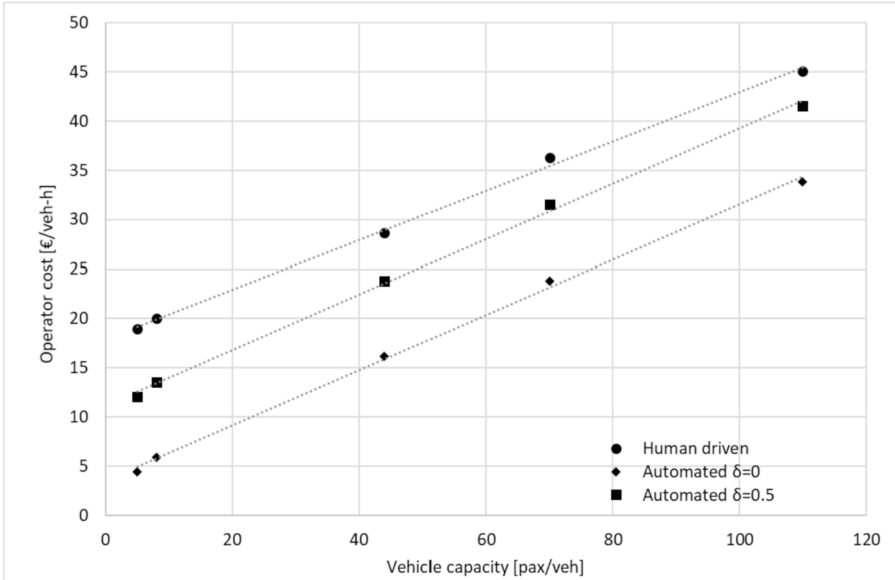

Fig. 3. Operator cost of human-driven versus automated vehicles, Munich values.

Table 4
Parameter $\boldsymbol{\alpha}$ for different levels (γ) of current driving cost to be kept with automation.

δ	α			$\sqrt{\alpha}$			$1/\sqrt{\alpha}$		
	Munich	Berlin	Santiago	Munich	Berlin	Santiago	Munich	Berlin	Santiago
0	0.20	0.23	0.44	0.45	0.48	0.66	2.24	2.07	1.50
0.25	0.41	0.44	0.61	0.64	0.66	0.78	1.56	1.51	1.28
0.5	0.63	0.64	0.77	0.79	0.80	0.88	1.26	1.25	1.14
0.75	0.84	0.85	0.94	0.92	0.92	0.97	1.09	1.08	1.03

Table 5
Parameters for model application.

Parameter	Unit	Munich	Santiago
Value of waiting time savings P_w	[€/h]	11.4	3.5
Value of in-vehicle time savings P_v	[€/h]	5.2	2.9
Ratio waiting time to headway a_1		0.6	0.6
Ratio trip length to route length a_2		0.34	0.31
Boarding and alighting time t_b	[s/pax]	4	4
Ratio maximum load to total demand θ		0.5	0.5
Route running time R	[h]	0.7	1.25
Route length L	[km]	13.5	25.9
Average speed	[km/h]	18.1	19.3
Factor to increase vehicle size φ		1.1	1.1

of the driving cost, but doubling running time (Scenario IV) still increases optimal frequency, but is not enough to reduce optimal fare, whereas in Scenario V users would unmistakably be worse off with automation, as they experience larger waiting times and fares than with human-driven vehicles.

Fig. 4 d shows that in all automation scenarios except V there is a reduction in the optimal subsidy per passenger, and the larger the cost savings due to automation, the larger the reduction in optimal subsidy. Relative subsidy reduction is the same as relative vehicle size reduction and equal to $\sqrt{\alpha}$ in Scenario II, as predicted by equations (12) and (13), i. e., the estimated increase in c_1 due to automation is not significant enough to materially influence the values of optimal frequency, vehicle size and subsidy, relative to the case in which it was assumed that c_1 is the same for human-driven and automated vehicles.

With optimal solutions, as in Fig. 4, we can compute average user costs (waiting time plus in-vehicle time), operator costs and total cost for all scenarios, plus the degree of economies of scale (calculated as $C_{tot}/(q\partial C_{tot}/\partial q)$) in each case, as shown in Fig. 5. Users' cost is reduced in Scenarios III and IV, owing to the reduction in waiting time due to the increase of service frequency. For operator cost, an interesting case is Scenario IV, as Fig. 5 b shows that for demand levels lower than 1800 pax/h, operation is cheaper with automated vehicles, but the opposite holds for demands larger than 1800 pax/h. Therefore, for low demand, saving all driving cost outweighs the increase in cost due to doubling running time, however, as demand increase, the rise in cost due to the larger fleet size requirement that stems from doubling the running time, is larger than the reduction in unit operator cost c_0 due to automation. Interestingly, all automation scenarios, even after doubling running times, have a lower degree of economies of scale (Fig. 5d), which show the large effect of driving cost in the degree of scale economies in public transport. The difference in scale economies is only noticeable for lower demand ranges, as for a demand larger than 3000 pax/h, the degree of scale economies is 1.03 or lower in all five scenarios.

