Optimal allocation of Autonomous Buses in line-based Public Transport Networks

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Abstract

In this study we investigate the optimal deployment of autonomous vehicles (AV) in fixed line bus networks. It is one of the few studies ascertaining the transition from conventional bus transportation systems to fixed line transportation systems utilizing autonomous technology. To assess on which lines AV have the highest potential we develop a modeling framework using a dynamic public transportation assignment and operations simulation model. We investigate both the simultaneous and the sequential deployment of AV on multiple lines. Deployment solutions are assessed in terms of the 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. A sensitivity analysis is carried out concerning the effects of different cost parameters and demand levels on the deployment of AV in fixed line operations.

Highlights:

- tactical planning framework for autonomous buses operating on fixed line networks
- optimization of social welfare with respect to service frequency, capacity and technology
- measured shift towards higher service frequency for autonomous buses
- application of framework to a case study in Kista, Stockholm
- the extent of the frequency shift is sensitive to demand level and fixed operating costs

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

1. Introduction

Autonomous Vehicles (AV) are expected to have a high impact on current traffic and transportation systems. During the last decades the technology has matured to a point where the first trials in realistic urban conditions and pilot studies in mixed-traffic conditions are performed. Friedrich (2016) have shown that AV carry the potential for more efficient, more reliable and a cheaper transportation solutions compared to the existing transportation systems. Ainsalu et al. (2018) present a comprehensive overview of ongoing and past EU based urban transportation projects utilizing AV technology.
With the reduction of human drivers the operating costs for public transportation (PT) services can be significantly reduced. According to a study for Sweden by Jansson (1980) bus company costs consist of 80% service operating cost, from which crew costs are 50%, bus capital costs are 25% and other costs like fuel, repair, maintenance, insurance, taxes etc. sum up to 25%. To investigate the future cost drivers of bus PT 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. The reduction of the crew/labor cost hence allow to potentially revolutionize the existing passenger transportation systems.

While the vast majority of research about the introduction of AV has focused on replacing or substituting conventional PT systems, there is a growing number of studies dedicated to the symbiosis effects of AV and PT systems. Currie (2018) claims that the best application for AV systems is in feeding passengers towards PT. The author explains that the occupancy of vehicles must be kept high to facilitate the rising passenger demand in the future. In ride hailing systems the vehicles are only occupied up to ca. 34% on average which is low compared to existing PT (San Francisco County Transportation Authority 2017). Scheltes and de Almeida Correia (2017) explore the performance of an Automated Last-Mile Transport (ALMT) system in Delft, 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.

Several studies analyze the impacts of AV systems on PT. Zhang et al. (2019) investigate the integration of different types of autonomous buses (semi-autonomous or fully autonomous) on fixed line networks analytically. The paper considers 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. The reduction in operating cost allows the operator to run smaller buses and larger fleets which in turn improves the level of service for the user. Rather then analyzing fixed line networks and applying analytical methods Wen et al. (2018) focus on the system-wide effects of AV 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 AV to a last-mile connection. The mode choice model predicts the OD-specific demand for a new mode which combines AV and PT (AVPT) based on the level of service for each trip, trip fares and the total number of trips. The main contribution is finding the optimal solution with respect to improved level of service and operating cost (fleet size). 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. Unlike the previous study by the same authors, this study neglects passengers modal shifts.

Besides the recent work focusing on the combination of AV and PT (modal split analyses, shared AV systems and last mile feeders), 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. The authors 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. This feeder service...
design problem (FSDP) is applied to a case study in Monmouth County, New Jersey where one line is acting as a feeder line for the main transportation line. In the model two limiting assumptions are made. First, the passengers arrive uniformly at the transfer station which does not represent stochastic, fluctuating arrival processes. Second, the arrival of trains at the transfer station follow posted schedules, which ignores potential delays induced by congestion. The authors conclude that the 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.

