Transitioning towards the deployment of line-based autonomous buses: 
Consequences for service frequency and vehicle capacity

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Abstract
The deployment of autonomous buses (AB) is expected to have consequences for service design facilitated by its cost function structure. We study the impacts of AB deployment in line-based public transport (PT) systems. In particular, we examine the transition phase where AB is sequentially deployed, involving the selection of lines for which AB will be introduced. To this end, we develop a modeling framework using a dynamic public transportation assignment and operations simulation model that captures users’ adaptive path choices. An analytical model is used to determine the initial solutions in terms of service frequency and vehicle capacity for the simulation framework. Due to their different cost function structures, the deployment of AB may be accompanied by changes in the service frequency and vehicle capacity settings and consequently also on passenger flow distribution across the network. Both the simultaneous and the sequential deployment of AB on multiple lines are investigated. Deployment solutions are assessed in terms of the both total operator and user cost. The decision variables are vehicle capacity per line, service frequency per line and vehicle technology per line - i.e. either manually driven or fully automated buses. The framework is applied to a case study in Kista, Stockholm. The study shows that AB service have the potential to attract passengers through improved service provision. A sensitivity analysis is carried out concerning the effects of different cost parameters and demand levels on the deployment of AB in fixed line operations.

Highlights:
• tactical planning framework for autonomous buses operating on fixed line networks
• shift towards higher service frequency when operating autonomous buses
• the framework is applied to a real world pilot study in Kista, Stockholm
• autonomous bus service have potential to attract passengers through improved service provision
• the sequence of technology introduction is different for operator focused and user focused design

Keywords: Resource Allocation, Autonomous Bus, Public Transportation, Agent-based Simulation, Service Design

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Preprint submitted to Journal of Transportation Research Part A
January 31, 2020
1. Introduction

Autonomous buses (AB) are expected to be gradually deployed and make for an increasing share of bus fleets worldwide, similarly to the uptake of electric buses in the last decade. In the last several years the technology has matured to a point where the first pilot studies in mixed-traffic conditions have been performed. In this study we focus on shared autonomous vehicle (SAV) concepts where the vehicles are not owned by a private person. This stands in contrary to other works which investigate the effect of privately owned AV. Ainsalu et al. (2018) present a comprehensive overview of on-going and past EU-based urban transportation projects utilizing autonomous technology. While the vast majority of research about the introduction of autonomous technology has focused on replacing or substituting conventional PT systems, there is a growing number of studies dedicated to the synergetic effects of autonomous vehicles (AV) and PT systems.

With the advances in driverless technology AB have the potential to significantly reduce the crew/labor cost and hence allow to potentially revolutionize existing passenger transportation systems. According to a study by Jansson (1980) bus company costs consist in the Swedish context of 80% service operating cost, from which crew costs account for 50%, bus capital costs amount to 25% and other costs like fuel, repair, maintenance, insurance, taxes etc. sum up to 25%. To investigate the future cost drivers of bus services in Sweden, Lidestam et al. (2018) conduct a questionnaire among the PT authorities in Sweden and focus groups. The authors identify peak-hour service as the most important cost driver, highlighting the importance of efficient use of PT supply systems. Cubukcu (2008) analyzes the cost structure of the urban bus transit industry in the U.S. using data for 264 transit bus agencies. The study concludes that ca. 56% of the total cost consist of labor costs. Studies investigating the operator cost structure in Singapore, Japan and Australia (Ongel et al., 2019; Abe, 2019; Tirachini and Antoniou, 2020) have shown similar results and indicate that the operating cost is the major cost parameter for PT bus operations.

A key question for the successful deployment of AB is the order in which existing lines or new lines should be automated. The aforementioned studies have assumed a system consisting exclusively of AB. However, the introduction of AB is expected to be piecemeal and involve the selection of lines for which AB will be introduced, resulting with intermediate situations where AB co-exist with humanly-driven buses. Due to the different cost function structure of AB, their deployment on selected lines may be accompanied by changes in the service frequency and vehicle capacity settings and consequently also on passenger flow distribution across the network. This sequence of introduction has not been studied yet in the literature. In this work we assess the best order in which a fixed-line AB network should be extended.

Several studies have analyzed the impacts of autonomous technology on PT based on economic cost assessments. Zhang et al. (2019) investigate the integration of different types of autonomous buses (semi-autonomous or fully autonomous) on fixed line operations, albeit limited to the case of a single line. They consider the minimization of the generalized system cost (waiting cost, riding cost, operating cost and capital cost) using bus size as the decision variable. The authors conclude that fully autonomous buses exhibit great potential to benefit all stakeholders in the transportation system. Similarly, Tirachini and Antoniou (2020) study the impacts of AB on PT networks with an analytical formulation based on the square root formula proposed by Jansson (1980). The authors apply their model to single line case studies in Germany and Chile. They conclude that automation benefits operators and users. In Abe (2019) the potential benefits of AB are investigated using a survey study in Japan. It is concluded that fixed-line automation modes primarily benefit transit agencies and operators whereas flexible automation services benefit more the passengers in urban environments. Wen et al. (2018) focus on the system-wide effects of AB on the modal split using a demand-supply interaction model based on agent-based simulation and an additional analytical mode choice model to determine the demand. They limit the application of AB to a last-mile connection. The mode choice model predicts the OD-specific demand for a new mode which combines autonomous vehicles and PT (AVPT) based on the level of service for each trip, trip fares and the total number of trips. The study reports a mode shift from private cars trips to AVPT of 82%, and 18% of previous bus trips are shifted.
to AVPT. Shen et al. (2018) propose a simulation-based analysis of an integrated AV and PT system to determine the impact of changing the supply mode on the total user cost. In their model AV are used during morning peak hours as feeder lines. A range of 52 different fleet size and ride-sharing scenarios are studied. Based on the comparison of passenger travel time and passenger car unit kilometers, the authors propose to preserve high demand bus routes while changing low-demand bus routes into shared AV routes. The results show that the integrated system has the potential of enhancing service quality, occupying fewer road resources and utilizing bus services more efficiently. Currie (2018) claims that the best application for AB systems is in feeding passengers towards PT. The author postulates that the occupancy of vehicles must be kept high to facilitate the rising passenger demand in the future. Scheltes and de Almeida Correia (2017) explore the performance of an Automated Last-Mile Transport system in Delft, the Netherlands. The authors propose an agent-based simulation model which focuses on the distribution of travel requests among available vehicles using a first-in-first-out (FIFO) principle. The case study is focused on the connection of the university campus with a train station. The authors show that a reduced average total travel time of 6 min and 45 sec is achieved compared to competing transportation modes like biking and walking.