5.2. Santiago

When analysing the effects of automation, the case of Santiago has some interesting differences relative to the case of Munich that deserve scrutiny. First, automation scenarios II, III and IV do present larger frequencies (Fig. 6a) and smaller vehicle sizes (Fig. 6b) relative to operating with human-driven vehicles, but the differences between automated and human operation are much smaller than in the Munich case, as expected from the analysis of α in Table 4. The optimal fare (Fig. 6c) is smaller with automation only in Scenario II, whereas in Scenario III optimal fare is roughly equal with automation and human-driven vehicles, and in Scenarios IV and V optimal fare is larger with automated vehicles. Finally, in the Santiago case, there is even one

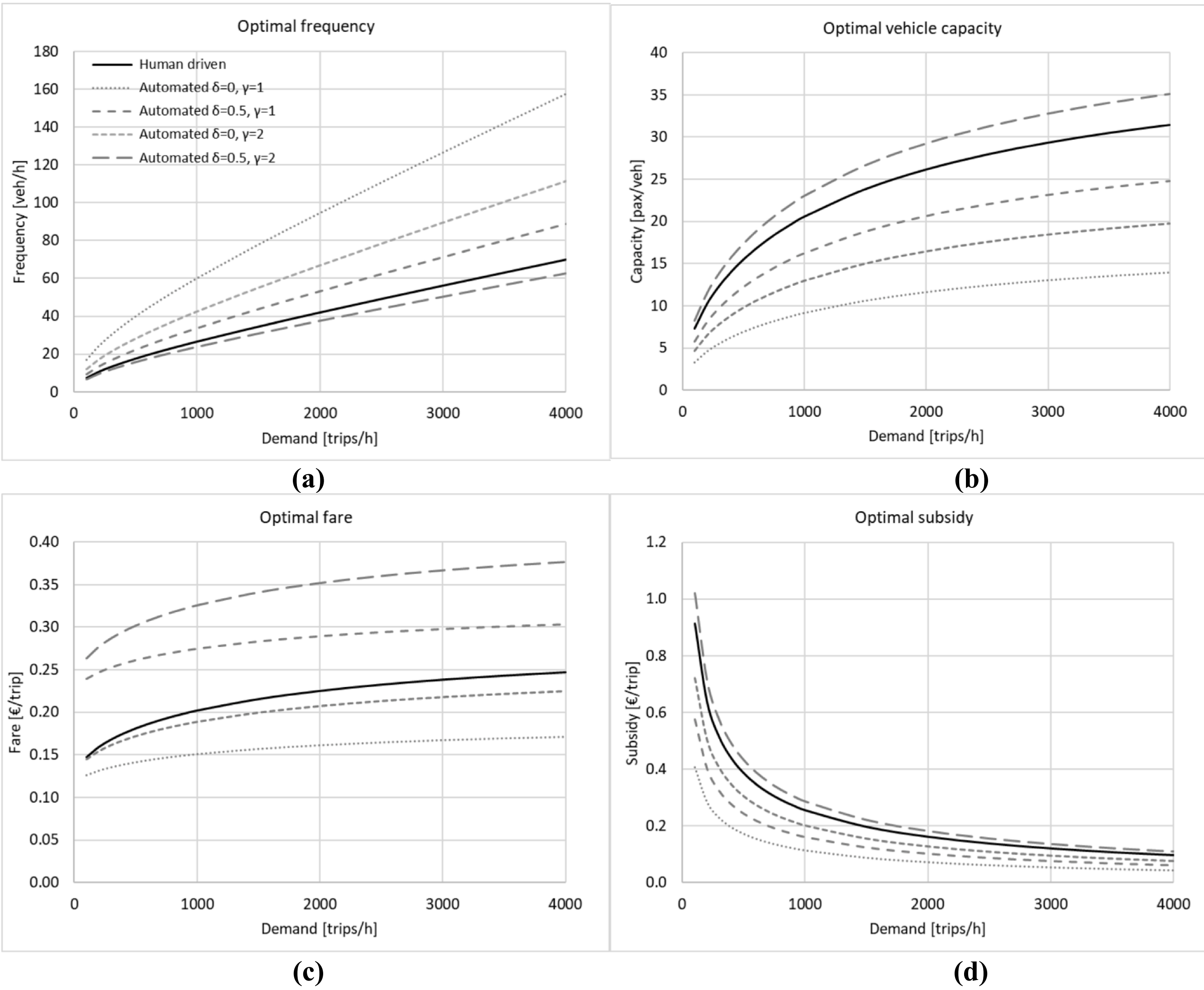

Fig. 4. Solution of optimisation model, Munich case study.

scenario (V) in which a larger subsidy would be required with automation, as shown in Fig. 6 d, something that is not observed in the Munich case (Fig. 4d). We clearly see that the level of current drivers' wages has a relevant impact on the future cost savings and increase in quality of service that can be attained with automation in public transport, with richer nations having more to gain than developing and underdeveloped countries. The analysis performed in this paper is a quantification under optimality conditions of such intuitive conclusions.