Related to the works presented above is the research field of resource allocation in PT. Ibarra-Rojas et al. (2015) presents a comprehensive literature review focusing on real-time control strategies and PT service planning methods. 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 a single line without considering network effects. Newell (1971) proposes an analytical formulation for headway determination by minimizing passengers’ waiting time subject to fixed cost of the vehicle dispatches required. Salzbom (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.

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Gwilliam et al. (1985) and Jansson (1980) present analytical models to determine vehicle capacities. The authors conclude that operating lower capacity vehicles than those commonly used is not profitable when demand levels are fixed. In contrast Walters (1982) 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) proposes a comprehensive approach for determining the line frequencies for an entire 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.

Another branch of research in resource allocation approaches the service planning problem using simulation studies. Cats and Glück (2019), Horni et al (2016) and Krajzewicz et al. (2012) propose different simulation frameworks for the analysis of multi-modal transit systems. 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. 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 analytical approaches allow for a general understanding of the underlying concepts for the resource allocation problem and the effect of the most influential variables like service frequency and vehicle capacity. In more complex networks, demand-supply interactions from one line to another and route adjustments based on travel experiences should be considered, which is more easily addressed using a simulation approach. With these more sophisticated models, non-linear and stochastic components to the optimization problem for example passenger comfort based on vehicle crowding, vehicle delays or headway irregularity can be investigated. Chakroborty (2003) mentions the difficulty of modeling the resource allocation problem with a mathematical programming formulation, since the discrete nature and the complexity of representing transfers and continuity in a mathematical formulation. Newell (1971) emphasizes that PT assignment is a non-convex optimization problem which is difficult to solve.

In the past work the topic of AV is investigated from various standpoints, impact of shared AV systems on different PT modes or the use of AV as a last-mile feeder. Most of these topics assume a free floating vehicle fleet which operates on demand and uses the entire road network as potential routes. In contrast, we assume AV operation on a fixed line network and focus on the effects these autonomous buses (AB) have on the PT system. In the past, research on resource allocation in fixed line PT systems has been studied extensively and simulation based or analytical methods have been applied. However none of these studies
considers AB technology deployment. In this work we extend these works by deploying AB in fixed line services. We then can address the question which bus lines should be operated autonomously and at which service frequencies and vehicle capacities. Furthermore, the sequential introduction of AB into a fixed line PT network is analyzed and the question where AB lines should be introduced first is answered.

The different allocation and introduction scenarios are rated in terms of the sum of user and operator cost. For this work a detailed representation of demand level, demand pattern and supply is essential for the robustness of the conclusions. Additionally, stochastic passenger behavior and service reliability effects need to be considered. To fulfill these two requirements a multi-agent based simulation model for dynamic PT assignment and operations simulation is utilized to determine the impacts of dynamic supply-demand configurations, vehicle crowding, denied boarding, boarding and alighting times. We simultaneously optimize the technology, service frequency and the vehicle capacity on each line in the potential AB specific network. The level of detail in the analysis allows for more reliable conclusions about the impact of AB on fixed line PT systems and how AB fleets should be operated in PT networks.

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 case study was chosen because it aligns with the first pilot project of AB operating in Sweden.

This work comprises four main contributions. First, the presentation of a tactical planning framework for autonomous buses operating on fixed line networks. Second, the developed framework optimizes the combination of the total user cost and operator cost with respect to service frequency, vehicle capacity and vehicle technology. Third, a shift towards higher service frequencies and lower capacities when operating autonomous buses is identified. Last, we perform a sensitivity analysis for the impact cost parameters and demand level have on the extent of the shift in resource allocation.

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 discussed respectively. After this the sensitivity analysis is presented in Section 5. The paper closes with a conclusion and outlook for future research in Section 6.

2. Methodology

In this section the studied autonomous bus allocation problem is specified. After that the agent-based simulation and the set of parameters are explained respectively.