Before the majoring of AB technology research on on-demand services has already been conducted. Chang and Schonfeld (1991) and Chien et al. (2001) developed an analytical model to compare the impact of on-demand services with fixed line services on the transit system. The authors compute the user cost based on waiting time, access time and in-vehicle time while the operator cost is proportional to the fleet size. They conclude that flexible services require smaller vehicles at higher frequencies than conventional services do. Chien et al. (2001) extend the framework of Chang and Schonfeld (1991) to allow for route-specific demand. Chien (2005) presents an analytical model to simultaneously determine the optimal headway, vehicle size and route of the feeder line. The authors conclude that the operator cost decreases with increased headway due to reduced dispatching frequency as well as fleet size. However, the user cost increases because of increased waiting time.

Resource allocation in the context of line-based PT services has been a subject of extensive research. The authors categorize previous works based on the method used and the specific problem formulation. Most of the first models are analytical approaches utilizing simplified assumptions and are applicable to single line networks without considering network effects. Newell (1971) proposes an analytical formulation for the optimal headway determination by minimizing passengers waiting time subject to fixed cost of the vehicle dispatches required. Salzborn (1972) and Ceder (2007) extend this formulation by considering trip chaining and different demand levels. Han and Wilson (1982) develop a framework to determine the optimal service frequency which guarantees maximum passenger flow subject to a given vehicle capacity on multi-line networks. This allows to represent the dependencies between demand and supply among different lines. Gwilliam et al. (1985) and Jansson (1980) present analytical models to determine optimal vehicle capacities and service frequency, respectively. The authors conclude that operating lower capacity vehicles than those commonly used is not profitable when demand levels are fixed. More specifically, Jansson (1980) developed several analytical formulations considering simplified user costs and operator costs to determine the optimal resource allocation on simple line networks if for dependent on the passenger flow, maximum crowding level and peak hour duration. Walters (1982) utilizes an analytical model to conclude that greater passenger demand motivates the operation of smaller vehicles capacities with higher frequencies. Oldfield and Bly (1988) describe an analytical model considering demand elasticity, financial constraints and congestion effects on multi-line networks. The model is used to investigate the trade-off between user cost and operator cost. The optimal bus size is found by maximizing the social benefit. The authors conclude that the optimal vehicle capacity lies between 55 and 65 seats for their use case in United Kingdom. Yu et al. (2011) propose a comprehensive approach for determining the line frequencies for a bidirectional network. The model accounts for crowding effects in vehicles and on bus stops, denied boardings and dwell times. However, passengers’ route choices are ignored and the demand rate is assumed to be constant.

Simulation models offer an alternative approach for performing an economic assessment of PT systems while accounting for network effects and system dynamics. Chakroborty (2003) mentions the difficulty of
modeling the resource allocation problem with a mathematical programming formulation, because of the discrete nature and the complexity of representing transfers and continuity in a mathematical formulation. Cats and Glück (2019) develop a framework for a transit operations evaluation and an agent-based assignment model that captures supply uncertainties and adaptive user decisions. Multi-agent simulation tools have also been used in the past to simulate autonomous vehicle systems. For example, Leich and Bischoff (2019) use MATSim to compare the level of service provided by shared autonomous vehicles (SAV) with that of fixed-line based bus services. The authors conclude that SAV lead to a minor improvement for users costs while operator costs increase because of the door-to-door operations. A similar study using SUMO has been done by Alazzawi et al. (2018). Here the authors analyze how a fleet of autonomous vehicles could be used to reduce traffic congestion in Milan. The simulation focuses on the impacts on traffic metrics like vehicle-km traveled and free floating vehicle movements. In their paper Shen et al. (2018) developed an agent-based simulation model for the integrated simulation of on-demand autonomous vehicle and fixed-line bus operations. The authors apply the simulation tool on a case study in Singapore to assess the efficiency of first-mile solutions. Krajzewicz et al. (2012) describe a microscopic, inter- and multi-modal, space-continuous and time-discrete traffic flow simulation platform. The focus lies on V2X functionality (e.g. traffic signal control) and route choice implications. The proposed studies do not include AV as a transportation mode and focus solely on the optimal allocation of conventional bus vehicles.

The key contribution of this study is the work on the sequencing of AB deployment with the developed simulation framework. The tactical planning framework for AB operating on fixed line networks is used to address this question. The effects on the vehicle allocation; the impact on level of service, passenger flow and occupancy on other modes, and; the sensitivity analysis of the service setting solutions and the sequential introduction to the cost parameters and demand level are used to assess and support the research question. By utilizing a dynamic passenger assignment model, we are able to examine more complex PT networks and network effects, extending beyond the set of lines that are subject to design. This enables the analysis of passenger shifts among lines at different stages of deployment, which cannot be studied with single-line analytical models. Furthermore, the sequential introduction of AB into a fixed line PT network is analyzed allowing to identify where AB should be introduced first. The framework and approach is applied to a case study in Kista, Stockholm. A network consisting of 91 PT lines and four potential AB lines is analyzed.

The remainder of this paper is organized as follows: Section 2 presents the methodology, where the framework and implementation are described in detail. In Sections 3 and 4 the case study is described and the results are discussed, respectively. The sensitivity analysis is presented at the end of Section 4. The paper concludes with a discussion of study implications and an outlook for future research (Section 5).
2. Methodology

With the proposed methodology the AB allocation problem is approached. The service frequency, vehicle capacity and vehicle technology for each line are selected to find the best overall service configuration. The methodology is based on a two step approach. First a simple analytical model for a single bus line is utilized. This model was first described by Jansson (1980) and is applied in this paper to generate an initial solution set. In the second step the initial solution set is refined and the distribution of passenger flows between different lines are considered using agent-based simulation. The entire framework is illustrated in Figure 1.

![Simulation framework overview](image)

Figure 1: Simulation framework overview

2.1. Analytical Model

An analytical solution for setting the optimal service frequency for single line with a given number of bus stops and trip length was proposed by Jansson (1980). The square root formula considers operating costs per hour and is derived from basic geometric and statistical considerations. Jansson (1980) also extends this formula to cope with peak and off-peak operations and including the vehicle capacity as a decision variable (see equation 1). In Equation 1, \( Q \) is computed as \( Q = B \cdot (J/R) \) representing the average passenger flow per hour scaled to the ratio of journey and trip length. The main difference compared to the basic formula is the additional vehicle occupancy term and the difference in passenger flow in off-peak and peak hours.
Table 1: Model parameters and variables

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Unit</th>
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<tbody>
<tr>
<td>conv</td>
<td>Conventional Bus</td>
<td>-</td>
</tr>
<tr>
<td>AB</td>
<td>Autonomous Bus</td>
<td>-</td>
</tr>
<tr>
<td>i</td>
<td>line index</td>
<td>-</td>
</tr>
<tr>
<td>p</td>
<td>passenger index</td>
<td>-</td>
</tr>
<tr>
<td>j</td>
<td>configuration</td>
<td>-</td>
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Decision Variable Description Unit