The Santiago and Munich cases demonstrate the relevance of two variables in determining the size of the effects of automation in costs for users and operators: the total driving cost reduction (reflected as a reduction of c_0) and whether or not running time R increases with automation in urban environments. As shown in equations (8) and (9), what actually matters is the product of c_0 and R to determine if there is a change in optimal frequency and vehicle size. As a generalisation of the previous analysis, using the relationship between the relative unit operator cost saving due to automation (α) and the percentage of current driving cost that is necessary with automation (δ) as shown in Equation (18), we are able to find the envelope of pairs (γ, δ), where δ is the relative increase in running time with automation, for which there is no change in optimal frequency and capacity in human-driven vehicles vs automated vehicles. The result, for Munich and Santiago, is depicted in Fig. 7. For all combinations of γ and δ that are under the curves, there is an increase in frequency and reduction in vehicle size, due to automation. The opposite occurs for combinations of γ and δ over the curves. This simple plot shows, once again, that the margin of action for automation to actually have an impact on optimal service outputs is larger in Munich than in Santiago. For example, if 30% of current driving cost are still required with automation ($\delta = 0.3$), Fig. 7 shows that automated running time could increase up to 120% in Munich ($\gamma = 2.2$), but only up to 60% in Santiago ($\gamma = 1.6$), in order to have a reduction in optimal vehicle size and an increase in optimal service frequency with automated vehicle operation.

5.3. *Sensitivity analysis: alternative modelling assumptions*

In this section we calculate the effects of a number of alternative assumptions, given the uncertainty behind some of the parameters of the problem as presented in Tables 1 and 2.

5.3.1. *Larger increase in vehicle cost due to automation*

As shown in the cost estimations presented in Fig. 1, there is large uncertainty in the costs of automation technology in the future, once the current pilot phase of development is over. In Tables 1 and 2, vehicle capital cost was increased between 24% and 57% due to automation, based on Wadud (2017). In this section, we increase by 50% those cost mark-ups due to automation, to values between 36% (articulated buses) to 86% (cars). Results are computed for the cases of full and 50% driving