A deployment solution is defined as a set of service frequencies \( f_i \), capacities \( k_i \) and vehicles technology \( v_i \), \( i \in \{1, \ldots, N\} \) on each line, where \( i \) is the line ID and \( N \) 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. This allows for the analysis of certain lines or areas of interest rather than looking at the PT network as a whole. 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 comparison of different solutions with respect to the technology deployed on each line of interest allows for the identification of an optimal sequence of AB deployment in the sub-network formed by the lines of interest. To extract the sequence the total costs for all solutions with one AB line are compared with each other. The best system-wide improvement can be achieved if AB are introduced in decreasing order of cost savings per line (see subsection 1.3).

The frequency and capacity of each line is constrained to a specific set of discrete values. For frequencies these values are defined as cyclic. The vehicle capacities are specified based on typical values for existing buses or prototype buses. The demand pattern and demand level stay unchanged, treating the demand as exogenous to the design dimensions considered in this study. The network design is kept constant, meaning that total number of bus routes and the bus stops per route stay unchanged. Hence we only adjust the level of service supplied to the customers by means of re-allocating resources to service lines.

The different deployment solutions are rated based on the total cost \( C_T \), which is the sum of user cost \( C_U \) and operator cost \( C_O \). The goal is to minimize the combined user and operator cost subject to the
Table 1: Model parameters and variables

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Unit</th>
</tr>
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<tbody>
<tr>
<td>conv</td>
<td>Conventional Vehicle</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>
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<thead>
<tr>
<th>Decision Variable</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>
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<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Unit</th>
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<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>
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2.1. 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 ($T_{piv,p}$), transfer penalty ($P_p$), total waiting time ($T_{w,p}$), access and excess times ($T_a,p$ and $T_e,p$) and denied boarding waiting time ($D_p$). 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 give the total user cost.

The perceived in-vehicle time ($T_{piv,p}$) is defined as the time a passenger spends in a vehicle multiplied with a factor representing the crowdedness of that vehicle. The more crowded a vehicle is the higher the perceived in-vehicle time is. Transfer penalty ($P_p$) adds additional time to the waiting time a passenger is experiencing when transferring to a new vehicle. Transfers are perceived as unattractive for passenger’s route choice and travel experience. The waiting time ($T_{w,p}$) describes the total time a passenger spends waiting between two connections. Access time ($T_a,p$) is computed as the time a passenger spends to get from the start location to his/her origin station, while the egress time ($T_e,p$) is the time a passenger spends to get from the destination station to the final destination of his/her trip. Denied boarding is defined as the time added to the total travel time of a passenger due to denied boarding at a bus stop. This extra waiting time is seen as frustrating for passengers and is represented with a higher cost term.

2.2. Operator Cost

In general the operator cost ($C_O$) can be split into capital costs and operating costs. For the correct calculation of these costs it is necessary to determine the cost parameters $\beta$ and $\eta$, which scale the 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 $t_i$).
The operating cost ($C_{\text{oper}}$) is the price for a vehicle per hour including the expenses of the operator for stewards and bus driver and the maintenance costs. The operating cost for AB is assumed to be lower than for conventional buses due to lower labor requirements. Specifically, the unit fixed operating cost parameter is reduced by $\eta$. The is summed over all potential AB lines to compute the total network operating cost.

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

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

The capital cost ($C_{\text{cptl}}$) is defined as the purchase price for a vehicle depending on capacity and vehicle technology. Equation 3 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.

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

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

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. Simulation model

This subsection highlights the details of the multi-agent simulation model as shown in Figure 1. As a first step the input for the simulation software need to be 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 want to travel between these two stops). The transit network information containing all the 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. The model requires travel demand, connectivity and spatial information of the network
(bus stops, routes and bus lines) as input.

3. Case Study

The framework is applied to a case study in Kista, a technology center in close proximity to Stockholm
that experiences 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 till June 2018. The automated line
was approx. 1.2km long with a total of three bus stops. The shuttle operated between two main transport
hubs (metro station/shopping mall and oces/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 20165, 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
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.,
(a) AB network and connection to Stockholm network

(b) Map of Kista area including bus stops and PT lines © OpenStreetMap contributors

Figure 2: Kista case study public transportation network

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
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<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>
<td>0.63</td>
<td>-</td>
</tr>
<tr>
<td>(\beta)</td>
<td>0.5</td>
<td>-</td>
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</table>

Table 2: Operator Cost Parameter

...that in-vehicle times, waiting times and transfers are valued the same by passengers for autonomous and for conventional vehicles.