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<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Unit</th>
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<tbody>
<tr>
<td>$k_i$</td>
<td>vehicle capacity per line</td>
<td>passenger/veh</td>
</tr>
<tr>
<td>$f_i$</td>
<td>service frequency per line</td>
<td>veh/h</td>
</tr>
<tr>
<td>$v_i$</td>
<td>vehicle technology per line</td>
<td>-</td>
</tr>
</tbody>
</table>

Parameter Description Unit

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_{oper}$</td>
<td>unit fixed operating cost</td>
<td>SEK/(h-veh)</td>
</tr>
<tr>
<td>$c_{cptl}$</td>
<td>unit fixed capital cost</td>
<td>SEK/(h-veh)</td>
</tr>
<tr>
<td>$b_{oper}$</td>
<td>unit size-dependent operating cost</td>
<td>SEK/(h-passenger-veh)</td>
</tr>
<tr>
<td>$b_{cptl}$</td>
<td>unit size-dependent capital cost</td>
<td>SEK/(h-passenger-veh)</td>
</tr>
<tr>
<td>$\eta$</td>
<td>reduced fixed unit operating cost</td>
<td>-</td>
</tr>
<tr>
<td>$\beta$</td>
<td>additional fixed unit capital cost</td>
<td>-</td>
</tr>
<tr>
<td>$v$</td>
<td>value of waiting time running and transitional</td>
<td>-</td>
</tr>
<tr>
<td>$E$</td>
<td>Extent of peak periods</td>
<td>h</td>
</tr>
<tr>
<td>$c$</td>
<td>value of riding time</td>
<td>-</td>
</tr>
<tr>
<td>$t$</td>
<td>boarding/alighting time per passenger</td>
<td>sec</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>size-independent bus cost component</td>
<td>-</td>
</tr>
<tr>
<td>$b$</td>
<td>size-proportional bus cost component</td>
<td>-</td>
</tr>
<tr>
<td>$B$</td>
<td>number of passengers boarding buses per hour</td>
<td>pas/h</td>
</tr>
<tr>
<td>$J$</td>
<td>average journey length (passenger journeys)</td>
<td>km</td>
</tr>
<tr>
<td>$R$</td>
<td>total round trip</td>
<td>h</td>
</tr>
<tr>
<td>$T$</td>
<td>running time plus total transitional (time of stopping and starting) time of the stops per round trip</td>
<td>h</td>
</tr>
<tr>
<td>$\rho$</td>
<td>maximum value of the occupancy rate</td>
<td>-</td>
</tr>
</tbody>
</table>

The optimal vehicle capacity then follows from equation 2:

$$F_{opt} = \sqrt{\frac{E \cdot B (\frac{v}{2} + c \cdot t \cdot Q) + \frac{b}{\alpha} \cdot B \cdot Q}{\phi_{max}} \cdot \tau \cdot T}$$  (1)

$$S_{opt} = \frac{Q}{\phi_{max} \cdot F_{opt}}$$  (2)

The analytical model in equations 1 and 2 is used in this work to generate the initial set of decision variables for each bus line. For each bus line in the AB network, the set of lines of interest, the initial service frequency and vehicle capacity are determined based on the analytical model.

2.2. Cost Formulation

A deployment solution is defined as a set of service frequencies $f_i$, capacities $k_i$ and vehicles technology $v_i$, $i \in \{1, \ldots, N\}$ for each line, where $i$ is the line ID and $N$ is the total number of lines of interest. The vehicle technology is either autonomous or conventional. The total number of lines of interest is a parameter with which a sub-network can be formed. Since the technology (autonomous or conventional) of the buses on a line of interest is a decision variable the number of automated lines in a given network varies between solutions.

The frequency and capacity of each line is selected from a set of discrete values. For frequencies these values are defined as cyclic or repetitive over two hour range. The overall demand for public transport is assumed unaffected, while passengers choose their routes based on the experienced level-of-service. The latter depends on service frequency and vehicle capacity. The network structure is kept constant, meaning that the total number of bus routes and bus stops per route are given. The different deployment solutions
are rated based on the total cost ($C_T$). The total cost is computed as the weighted normalized sum of the user cost ($C_U$) and operator cost ($C_O$). The weight terms allow for steering towards a user-focused or operator-focused analysis. The goal is to minimize the combined user and operator cost subject to the set of decision variables:

$$\min_{j} w_u \cdot \frac{C_{U,j} - C_{U,\text{min}}}{C_{U,\text{max}} - C_{U,\text{min}}} + w_o \cdot \frac{C_{O,j} - C_{O,\text{min}}}{C_{O,\text{max}} - C_{O,\text{min}}}$$

subject to:

$k_i \in \{\text{set of vehicle capacities}\}$

$f_i \in \{\text{set of service frequencies}\}$

$v_i \in \{\text{autonomous or conventional}\} \forall i \in \{1, \ldots, N\}$

(3)

where $j$ represents the index for a given configuration for service frequency and vehicle capacity per line $i$. $C_{U,\text{min}}$, $C_{U,\text{max}}$, $C_{O,\text{min}}$ and $C_{O,\text{max}}$ represent the minimal and maximal user cost and operator cost from all investigated configurations. The difference is constant for a given problem formulation.

**User Cost.** The total user cost ($C_U$) for all passengers is computed using the output generated by the simulation and depends on the perceived in-vehicle time, transfer penalty, total waiting time, access and excess times and denied boarding waiting time. Each component is multiplied with a cost parameter and then summed over each passenger ($p \in \{1, \ldots, M\}$), where $M$ is the total number of passengers, to derive the total user cost. The perceived in-vehicle time is defined as the time a passenger spends in a vehicle multiplied with a factor representing the crowdedness on-board that vehicle. The more crowded a vehicle is the higher the perceived in-vehicle time is. Transfer penalty reflects the additional impedance due to transferring to a new vehicle. Transfers are perceived as unattractive for passenger’s route choice and travel experience. The waiting time describes the total time a passenger spends waiting between two connections. Denied boarding refers to the additional waiting time experienced in the event a passenger fails to board a vehicle due to capacity limits. This waiting time induces greater impedance than the initial waiting time. Access time is the time a passenger spends to get from the start location to his/her origin station, while the egress time is the time a passenger spends to get from the destination station to the final destination of his/her trip.