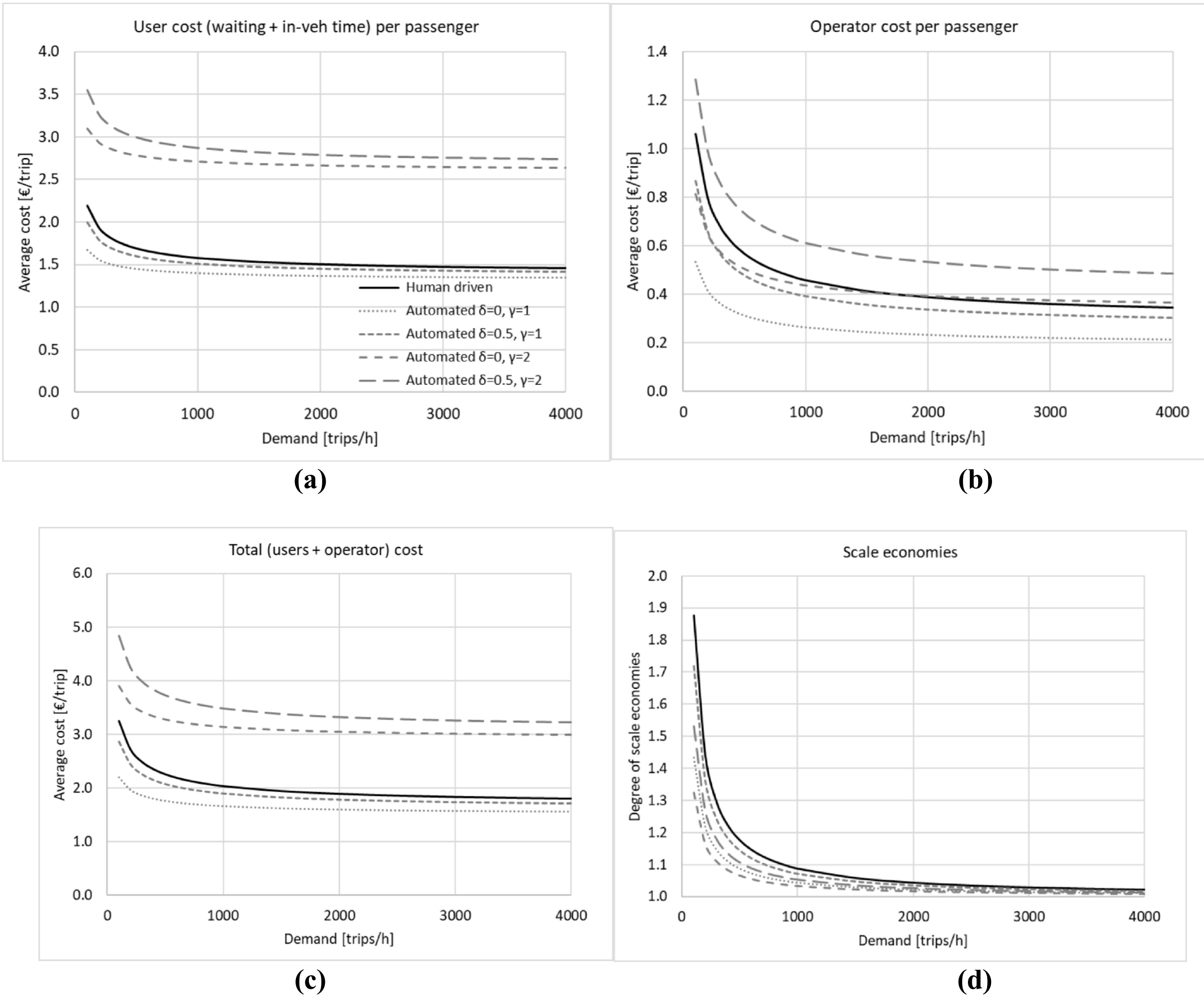

Fig. 5. Average costs and degree of scale economies, Munich case study.

cost saving. Fig. 8a shows that when there is full driving cost reduction, the effect of a larger automation cost is noticeable as reducing optimal frequency (compare curves with $\delta = 0$ in Fig. 8a), but even in this case, optimal frequency is far larger than with human-driven vehicles. However, when 50% of driving cost is still necessary with automation, the difference in optimal frequency when increasing automation cost by 50% is negligible (compare the curves with $\delta = 0.5$ in Fig. 8a), the latter result explained by the much larger effect of driving cost than that of automation cost in total operator cost, even after 50% of driving cost is assumed to be required with automation.

5.3.2. *Increased service reliability due to automation*

Automated vehicles may provide a more reliable operation in terms of more stable travel times and headways, therefore increasing general service reliability. A lower headway variance reduces waiting time (Osuna and Newell, 1972) and more stable travel times also have a benefit for users that are willing to pay for reductions in in-vehicle time variability (see, e.g., Börjesson et al., 2012). In this section, we model the case in which automation reduces headway variability, which in our model is expressed as a reduction in waiting time through the parameter a_1.[9] We do so in Scenario III, driving cost saving accounting for 50% of human-driven vehicles and no change in running time ($\delta = 0.5$, $\gamma = 1$). In the base case, we assumed $a_1 = 0.6$ for both automated and human-driven vehicles (justification is provided in the Appendix). In this section, we include the case of $a_1 = 0.5$ for automation and compare it also against the case $a_1 = 1$ with human-driven vehicles. Fig. 8 b shows that the difference in optimal frequency in both scenarios with automation is small, given that the assumed difference in reliability is small ($a_1 = 0.5$ vs 0.6), but the reduction in waiting time cost is between 9% and 14% (depending on demand level) if $a_1 = 0.5$, with respect to $a_1 = 0.6$. The comparison of reliable automated operation ($a_1 = 0.5$) vs unreliable human driving operation ($a_1 = 1$) shows optimal frequencies that are closer together than when human-driving operation is also reliable. This is because under unreliable operation, the model increases optimal frequency in order to reduce waiting times (Tirachini et al., 2014).

[9] An analysis of the effect of travel time variability in optimal bus frequency, capacity and fare is shown in Tirachini et al. (2014).