Line 1 is connecting bus stops Kista and Helenlund, line 2 is connecting bus stops Helenlund 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 adjust for different units of both cost terms 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)).

For each decision variable a set of feasible values is defined. The frequencies range from \(f_i \in [5, 10, 15]\) and the capacities are within \(k_i \in [10, 60, 100]\). 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 3 shows the impact on the operation cost for a range of decision variables. The costs are computed using the formulations in equations 3 and 2 for potential AB line 1 and assuming only conventional buses (green) and only AB deployment (orange) solutions. The capital costs for AB are set to be ca. 33% higher than for conventional vehicles. The operation costs are ca. 50% lower for AV than for conventional vehicles (Australian Transport Council, 2006).

The number of solution analyzed in this network is 1296. One solution is illustrated in Figure 4. Here the solution is defined with autonomous vehicles on line 1 with frequency 10 veh/h and capacity of 10 passengers...
Figure 3: Model specification for change in service frequencies and vehicle capacities

and on line 4 with frequency 5 veh/h and capacity of 60 passengers.

The total computation time for this set up is approximately 30 h. The hardware used is Intel(R) Core(TM) i7-8750H CPU @ 2.90GHz and RAM 16.0 GB 2400Mhz. The simulation was not using graphics cards or parallel threading.

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 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 lines. For each line there is one OD pair, which each have a demand rate of 20 passengers per hour. This demand is approximated by matching the recorded demand data from the pilot phase. Other OD pairs which use multiple AB lines are present in the total network demand data but. These OD pairs are not effected by the estimated demand.

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.
four added potential AB lines the trip times are adjusted to the actual driving times of existing bus lines on these links.

3.3. Hyperparameter setting

For the setting of the simulation specific hyperparameters a pre-study is done. The hyperparameters are related to the simulation configuration and simulation setup. The two hyperparameters studied are the number of simulation replications. The same base demand is assigned for all the simulation runs. Both hyperparameter settings result in the same qualitative solution space if the number of simulation replications is set high. However the absolute numbers are different which is negligible for the purpose of this work since the same conclusions about general trends in the solution space can be drawn throughout all parameter settings.

To account for stochastic variance in the simulation outputs each solution is simulated multiple times. In Figure 5 the confidence interval for the network is shown. The black line is the mean value of a specific setting and the value used for further analysis in this work. The red points mark the 95th percentile of each solution. We can conclude from this that 10 simulation runs meet the accuracy requirements for this application. The variance of the objective value is negligible compared to the overall trend and magnitude of the total cost.

For the generation of the confidence interval (Figure 5) the results are sorted in descending order. The dark blue points in the heatmap here the combination of medium capacity and medium frequency on lines 1 and 3 are combined with low frequency and high capacity on lines 2 and 4. These solutions allow for a balanced supply and demand distribution on the 4 lines - a general reason for this drop cannot be found.
from the data analyzed. It is network specific and is present in this case due to the limited number of total solutions analyzed.

![Figure 6: Total cost for constant service frequency](image)

4. Results

The total system cost is composed of three parts: user cost, capital cost and operating cost. There are three consequences of the model specification. First, the operating cost is highest for conventional vehicles. Second, the capital cost increases with the number of autonomous buses and service frequencies. Third, high vehicle capacities lead to high capital costs. The ranges of these three cost components are network-specific and depend on the number of potential AB lines in the network under investigation. The cost reduction achieved per line is proportional to the trip length on that line. The longer the line is the larger are the savings. Besides that also the optimal service frequency and vehicle capacity on each line determines the total cost reduction. In the Kista case study a small number of lines (4 out of 91) are subject to investigation and hence the total range of capital cost and operating cost is smaller than the user cost. The user cost is computed using all passengers in the network while the operating cost and capital cost are computed considering the fleet size on all four potential AB lines. The total cost is therefore dominated by the values of the user cost.