**Operator Cost.** The operator cost ($C_O$) is split into capital costs and operating costs. The AB are assumed to have different operator costs than those of conventional buses. We therefore introduce the cost parameters $\beta$ and $\eta$, which scale the operator cost with respect to the vehicle technology and fleet size. The fleet size can be estimated by using the frequency and round trip time of a bus line ($n_i = t_i \cdot f_i$, where $n$ is the fleet size for a given line $i$ and $t_i$ is the cycle time for that line). The operating cost ($C_{\text{oper}}$) is the price of running a vehicle per hour including the expenses of the operator for stewards, bus driver and the maintenance costs. This cost is expected to be lower for AB compared to conventional buses. The cost is summed over all potential AB lines to compute the total network operating cost.

$$C_{\text{oper,conv}} = \sum_{i} n_i \cdot (c_{\text{oper}} + b_{\text{oper}} \cdot k_i)$$

$$C_{\text{oper,AB}} = \sum_{i} n_i \cdot ((1 - \eta) \cdot c_{\text{oper}} + b_{\text{oper}} \cdot k_i)$$

The capital cost ($C_{\text{cptl}}$) is defined as the purchase price per vehicle depending on its capacity and technology. Equation 5 shows the computation for the capital cost as the summation over all potential AB lines in the network. The cost for one line is the product of fleet size, driving time and the unit fixed/size-dependent capital costs. For the computation of the capital cost of AB lines an additional fixed unit capital
cost ($\beta$) is added. Hence we assume higher capital costs for AB compared to conventional buses.

$$C_{cptl,conv} = \sum_{i} n_i \cdot (c_{cptl} + b_{cptl} \cdot k_i)$$

$$C_{cptl,AB} = \sum_{i} n_i \cdot ((1 + \beta) \cdot c_{cptl} + b_{cptl} \cdot k_i)$$ (5)

The formulation of the operating and capital costs for conventional buses and AB is in line with the formulations presented in the work of Zhang et al. (2019).

2.3. Sequence of Technology Introduction

When deploying AB on a fixed-line network the sequence of introducing these services is important for the total costs of each introduction stage. Bus lines operated with AB should be sharing at least one bus stop so that the buses can reach every point in the network autonomously, hence the extension of the AB network results in a connected network. It could therefore be beneficial for the total system to connect, e.g. two areas with high demand first, before extending each area with autonomous bus lines. In that case, high levels of unsatisfied demand could be prevented due to AB lines which could be added in both high demand areas. To extract the sequence at which autonomous bus lines should be introduced to a fixed-line network a path-dependent approach is utilized. The computation of the path-dependent sequence strategy is based on a shortest path algorithm (Dijkstra, 1959).

For the determination of the sequence strategy a graph is constructed. In that graph a node represents one of the $2^i$ possible vehicle technology configurations on the $i$ lines. The weight on an edge connecting two nodes represents the total cost for that second nodes vehicle technology configuration. Since there are multiple scenarios with the same vehicle technology the edge length takes the minimal total cost value from all of these scenarios. For the connectivity of the nodes through edges three rules are applied (1) Two connected nodes cannot have the same number of automated lines. (2) Two nodes can be connected if the vehicle technology configuration of the second node has one AB line more. (3) The additional AB line in the second node has to be connected (share a bus stop) with any of the AB lines from the first node. With these three rules it can be guaranteed that all AB lines in the resulting sequencing strategy are connected and that no AB line is removed after its deployment. The connectivity is important to guarantee so that AB can reach every point in the network without human interaction and the network can therefore operate fully autonomous.

2.4. Simulation Model

This subsection highlights the details of the multi-agent simulation model (see in Figure 1). As a first step the input for the simulation software is created. The travel demand is provided in an origin-destination (OD) matrix. The matrix defines a passenger arrival rate for each origin-destination bus stop pair in the network (the higher the rate the more people travel between these two stops). The transit network information containing all bus routes, path sets and bus line definitions for the given network are also forwarded to the simulation module. The bus routes define the links on which vehicles can move within the network. They represent the spatial properties of the network, e.g. the length of connection links, junctions and turns. Bus lines are defined by an OD pair, a bus route, a sequence of bus stops and a sub-set of time point stops. They combine the spatial information provided from the route definition with the temporal line-specific information. As a third input the simulation-specific parameters like number of replications and simulation duration are provided. Service frequencies, vehicle capacities and vehicle technologies are defined in the deployment solution. At the end of the simulation, total travel time, passenger load and other metrics are extracted for the entire simulated network. With these performance indicators the total cost is computed. In this work the solutions are created based on a combinatorial algorithm to generate all possible solutions.
The process is repeated until all simulated solutions are analyzed.

The model utilizes the agent-based simulation software BusMezzo [Cats et al. (2010)]. This simulation tool includes a dynamic PT assignment and operations simulation based on the definition of bus stop locations, bus lines, bus routes, vehicle technologies, demand level, planned schedule, server characteristics and further traffic related parameters the passenger arrival, boarding and alighting processes as well as route choices are stochastic. Passengers make their path choice decisions based on a random utility maximization model. For each potential travel option from the current position to the final destination each passenger evaluates utility considering the cost of in-vehicle time, waiting time, transfers etc. Each passenger has information about the traffic situation of the remaining part of the journey. To account for the stochastic processes in the decisions each scenario is simulated in multiple replications and final outputs are the averages of all simulation runs.
3. Case Study

The framework is applied to a case study in Kista, a technology center in close proximity to Stockholm that attracts large numbers of commuters. The case study is connected to the first autonomous bus shuttle pilot project in Sweden. The pilot was running from January 2018 until June 2018. The automated line was approximately 1.2km long with a total of three bus stops. The shuttle operated between two main transport hubs (metro station/shopping mall and train station). The vehicles in use were Easymile EZ10. In Figure 2 the shuttle line (AB1) is shown in green. To the right the AB line (light green) is drawn on top of a map of the area. The maximum operating speed during the first four months was 12 km/h, and increased to 15 km/h during the last month. The total number of registered travelers during the pilot was ca. 20000, on average 182 passengers per day (Chee Pei Nen et al. 2018).

3.1. Experimental setup

To investigate potential additional AB lines in the Kista area the network is extended to four bi-directional potential AB lines (AB1-AB4) and the intermediate stop on line 1 is removed. Hence the potential AB network consists of four lines and four bus stops. Additional to the general assumptions described in Section 2 two additional assumptions are made in the setup for the case study. First, it is assumed that all vehicles have the same speed. Pilot projects show that the travel speed for autonomous vehicles has an increasing trend but is currently still lower than for conventional vehicles. In future scenarios the travel speed of both technologies is predicted to be equal. Second, it is assumed that people perceive all vehicles the same, i.e., that in-vehicle times, waiting times and transfers are valued the same by passengers for autonomous and for conventional vehicles.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
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<tbody>
<tr>
<td>$c_{oper}$</td>
<td>334.60</td>
<td>SEK/(h-veh)</td>
</tr>
<tr>
<td>$c_{opt}$</td>
<td>14.24</td>
<td>SEK/(h-veh)</td>
</tr>
<tr>
<td>$b_{oper}$</td>
<td>0.75</td>
<td>SEK/(h-passenger-veh)</td>
</tr>
<tr>
<td>$b_{opt}$</td>
<td>1.01</td>
<td>SEK/(h-passenger-veh)</td>
</tr>
<tr>
<td>$\eta$</td>
<td>0.63</td>
<td>-</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.5</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 2: Operator Cost Parameter

Line 1 is connecting bus stops Kista and Helenlund, line 2 is connecting bus stops Helenelund and Sollentuna, Line 3 is connecting bus stops Sollentuna and Husby, Line 4 is connecting bus stops Husby and...
Kista. The AB network is contained by the red circle in the left and right images in Figure 2. The entire simulated network consists of the AB network and the entire Stockholm PT network. The total network consists of 1072 bus stops and 91 lines. All the AB stops are integrated into the Stockholm network so that passengers can transfer to and from the AB bus stops to metro lines or other bus lines in the Stockholm network. The model of entire Stockholm allows for potential passenger distribution shifts that may result from certain resource allocations, such as changes in service frequency.