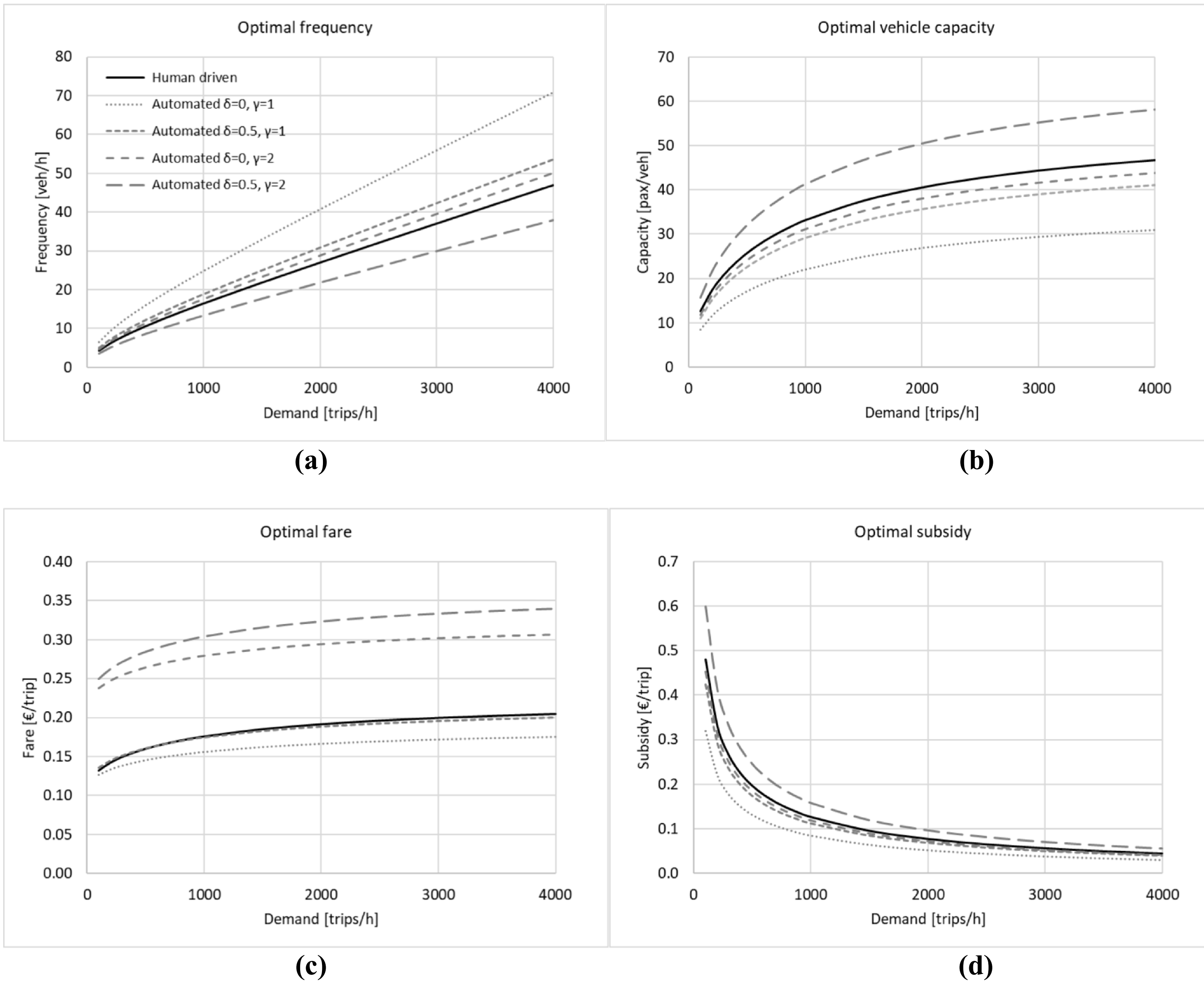

Fig. 6. Solution of optimisation model, Santiago case study.

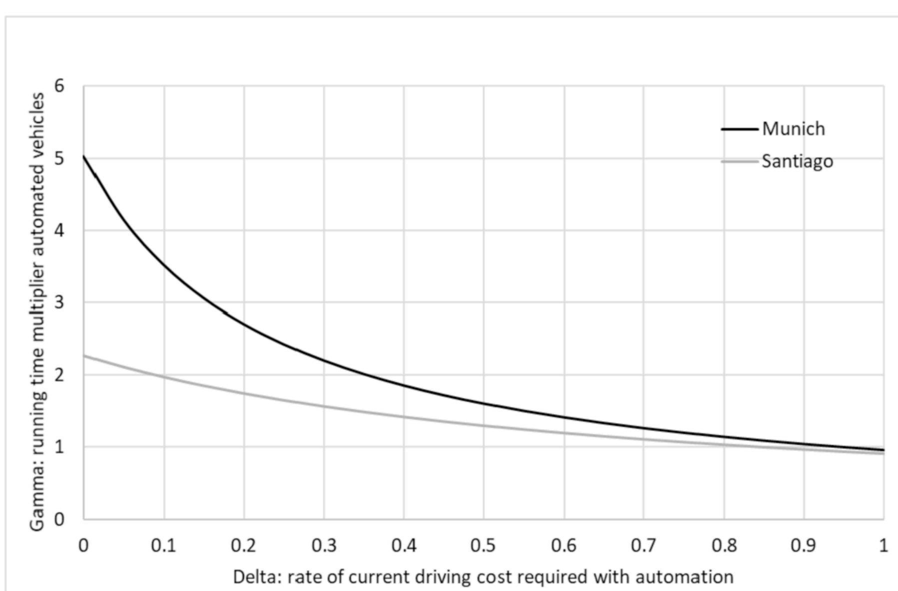

Fig. 7. Envelope for increase in optimal frequency and reduction in optimal vehicle size and optimal subsidy, due to vehicle automation.