![Figure 7: Total cost for constant vehicle capacity](image)
In Figure 6, the influence of increasing the vehicle capacity on all lines while keeping the service frequency constant is shown, for conventional (left) and autonomous (right) buses. For this comparison all lines are either operated by conventional or autonomous buses and the service frequency is set constant to 10 veh/h on all lines. It can be seen that the overall trend is similar. An increase in capacity does reduce the user cost, because of a reduction in waiting time due to denied boarding (Figure 8a) while the operating cost increases linearly with the capacity. The total cost decreases from ca. 27 500 SEK/h to ca. 27 200 SEK/h when operating conventional buses. For AB the decrease is from ca. 26 500 SEK/h to ca. 26 200 SEK/h; the difference between AB and conventional buses is due to the reduced operating cost.

Figure 7 shows the influence of increasing the service frequency on all lines while keeping the vehicle capacity constant at 10 passengers for conventional (left) and autonomous (right) buses. Compared to vehicle capacity increased frequency has a larger impact on the total cost. This is true for both autonomous as well as conventional vehicles. The increase from 5 veh/h to 10 veh/h results in a substantial increase in total cost resulting from the higher operating costs. The higher operating costs result from the larger fleet size required. The user costs stay almost unchanged because of two effects. First, due to a higher number of transfers and the resulting larger walking times (Figure 8b and Figure 8c) the user costs increase slightly. Second, this increase is compensated by the reduction of waiting times for all passengers on the four lines when the service frequency is raised to 15 veh/h (Figure 8d). The difference between AB and conventional buses is therefore due to the reduced operating cost.

Figure 8: Change of user cost terms with respect to service frequency and vehicle capacity on each potential AB line
Figure 9 gives an overview of the user cost for different frequency and capacity values on different lines. On the x-axis all the different vehicle capacities are listed. On the y-axis the service frequencies are shown. The green rectangle on the bottom left represents the user cost for the solution using a service frequency of 5veh/h and vehicle capacity of 10 passenger on all four lines. The other rectangles show the user cost following the same scheme.

Figure 10 shows the total cost for every 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 marked in red represents the deployment of conventional buses on lines 2 and 3 and autonomous buses on lines 1 and 4. Within a rectangle the naming convention from Figure 9 is applied. 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 user cost pattern is clearly visible for all vehicle deployment solutions; thus the introduction of AB does not change generally inferior deployment solutions. However, as indicated by the red circles, the optimal service frequency and vehicle capacity differ between conventional and autonomous buses. The details of this network-specific shift is highlighted in the next subsection. From Figure 10 it can be seen that the total cost can generally be reduced by deploying AB on each line (indicated by the color shift towards blue from top to bottom and left to right).

4.1. Service design

Two chief observations can be made based on Figure 10. 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 the deployment if the vehicle utilization is high and outweigh the higher initial investment costs. Second, specific frequency and capacity solutions which have a high total cost when operating with conventional vehicles become more attractive when the line is operated with AB. For example, operating with a service frequency of 15veh/h and a vehicle capacity of 60 passengers on lines 1 and 3 and on lines 2 and 4 with a service frequency of 5veh/h and a vehicle capacity of 100 passengers while all vehicles are conventional buses the total cost is ca. 5% higher than the same solution but with AB. Similarly, inferior solutions stay persistent throughout the entire solution space. The worst solutions throughout all deployment options all have frequency 10veh/h and capacity 10 passenger on every line, which is due to unsatisfied demand resulting in high penalties for denied boarding. 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 2 and 3 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 optimal frequencies and capacities through the introduction of AB is apparent in Table 3. It can be seen
that there is a shift towards higher frequencies on lines 1 and 3. Thus, the surrounding commuter train and metro lines are supported by frequent bus lines to accommodate the total demand, so that the crowding can be reduced on these stretches. Consequently, the overall system performance is improved. For these optimal solutions the total cost reduction stemming from AB deployment is ca. 3.2%.