The set of parameters used for the calculation of user cost and operator cost are stated in Table 2. Unless explicitly stated otherwise, these parameters are used in all the results described in Section 4. To compare monetary values the user cost value is multiplied with the average value of time for a traveler in Stockholm during rush hour (69 SEK/h (Cats et al., 2016)).

In figure 3 the blue line separates the two areas when conventional buses have lower operational costs and when autonomous buses have lower operational costs. Using the operator cost formulation as stated in section 2 and the parameter settings from table 2 the point of operation can be computed. It can clearly be seen that in this work we operate in a strong favor of autonomous buses and conventional buses are only cheaper in operation if the capital costs for autonomous vehicles are very high.

![Figure 3: Point of operation for given operator cost parameters](image)

3.2. Data preparation
The demand pattern and level for the case study is generated in a three-step approach. First, the OD matrix for entire Stockholm is taken from a previous study on the Stockholm area (Cats et al., 2016). The morning peak hour demand from (7:00-8:00am) is included in the simulation and approximately 34000 autonomous and conventional vehicle trips are simulated. The demand matrix used is created with the SIMS demand model (Algers et al., 1996), utilizing the PT travel times from a Visum model. The route and line information is taken from GTFS files of Stockholm. The network definition includes all frequent bus, metro and commuter train lines in Stockholm including their schedule information. This enables the modeling of passenger flow distribution under alternative service design solutions. For the four added potential AB lines the trip times are adjusted to the actual driving times of existing bus lines on these links.
The second step is to extract all the relevant OD pairs for the Kista study. Since not all passengers traveling within the Stockholm network are affected by the PT lines in Kista, only the passengers which can travel through Kista and therefore use the AB lines are considered. This is primarily done to reduce the total number of passengers traveling in the network and focus the analysis on the passengers being affected by the changes in the sub-network. Therefore the computation time is reduced without affecting the results.

The third step is the addition of the estimated demand for the AB specific bus stops. For each AB stop pair there is one OD pair defined. The demand rate for each OD pair is estimated using the recorded vehicle trips per day from the pilot project and the SIMS demand levels for the surrounding stops. Figure 4 shows the demand pattern for the AB stops within the Kista area. The thickness of the connection between the stops indicates the number of passengers traveling between the stops. The black color indicates all passengers traveling through the area of interest which means they have either their origin, their destination or both outside the area of interest.
### Table 3: Resource allocation based on the analytical model for each line

<table>
<thead>
<tr>
<th>Service Frequency</th>
<th>Line 1</th>
<th>Line 2</th>
<th>Line 3</th>
<th>Line 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>veh/h</td>
<td>20</td>
<td>28</td>
<td>20</td>
<td>16</td>
</tr>
<tr>
<td>Vehicle Capacity</td>
<td>pas</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>22</td>
<td>35</td>
<td>22</td>
</tr>
</tbody>
</table>

3.3. Decision Variable Specification

Utilizing the analytical formulas \(1\) and \(2\) with the parameter settings as shown in table \(4\) and the demand level defined in figure \(4\) gives the optimal values for service frequency and vehicle capacity for each line if analyzed in isolation from the rest of the network. The frequencies and capacities for each line are reported in table \(3\). Based on these values the set of service frequencies and vehicle capacities for the iterative simulation study was chosen.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>(c_{\text{oper}})</td>
<td>334.60</td>
<td>SEK/(h-veh)</td>
</tr>
<tr>
<td>(c_{\text{cptl}})</td>
<td>14.24</td>
<td>SEK/(h-veh)</td>
</tr>
<tr>
<td>(b_{\text{oper}})</td>
<td>0.75</td>
<td>SEK/(h-passenger-veh)</td>
</tr>
<tr>
<td>(b_{\text{cptl}})</td>
<td>1.01</td>
<td>SEK/(h-passenger-veh)</td>
</tr>
<tr>
<td>(\eta)</td>
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<td>-</td>
</tr>
<tr>
<td>(\beta)</td>
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<td>-</td>
</tr>
<tr>
<td>(v)</td>
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<td>-</td>
</tr>
<tr>
<td>(E)</td>
<td>4</td>
<td>h</td>
</tr>
<tr>
<td>(c)</td>
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<td>-</td>
</tr>
<tr>
<td>(t)</td>
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<td>sec</td>
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<tr>
<td>(a)</td>
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<tr>
<td>(b)</td>
<td>0.75</td>
<td>-</td>
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<td>km</td>
</tr>
<tr>
<td>(R)</td>
<td>[0.32, 0.44, 0.6, 0.36]</td>
<td>h</td>
</tr>
<tr>
<td>(T)</td>
<td>[0.64, 0.88, 1.2, 0.72]</td>
<td>h</td>
</tr>
<tr>
<td>(\rho)</td>
<td>1</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 4: Operator Cost Parameter

The frequency sets for each potential AB line are \(f_1 \in \{12, 15, 20, 25, 30\}\), \(f_2 \in \{12, 15, 20, 25, 30\}\), \(f_3 \in \{12, 15, 20, 25, 30\}\) and \(f_4 \in \{5, 10, 12, 15, 20\}\) for lines 1, line 2, line 3 and line 4 respectively. The capacities are within \(k_i \in \{10, 45\}\) for all \(i\). This set up was chosen to match the existing values for the area in the network as well as to give enough flexibility to find improved system designs. Figure \(5\) shows the impact on the operation cost for a range of decision variables. The costs are computed using the formulations in equations \(3\) and \(4\) for potential AB line 1 and assuming only conventional buses (green) and only AB deployment (orange) solutions. The unit fixed capital cost for AB are set to be ca. 50% (see \(\beta\) in table \(4\) and equation \(5\)) higher than for conventional vehicles. The unit fixed operation costs are ca. 63% (see \(\eta\) in table \(4\) and equation \(4\)) lower for AV than for conventional vehicles (Australian Transport Council, 2006).