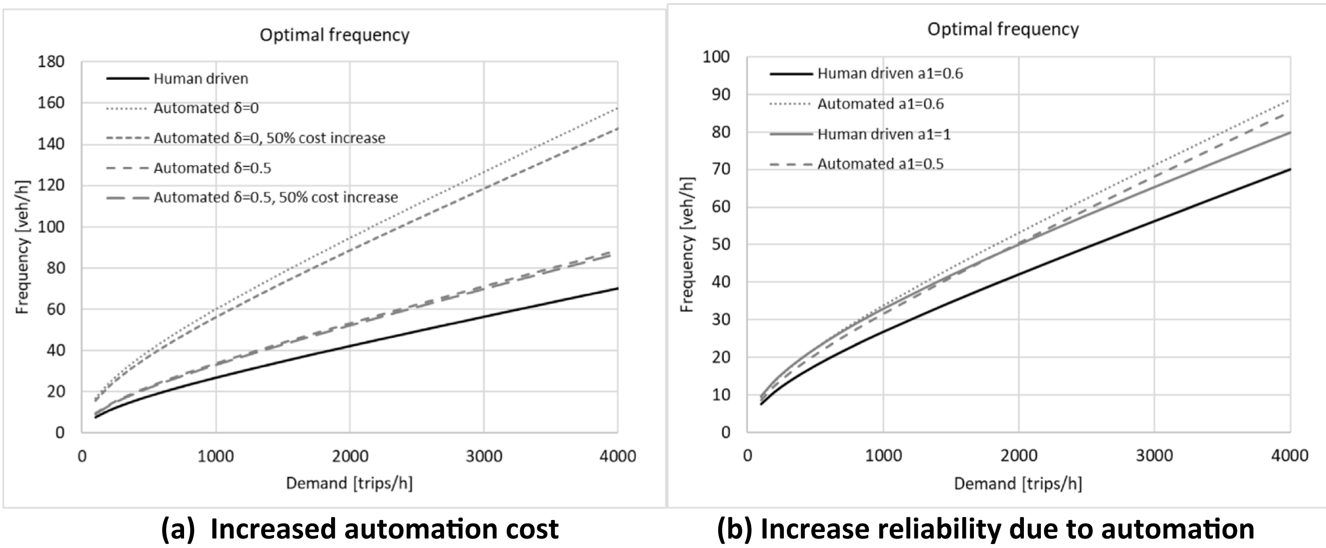

Fig. 8. Optimal frequency, alternative scenarios, Munich case study.

5.3.3. *Reduction in energy consumption due to automation*

Automation may result in a lower energy consumption per veh-km, due to a more balanced vehicle driving and efficiency gains due to V2V and V2I communications. In Scenario II, we model the case in which energy consumption per kilometre is reduced by 25% due to automation. We find a negligible numerical difference between optimal service frequency in both cases (0.4%), and the operator cost saving goes between 0.9% from 100 pax/h to 1.9% for 4000 veh/h. Actual savings might be even lower given current estimations of running cost in the range 5%–10% only (Wadud, 2017; Bösch et al., 2018). Therefore, the effect in total cost operator saving, even when present, is minor, and there is no effect on users cost.

6. Concluding remarks

In this paper, we have presented an optimisation model to analyse the effects of vehicle automation on public transport provision. Service supply, comprising vehicle size and service frequency, plus pricing decisions (fare and subsidy), are optimised for human-driven vehicles and under different scenarios of automation, depending on the final level of driving cost saving due to automation and the speed at which automated vehicles will be allowed to circulate in cities. A general model is developed for one single route, which is then applied assuming an operation with electric vehicles. Databases for two countries, Chile and Germany, are constructed and used for the numerical application of the model (using Munich, Berlin and Santiago for city applications), as illustrative of the situation of developed and developing countries. We theoretically and numerically analyse the effects of several factors that intervene in the deployment of public transport services.

We find a wide range of scenarios for which the driving cost saving due to automation is expected to be larger than the increased capital cost of automated vehicles, and that the relative cost saving due to automation is much larger in Germany than in Chile due to present differences in labour cost. We find a frontier curve of the value of increased running time (in urban environments) and the percentage of driving cost that is saved with automation, that sets the conditions for automation to increase optimal frequency, reduce optimal vehicle size and reduce optimal subsidy. In such a case, there are benefits from automation for users, operators and the public sector. Automation causes smaller vehicles to be optimal for public transport services across a large spectrum of demand. Automation reduces the degree of economies of scale in public transport. Numerically, we find that for automation to have a significant effect on reducing optimal fares, a large fraction (larger than 50%) of current driving cost must be saved.