![Figure 10: Total cost [SEK/h] for entire solution space. The shift in optimal frequency and capacity is highlighted with a red arrow. The x-axis show the vehicle capacities $c_i$ per line $i$, on the y-axis the service frequencies $f_i$ per line $i$ is visualized.](image)

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Table 3: Optimal operation solutions with exclusively conventional vehicles and automated vehicles, respectively.
4.2. Passenger load

The different optimal deployment solutions for conventional and autonomous buses as described in Table 3 do not result in very different passenger loads on the four lines (Figure 11). The minor differences between conventional and autonomous are due to statistical effects. The total number of passenger traveling on line 1, line 2, line 3 and line 4 is ca. 8000 passengers in the conventional case and ca. 7500 passengers when operating autonomous buses. The introduction of autonomous buses on lines 1 to 4 does reduce average waiting time per passenger (Figure 12) while the other cost parameters do not change considerably.

However, this does not translate to an increase in passenger load on these 4 lines. A reason for this can be found when analyzing the overall passenger flows. The vast majority of passengers are traveling through the area of investigation, utilizing the AB lines for their travel would result in additional transfers.
and waiting times, which would in turn reduce the utility of their trip. This can be seen by looking at passenger load of lines 1, 2 and 4 (Figures 11a, 11a and 11d) respectively. Despite the total load on the line segment being high only a few passenger choose to travel with the AB line, since their trip starts and ends outside the area of investigation. Only if the additional transfer and waiting time is increasing the trip utility the passenger loads of the four AB lines are effected. Since only a few passengers journeys have such characteristics the passenger loads do not change much. The connection between Kista and Sollentuna (11e) shows such characteristic. Passengers traveling between Kista and Sollentuna can reduce increase their trip utility by switching from bus line 179 to AB line 1 & 2 or AB line 3 & 4 respectively. Therefore the passenger load on the existing conventional bus line 179 is reduced.

4.3. Vehicle deployment sequence

For the transition towards full AB systems it is important to analyze the most beneficial lines for the deployment of AB. In Figure 13 the total cost reduction for the best deployment sequences compared to the base case is shown. In the base case all lines are operated with conventional vehicles. From left to right the number of AB lines is increased from one to four. The optimal frequency and capacity are used for each deployment solution. From Figure 13 the following sequence is found: line 3 → line 1 → line 2 → line 4. This sequence results in the largest total cost reduction. If one line should be automated the total cost reduction is maximized by operating AB on line 3 which leads to a cost reduction of ca. 307 SEK/h. Adding a second and third AB line reduces the total cost by ca. 574 SEK/h and 686 SEK/h respectively.

![Figure 13: Sequence of AB deployment on a fixed line network based on total cost reduction [SEK/h]](image)

Since the optimal frequency and capacity change when operating more lines with AB, the total cost reduction is not additive per line and the sequence of introduction might change from operating one AB line to two AB lines. For example if we compare the total cost reductions resulting from having one AB line in the network (Figure 14), we can see that line 3 gives the largest cost reduction with ca. 307 SEK/h and line 1 with ca. 133 SEK/h the second largest. However, as seen in Figure 13 the actual cost reduction computes to ca. 574 SEK/h.
5. Sensitivity analysis

Due to the high uncertainties when analyzing AB systems a comprehensive sensitivity analysis is performed. First, the impact of the demand level is investigated. Second, the effect of different cost parameters in the operator cost formulation is analyzed. With these two investigations different future developments in terms of user acceptability (demand level) and technological development (cost parameter) can be understood. The demand level represents the passenger rate of arrival at each of the four AB bus stops. For the scope of this work all four AB bus stops have the same demand rate. If not further specified the base case for comparison in this section has a passenger arrival rate of 20 passengers between OD pair of each AB line and the cost parameters as described in Section 3.