The number of solutions analyzed in this network is \((5 \cdot 2 \cdot 2)^4 = 160000\). To account for stochastic variance in the simulation outputs each solution is simulated multiple times. When looking at the variance within all the simulation runs and the magnitude of the total cost values it could be conclude that 10 simulation runs meet the accuracy requirements for this application (see Cats and Glück (2019); Burghout (2004)). The variance of the objective value is negligible compared to the overall trend and magnitude of the total cost. The total computation time for this set-up is approximately 72 h. The hardware used is Intel(R) Core(TM) i7-7820HQ CPU @ 2.90GHz and RAM 16.0 GB 2400Mhz. The simulation was not using graphics cards or parallel threading.
Figure 5: Model specification for change in service frequencies and vehicle capacities
4. Results

The result section is organized in four parts. First an overview over the simulation results is given (Section 4.1), then autonomous bus scenarios are compared with conventional bus scenarios (4.2). Third, the findings of the sequential technology introduction study are presented (4.3). The last subsection presents the comparison of the simulation results with the analytical study (4.4).

4.1. Impact of service frequency and vehicle capacity on service performance and level-of-service

In Figure 6 the influence of increasing the vehicle capacity and service frequency on all lines on the total cost is shown. The cost values represent the mean values over all configurations which share the same low, medium or high service frequency or low or high vehicle capacity, respectively. It can be seen that the overall trend is similar for increasing the service frequency and vehicle capacity. An increase in service frequency and vehicle capacity increases the service capacity and with it the total cost mainly due to an increase in operating cost whereas the user cost is reduced. The reduction in user cost is mainly because of a decrease in waiting time (Figure 7). The user cost is reduced by 19% thanks to an increase in service frequency and by 24% due to an increase in vehicle capacity. The operator cost (summation of capital and operating cost) is increased by 168% through an increase in service frequency and by 23% because of an increase in vehicle capacity. This observation directly follows from the problem formulation. An increase in service frequency leads to a larger fleet size which leads to a larger increase in capital and operating cost. An increase in vehicle capacity translates mainly to an increase in capital costs.

From Figure 6 it can be seen that an increase in service frequency has a negative effect on the in-vehicle time, walking time and number of transfers, whereas an increase in vehicle capacity has a positive effect on in-vehicle time and walking time. This is mainly because of reduced crowding in the buses.
4.2. Effect of Vehicle Automation on Service Design

Figure 8 shows the total cost for each feasible deployment solution i.e., the entire solution space. The heatmap can be split into 16 rectangles of equal size each representing a different vehicle technology deployment solution. For example, the rectangle in the top right represents the deployment of conventional buses on lines 1 and 2 and autonomous buses on lines 3 and 4. The top left rectangle represents the deployment of only conventional buses on all four lines and in the bottom right rectangle only AB are deployed. All other options follow the same principle. The total cost pattern is clearly visible for all vehicle deployment solutions. The introduction of AB does not change generally inferior deployment solutions. However, as indicated by the red circles, the best service frequency and vehicle capacity settings differ for the cases of conventional and autonomous buses.

Two chief observations can be made based on Figure 8. First, there is a general reduction of the total cost when deploying autonomous buses. The lowest total cost is achieved when all vehicles are automated. The lower operating costs of AB motivate their deployment if the vehicle utilization is high and outweigh the higher initial investment costs. Second, the worst solutions throughout all deployment options have the same configuration on each line. Hence, solutions with inadequate service supply specifications cannot be made attractive by switching to AB systems.

A general shift towards higher frequencies and lower capacities can be expected based on the cost formulations in Equation 4 and 5 when switching from conventional to automated vehicles. This is due to the combined consideration of user and operator cost which exercise conflicting objectives. The shift in best frequencies and capacities for the analyzed case study through the introduction of AB is apparent in Table 5. These two configurations are also marked in red in Figure 8. It can be seen that there is a shift towards higher frequencies on lines 1 and 4. The vehicle capacity stays unchanged. For the remainder of this section the service frequency and vehicle capacity configurations for the conventional and autonomous cases are as stated in Table 5.

The deployment of AB on all four lines leads to a total cost reduction of ca. 34% when assuming equal weights between user cost and operator cost. The user cost is reduced by ca. 6%, the capital cost increases by ca. 51% and the operating cost is reduced by ca. 49%. Figure 9 shows the absolute cost terms when shifting from conventional buses to autonomous buses.
The increase in capital cost can be explained by the larger fleet size required to operate at the high frequencies on line 1 and 4 in the autonomous scenario. This cost increase is compensated through the large reduction in operating cost and the slight reduction in user cost. The reduction in user costs can be explained by comparing the key performance indicator for the conventional and the autonomous deployment scenarios (see Figure 10). In this figure two main observations can be made. (1) The introduction of AB leads to improved performance on almost all lines for almost all indicators. (2) On line 1 and line 3 the number of transfers slightly increases when operating with AB (see Figure 10). The first observation indicates a generally improved level of service for the passenger in the PT system. The higher service frequency increases the transportation supply and by that reduces the time passengers spend traveling from their origin to destination. The second observation indicates that more passenger transfer towards and/or from line 1 and 3. When considering the change in passenger load (Figure 11) on line 1 and 3 the increase in

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<td>5</td>
<td>10</td>
<td>10</td>
<td>10</td>
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</table>

Table 5: Best operation solutions with exclusively conventional vehicles and automated vehicles, respectively.
Figure 9: Total Cost [SEK/h] for the best configuration using only conventional buses and best configuration using only autonomous buses.

transfers can be explained as a direct consequence of the higher passenger load on these lines. Comparing the weighted in-vehicle time on line 1 with the recorded in-vehicle time on the same line (see Figures 10c and 10d) leads to the conclusion that the higher number of vehicles on line 1 increase the traffic on that line but reduced the crowding in the buses to further reduce the weighted in-vehicle time.
Passenger load. The different deployment solutions for conventional and autonomous buses as described in Table 5 do not significantly change the load profile for the four lines (Figure 11). Clockwise and counterclockwise is the direction of travel on the line, e.g. counterclockwise on line 1 means traveling from Stop Kista to Stop Helenelund. The main difference between conventional and autonomous can be seen on lines 1 and 4. The passenger load increases on these lines from approximately 1420 pas to 1500 pas and from approximately 320 pas to 380 pas in total, respectively. This increase is due to the increased service frequency on these two lines. The total number of passengers traveling on the four potential AB lines increases by approximately 5% when switching from exclusively conventional to autonomous buses.

On lines 2 and 4 the absolute passenger load is lower than the demand between the respective bus stops on these lines. Especially line 2 attracts very low passenger loads. Whereas line 1 and 3 have higher load
than the direct demand would suggest. This is due to a passenger flow choosing other lines over lines 2 and 4. For line 2 this is the commuter train connection which operates high frequency train services and for line 4 the metro line is running in parallel to the potential AB line 4 (see Figure 2). From this result it can be said that in the Kista area AB attract more passenger because of the increase in service frequencies compared to the conventional deployment scenario, yet it still competes with partially parallel longer-distance high-capacity metro and commuter train services.