Our research findings provide some insights about the future value of automation in public transport. The question that remains is which environments are suitable for automated public transport in cities. Current wisdom suggests that dedicated roads that eliminate or largely reduce interactions between automated vehicles and pedestrians, cyclists and other vehicles, are better suited for the deployment of automated vehicles (Kyriakidis et al., 2019). Then, our findings could apply to large-capacity dedicated corridors such as current Bus Rapid Transit (BRT) systems. On the other side of the spectrum, using small automated vehicles for last-mile solutions at reasonable speeds is also likely to be constrained by the presence of other users on the public space. Mixed solutions in which human-driven vehicles are deployed in complex city roads, as feeders to automated trunk services running along dedicated roads, are also plausible.

The analysis presented in this paper on the effects of automation on public transport provision could be extended in several ways, for example including a crowding externality as increasing the value of travel time savings, which is known to increase optimal frequency and vehicle size (Jara-Díaz and Gschwender, 2003). Including congestion in the form of queuing delays in bus stops reduces optimal service frequency (Tirachini and Hensher, 2011) Bus stop spacing was fixed in our model, future research should analyse how the location of bus stops should be adjusted with automated vehicles and what is the effect of this variable on optimal frequency and pricing rules, and on the degree of scale economies. The effect of vehicle automation on the design of real-world public transport networks is also a promising avenue of further research. Differences in travel time variability due to automation should also be incorporated, provided empirical data on the matter become available. With our model, we have shown that the optimal subsidy per trip goes down if there is an operator cost reduction due to vehicle automation, but to study the effect of automation on the total subsidy it would be appropriate to have an elastic demand model, that takes into account the effect of automation on public transport demand levels.

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Appendix. Data sources and assumptions for the estimation of parameters in Tables 1, 2 and 5

Five vehicle types are considered for the operator cost estimation, based on current sizes of vehicles for private and public transport. Capacity of each vehicle is assumed to be different for buses in Santiago and Munich, as explained in Section 4.

For Munich (Table 1), car and van prices and energy consumption are those of an electric Kia Soul and an electric van Nissan E-NV200, as advertised in the corporate website of vehicle manufacturers in Germany. Very limited updated cost data on electric buses are available in Europe in general, and in Germany in particular, we rely mainly on information from the European Union's Horizon 2020 'Eliptic' Project on electrification of public transport (Meishner et al., 2018), regarding vehicle costs, energy consumption rates, electricity cost and maintenance cost for standard (12-m long) and articulated (18-m long) buses. The mini-bus of 8 m with a capacity for 44 people is based on Vienna's electric bus.[10] Buses without including the cost of batteries are assumed to cost €300,000 (standard bus) and €532,000 (articulated bus), based on recent deployments of electric buses in Germany and Spain (Meishner et al., 2018). Their cost of batteries is calculated as €119,429 and €95,696 using current battery prices per kWh as estimated by Bloomberg (2018). The current average speed of buses in Munich is 18.1 km/h (MVG, 2018). The average energy cost per vehicle-kilometre, is obtained as the product between energy consumption rate, the cost of energy and the average speed. Table 1 shows that estimated energy cost goes from 0.6 €/veh-h for car to 3.7 and 5.3 €/veh-h for standard and articulated buses. The gross salary of bus drivers in Munich currently is 2700 €/month (based on the current official bus driver recruitment information), which translates into 15.3 €/h.

Concerning vehicle capital cost per hour, annualised capital cost C_{annual} is obtained through (19), assuming a discount rate $r = 7\%$, a residual value $V_r = 5\%$ of the initial purchase price C_{cap}, and an asset life of n years.

$$C_{annual} = C_{cap}(1 - V_r)\frac{r}{1 - \frac{1}{(1+r)^n}} \tag{19}$$

In general, the useful life of vehicles depends on several factors including road quality, intensity of vehicle use and level of maintenance. The effect of shorter or longer asset life durations on the relationship between driving cost and total operator cost was assessed in Fig. 2.

For Santiago, based on official data from the public transport authority (DTPM, 2017), we estimate that an average bus operates for 3700 h per year, at an average speed of 19.3 km/h, totalling 71410 km/year. No data of hours of operation are available for Munich. To have a common base for both cities, we assume 12 years as asset life for buses in both Munich and Santiago, which is the lifetime of electric buses in the business cases of Meishner et al. (2018). Assuming 3700 h of operation for Munich as well and current bus speed (18.1 km/h), total useful life for buses is approximately 804,000 km in Munich and 856.000 km in Santiago. Current bus concessions assume a nominal useful life of 1,000,000 km per bus. In Santiago, however, given a faster than expected depreciation of buses (due to a number of factors including low quality of some roads, poor maintenance and vandalism), a discussion to reduce such nominal duration in the next concession contracts is underway, therefore the value assumed in this paper is reasonable.