![Passenger load on lines 1 through 4 when operated exclusively with AB](image1)

![Passenger load on lines 1 through 4 when operated exclusively with conventional buses](image2)

(a) Passenger load on lines 1 through 4 when operated exclusively with AB  
(b) Passenger load on lines 1 through 4 when operated exclusively with conventional buses

Figure 11: Comparison of passenger load on the four potential AB lines for the autonomous (a) and conventional (b) configuration

In summary the autonomous technology has shown to be beneficial in terms of user cost as well as operator cost in our case study. The user cost is mainly reduced by shorter waiting times attained by an increased service frequency on certain AB lines in the network. The higher frequency leads to a larger vehicle fleet which increases the capital costs for such a system. Notwithstanding, in our case these higher capital costs are compensated by a drastic reduction in operating costs.

Besides the reduction in waiting time the higher service frequency on AB lines also leads to an increased passenger load on these lines due to the re-distribution of passenger flows across the network, also for those that have their origins and destinations outside of the study area that is subject to design.

4.3. Sequential technology introduction

For the transition towards full AB systems it is important to analyze the sequence in which PT lines should be operated autonomously. Two basic approaches are analyzed in the following section. A myopic approach which always chooses to automate the feasible line which gives the most cost reduction next. Meaning that decisions are made based on only current available information. The myopic approach is prone to result in local optimal solutions. The path-dependent approach, which determines the sequence of deployment based on the shortest path, finds the best combination considering also future decisions. This approach is capable of finding global optimal solutions. For both approaches the same graph can be constructed. In the graph, nodes represent a vehicle technology configuration and the edges are the total cost (Equation 3) associated with the next configuration. For each node the best combination of service frequency and vehicle capacity is chosen. For example, node 0 stands for the configuration where all lines are exclusively operated by conventional buses and node 15 represents the configuration for all AB operations. Figure 12 depicts the graph obtained for our application.

20
When comparing the results for the myopic and path-dependent approaches, the sequence of introduction obtained for our application does not differ. The sequence obtained is as follows: Node 2 → 6 → 14 → 15 which implies introducing AB on lines 3 → 2 → 1 → 4. This sequence is found locally as well as globally optimal when the weights for operator cost and user cost are equal. If the weights shift towards user focused design the sequence obtained under both approaches is (see Figure 12b). Nodes 8 → 12 → 14 → 15, implying the following line sequence 1 → 2 → 3 → 4. The operator focused sequence in Figure 12a is the same as the one obtained for the equal weights.

\[\text{Figure 12: Sequence of autonomous technology introduction on the four lines.}\]

The operator focus sequence deploys AB on lines with high frequency and high vehicle capacity first. If the lines are similar in these dimensions, then lines with long cycle times should be automated first. The user costs however focuses on high passenger load lines. These lines are then connected with a low cycle time line. In our application line 1 should be automated first and line 3 should be connected through line 2 since this line is shorter than line 4.

4.4. Comparing simulation results with analytical single-line formulation

The direct comparison of the service frequencies and vehicle capacities for the analytical model and simulation model (see 3 and 5) shows two main things. First, the service frequencies from the analytical model are slightly higher than the final results from the simulation. Accordingly the capacities are slightly smaller in the analytical model. This might be due to the discrete set of decision variables and the simplifications made in the analytical model. The second observation is the over estimation of line 2, 3 and 4 through the analytical model. Since the analytical model is computing the service frequency and vehicle capacity without considering the surrounding network the values do not reflect network effects like passenger flow away or towards the lines. In the simulation however this passenger flow is captured and the resulting frequency and capacity values show that discrepancy.

When introduction autonomous technology the cost formulations as presented in the equations 1 and 2 are slightly changed. Since the operational cost and capital cost parameters are assumed to be different when operating AB the optimal service frequency and vehicle capacity are also changing accordingly. Tirachini and Antoniou (2020) derive a relationship between changed optimal service frequency and vehicle capacity for a similar version of the "square root formula". Using the same approach to formulate the same approach in integrating the autonomous technology in the model as Tirachini and Antoniou (2020) we can derive the
following relationship between service frequency and capacity in the conventional and autonomous scenario.

\[ F_{AB}^{opt} = \frac{F^{opt}}{\sqrt{(1 - \eta) \cdot \gamma (1 + \beta)}} \]

\[ S_{AB}^{opt} = S^{opt} \cdot \sqrt{(1 - \eta) \cdot \gamma / (1 + \beta)} \]

(6)

Here \( \eta \) and \( \beta \) are the AB specific cost parameter, reduced fixed unit operating cost parameter and additional fixed unit capital cost respectively. \( \gamma \) is the ratio of running time of autonomous to conventional bus lines \( \gamma = T_{AB} / T_{conv} \). In comparison with Tirachini and Antoniou (2020) the additional fixed unit capital cost is assumed to be larger than 1 and \( \gamma = 1 \) since in the simulation running times are not adjusted to the vehicle technology. Using the parameters from the case study the factor turns out to be \( \sqrt{(1 - \eta) \cdot \gamma / (1 + \beta)} = 0.4967 \) which translates to a doubling of the service frequency and halving of the vehicle capacity in the AB scenario.

Comparing the analytical solutions for optimal service frequency and vehicle capacity for AB operation with the simulation based values a similar effect as in the conventional configuration is present. Lines 2, 3 and 4 are still overestimated by the analytical model. Additionally the simulation model does not capture changes in the capacity most probably because the feasible vehicle capacities are not detailed enough. However the change in service frequency is showing similar trends for lines 1 and 4 in the simulation and analytical model. On both of these lines the values almost double from 12 veh/h to 20 veh/h on line 1 and from 5 veh/h to 10 veh/h on line 4. The analytically derived estimation of AB impact seems therefore to be in agreement with the relations derived through the simulation framework.

4.5. Sensitivity analysis

Due to the high uncertainties associated with the introduction of AB systems, we perform a comprehensive sensitivity analysis. First, the impact of the demand level is investigated. Second, the effect of different cost parameters on the operator cost formulation is analyzed. Unless specified otherwise, the base case for comparison in this section has a demand level and cost parameters settings as described in Section 3.

Sensitivity analysis with respect to demand level. When halving the demand level the impact of the operational cost savings of AB persists as well as the shift for AB towards higher frequencies in the best solution (Table 5). Vehicle capacities however stay at 10 pas/veh for all lines. The introduction sequence of AB lines stays unchanged for the low demand level.

When doubling the demand the user cost dominates the total cost. All scenarios investigated result in a higher total cost due to the higher user cost. For a higher demand level the optimal solution is found with the highest capacity and highest service frequency on all four lines. For the high demand level the introduction sequence of AB lines also stays unchanged.

It can be concluded that (i) savings stemming from the deployment of autonomous vehicles are sensitive to the demand level; (ii) a shift in vehicle capacity is less sensitive to the demand level. (iii) the introduction sequence of AB lines is found to be insensitive to the demand level in this case study. The specific shift characteristics are network dependent and are constrained by the demand level and AB network layout.
Sensitivity analysis with respect to cost parameters. For the cost parameter sensitivity analysis all parameters from Table 2 are investigated. The investigation is conducted using a base value, a minimum value and a maximum value for each parameter (Table 6). Due to the limited number of available operating and capital cost data of AB and the early stages of the technology, we explore a wide range of values for the cost parameters. An increase of the unit fixed operating cost represents a higher maintenance cost, fees and energy consumption. A change in the unit fixed capital cost might be due to advances in mass production or a break through in production technology. A decrease in unit size-dependent operating cost and unit size-dependent capital cost can represent the shift in vehicle fleet characteristics. If the size-dependent costs are minor, larger vehicles will become more affordable and therefore can be utilized more often in the fleet. Up to this point the technology required to perform autonomous driving is expensive which increases the capital cost of such vehicles. Whereas the operating costs are reduced to the elimination of a vehicle driver. The changes are subject to policy regulations, utilized technology and mode of operation (fully autonomous or operated with an on-board steward). The minimum and maximum values are therefore chosen to represent the full range of possible changes. We assess the impact of each parameter on the results individually while keeping all other variables unchanged.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Base</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
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<tbody>
<tr>
<td>$c_{oper}$</td>
<td>SEK/veh/h</td>
<td>334.60</td>
<td>300</td>
<td>400</td>
</tr>
<tr>
<td>$c_{cptl}$</td>
<td>SEK/veh/h</td>
<td>14.24</td>
<td>10</td>
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<td>$b_{oper}$</td>
<td>SEK/veh/h</td>
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</tr>
<tr>
<td>$\eta$</td>
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<td>0.63</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>$\beta$</td>
<td>-</td>
<td>0.5</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 6: Operator Cost Parameter

The optimal service design is found to be insensitive to changes in $b_{cptl}$, $b_{oper}$, $c_{oper}$, $c_{cptl}$ and $\beta$ parameter values. The same solution characteristics (difference in frequency and capacity between conventional and autonomous buses) and sequence of deployment as in the base case are attained when varying their values. Conversely, lowering the reduced fixed unit operating cost parameter for autonomous buses ($\eta$) erases the shift in optimal deployment solution. Since both vehicle technologies have practically the same cost, the optimal deployment solution for conventional vehicles is the same as for autonomous vehicles.

For a higher reduction in the operating cost for AB, the shift in service frequency has the same characteristics as in the base case. This observation goes along with expectations based on the mathematical formulation embedded in the framework. If the operation of autonomous vehicles becomes cheaper, the higher capital costs are compensated at higher frequencies and allow the deployment of larger fleets on more lines. If $\eta$ is set to 0, the fixed unit operating cost for AB are not reduced compared to the conventional fixed unit operating costs. Still the sequence does not change in any of the tested cost parameter combinations.

In conclusion, the best deployment solution is found to be sensitive to the demand level and the reduced fixed unit operating cost parameter ($\eta$). The shift of optimal service frequency and vehicle capacity depends on the change in demand level. While a low reduced fixed unit operating cost parameter will remove the shift. In this case AB have a higher operating cost and the deployment of AB in the network is not profitable. The sequence of deployment stays the same independent of demand level and cost parameter values.
5. Discussion and Conclusion

In this paper a tactical planning framework for autonomous buses operating on a fixed line network is proposed. Within the framework the best deployment strategy for AB in an existing PT network is determined based on the normalized weighted sum of the operator and user costs. A deployment strategy is defined out of a set of predetermined service frequencies, vehicle capacities and the vehicle technology of each line. Different deployment solutions of autonomous buses on fixed line PT are analyzed and evaluated using a dynamic PT assignment and operations simulation model. The focus of this work lies in the analysis of impacts of deploying autonomous buses compared to conventional vehicles on fixed line PT networks. With the proposed framework we are able to conclude which bus line will result in the largest total cost reduction in terms of user and operator cost when operated autonomously. We analyze the introduction sequence of AB lines, hence the order in which bus lines should be automated. Finally, we observe a shift towards higher service frequencies when deploying AB in fixed line services. Our findings show that the deployment of AB leads to the biggest total cost reduction if the AB operate with their line specific optimal frequency and capacity. The pure replacement of conventional buses without reconsidering the service supply design for AB lines does not utilize the full potential of this vehicle technology, and hence will not lead to the largest attainable reductions. With the proposed framework any PT network can be studied.

We analyze the case study of a pilot project in Kista (Stockholm, Sweden), where autonomous bus shuttles are in operation. From the study four main conclusions can be drawn:

1. Deploying AB on fixed lines leads to overall cost savings. The operational costs savings outweigh the capital costs and therefore lower the total system costs. In the case study in Kista the total cost saving due to AB amounts to ca. 34%.
2. When deploying AB on fixed lines a shift towards higher service frequencies on high load lines can be noticed. The shift characteristics are use case specific and depend on demand level and on surrounding PT lines.
3. Solutions with inadequate service supply specifications cannot be made attractive by switching to AB systems. Hence, service frequency and vehicle capacity solutions stay inferior regardless of the vehicle technology used for operation.
4. The shift in frequency and capacity is sensitive to demand level and the reduced AB fixed unit operating costs respectively. The savings stemming from the deployment of AB scale proportionally with demand.
5. The sequence of technology introduction is different for operator-focused and user-focused design.
6. The introduction of AB increases the passenger load on certain lines. However high passenger volume modes, e.g. metro or train are more attractive to passengers than high frequency AB lines.

The results as presented in this study give an insight on how autonomous driving technology can be integrated into existing PT networks. Policy makers should consider the network-wide impacts high frequency lines have on the existing public transport network. As results of our analysis highlight, the deployment of AB can lead to a redistribution in passenger flows amongst lines in the study area as well as new route choices by travelers traversing the study area. The planning process should therefore not be done in isolation but with the exiting PT network in mind. The sequence in which AB are deployed has consequences for user costs as well as operator costs. Furthermore, the replacement of conventional buses with AB on existing lines might have the consequence that existing infrastructure (e.g. platform capacity and road structure) needs to be adapted. More passengers at the AB stops can be expected and a larger fleet size leads to more frequent station occupancy which in turn increases the requirements on the platform design and road structure. An holistic planning process is therefore required if AB system is to be successfully integrated into urban PT system.

Future work utilizing the presented framework may improve its generalization by investigating a larger solution space with a larger set of decision variable values. To this end, search heuristics can be applied to understand the characteristics of the network specific shift better and to converge faster to the optimal deployment solution, where brute-force is not an option. Deploying meta-heuristics will also allow to study
large-scale deployment strategies of AB vehicles. With the deployment of AB vehicles within larger areas it is interesting to further examine the sequencing of such fleets, since long term planning process are expected to outperform myopic planning strategies.

Acknowledgment

This research was funded by the Swedish Agency for Innovation Systems (Vinnova) through the projects iQMobility and Autopiloten, as well as KTH Integrated Transport Research Lab (ITRL). We would like to thank Nobina for kindly providing information about the pilot study in Kista.
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