For taxis, useful lifetime is much shorter than for buses. For example, Bösch et al. (2018) use 300,000 km for Switzerland, Abe (2019) use 431,760 km for Japan, which with our assumptions on hours of operation per year and speed, yield useful lifetimes of 4.2–4.5 years (300,000 km) or 6.0–6.4 years (431,760 km). We assume 6 years as a reasonable useful life for cars and vans in our calculations for both cities. With these assumptions, vehicle capital costs in €/veh-h are obtained as in Tables 1 and 2. Maintenance costs for buses are based on Meishner et al. (2018), bus values are scaled down proportional to vehicle length for an estimation of maintenance costs of cars and vans. Electricity charging infrastructure cost are 0.12 €/km for standard buses and 0.21 €/km for articulated buses (Meishner et al., 2018), these values are scaled down for smaller vehicles proportional to vehicle length. For the increased capital cost due to automation in vehicle, percentage values between 57% for cars and vans, and 24% for large buses are used for both cities, based on Wadud (2017).

For Santiago, several other cost parameters are different from those in Munich, given the local context. First, the capacity of buses has been increased, to reflect that larger crowding levels are observed and socially accepted in public transport in Santiago, relative to Germany. Thus, for example, nominal capacity of a standard 12-m long bus is estimated to be 70 passengers in Germany (Meishner et al., 2018) and 90 passengers in Chile (Espinoza, 2017).

With respect to vehicle capital costs, Grütter (2014) reported that in 2012 an electric bus was around 30% cheaper in Latin America than in Europe. This figure is similar today, as the fleet of 100 electric 12-m long buses acquired in Santiago in 2018 from the Chinese manufacturer BYD, had a cost of around €283.000 per vehicle, which is 32.5% cheaper than the corresponding 12-m long bus in Germany (€420,000). In order to make the operator cost regression for Chile, we assume that this 32.5% difference to apply to all bus-size vehicles, whereas for cars and vans, the same price is assumed in Chile and in Germany, as current prices show.[11] Driver cost represents average gross salary for bus drivers in Santiago (Librium, 2013), updated to 2018. Cost of electricity is based on current electricity prices as informed by the electricity provider. Cost of maintenance and cost of charging infrastructure are assumed to be the same as in Munich, given lack of local data for electric vehicles.

Finally, for Table 5, values of time are based on Steck et al. (2018) for Germany and Navarrete and Ortúzar (2013), the latter values are updated to 2018 using the accumulated inflation rate. For parameter a_1, in Santiago we use Guevara et al. (2014) who estimated average scheduled waiting time to be 5.44 min while average actual waiting time is 6.86 min, which translates into an excess waiting time of 1.42 min on average. We use these values to estimate a_1 as $6.86/5.44/2 = 0.63$. For London, we estimate a_1 to be 0.59, based on scheduled and actual waiting times reported by TfL (2019). Given the similarity of Santiago and London values and that there is no local data for Munich, we assume a_1 to be 0.6 in both Santiago and Munich in Table 5. The calculation of $a_2 = 0.31$ for Santiago is based on route lengths reported in DTPM (2016) and average bus trip length from SECTRA (2014). For Munich, we obtain route length from MVG (2018) considering 2-direction routes. There is no information available of average bus trip length for

[10] https://wien.orf.at/v2/news/stories/2549394/, accessed 30 July 2019.

[11] For example, as of March 2019, a Nissan Leaf electric car cost around € 37.000 in both Chile and Germany, as advertised online by official country retailers.

Munich; however, Moovit estimates average trip length by all public transport modes (bus, trams, subway and commuter trains) to be 9.2 km in Munich.[12] Bus trips are in average shorter than those of rail modes, if we assume bus trips 50% shorter than that average (that is, 4.6 km), we obtain a_2 to be 0.34, which is used in Table 5. Boarding and alighting times in general depend on vehicle size. In this paper, for simplicity we use 4 s per passenger for all vehicle sizes (for an optimisation that considers different boarding and alighting times based on vehicle size, see Jara-Díaz and Tirachini, 2013). Given average route length L, running time R is chosen to closely reproduce average observed speeds of 18.1 km/h in Munich (MVG, 2018) and 19.3 km/h in Santiago (DTPM, 2017). Parameter θ depends on spatial demand patterns, we assume that half of total route passengers travels along the most loaded section of a route, in average. Finally, following Tirachini et al. (2010), we assume that vehicle size is estimated as to having a 10% spare capacity ($\varphi = 1.1$) over average maximum demand.

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