5.1. Sensitivity analysis with respect to demand level

Figure 15 shows the total cost for two different demand levels on the four potential AB lines. In the first row (Figures 15a-b) the color coding is based on the demand level specific range. In the second row (Figures 15c-d) the color coding is uniformly scaled to the total range over all two demand levels.

At demand level of 20 passenger/h the impact of the operational cost savings of AB is present as well as the shift for AB towards higher frequencies in the optimal solution (Table 3, top). Vehicle capacities do not reach the largest value due to the lower demand level compared to the base demand.

When increasing the demand to 50 passenger/h on the four lines the user cost is dominating the total cost (Figure 15b). All scenarios investigated result in a higher total cost due to the higher user cost. The heatmap indicates that for a higher demand level the optimal solution is found with the lowest capacity and lowest service frequency on all four lines. This result is somewhat surprising since one would expect operating with more and larger vehicles on the high demand lines is beneficial for the system. An explanation can be found when looking at the user cost terms individually. With an increase of service frequency and vehicle capacity the total waiting time can be reduced (Figure 16a). The reduction of user cost due to the lower waiting times is however compensated by an increased number of transfers (Figure 16b) and walking times (Figure 16c). Which results in an increased in-vehicle time (Figure 16d) and longer total travel times, respectively. Hence, the total user cost does not change considerably and the optimal strategy is the one with lowest operating costs, therefore the low frequency and capacity are optimal for this case.

In general it can be concluded that (i) savings stemming from the deployment of autonomous vehicles are sensitive to the demand level; (ii) there is a demand level dependent shift in optimal frequency when operating autonomous buses towards higher frequencies. The specific shift characteristics are network dependent and are constrained by the demand level and AB network layout.
Sequence of deployment. The introduction sequence of AB lines is found to be insensitive to the demand level. The sequence does not change in any of the four cases. The operating cost, capital cost and user cost scale with the demand level so that the sequence remains unchanged.
5.2. Sensitivity analysis with respect to cost parameters

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Table 4: Operator Cost Parameter

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 4). Due to the limited number of available operating and capital cost data of AB and the early stages of the technology, the range for the cost parameters is set to be large. An increase of the unit fixed operating cost represents a higher maintenance cost, higher fees, higher energy consumption is assumed for the simulation. A change in the unit fixed capital cost might be due to advances in mass production or a break through in production technology. A change 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 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 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.

The results are not sensitive to changes in $b_{\text{cptl}}$, $b_{\text{oper}}$, $c_{\text{oper}}$, $c_{\text{cptl}}$ 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. On line 1 and 3 the frequency shifts from 5 veh/h to 10 veh/h. The sequence of AB introduction is: line 3 $\rightarrow$ line 1 $\rightarrow$ line 2 $\rightarrow$ line 4.

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 in the framework. If the operation of autonomous vehicles become cheaper, the higher capital costs are compensated at higher frequencies and allow the deployment of larger fleets on more lines.

**Sequence of deployment.** If $\eta$ is set to 0, the fixed unit operating cost for AB are not reduced compared to the conventional fixed unit operating costs. In combination with the higher capital costs for AB the conventional buses are always the preferred solution.

In conclusion, the optimal 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 since AB have a higher operating cost and therefore no AB will be deployed in the network. The sequence of deployment stays the same independent of demand level and cost parameter values.

## 6. Conclusion and future research

In this paper a tactical planning framework for autonomous buses operating on a fixed line network is proposed. Within the framework the sum of the operator and user costs is optimized with respect to service frequency, vehicle capacity and the vehicle technology. 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 in deployment frequency and capacity 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 bus 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. The proposed framework is generally applicable to any PT network.

We analyze the case study of a pilot project in Kista (Stockholm), 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. 3.2%.

2. When deploying AB on fixed lines a shift towards higher operational frequencies 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 cost parameter $\eta$ – reduced AB fixed unit operating costs respectively. The savings stemming from the deployment of autonomous vehicles scale proportionally with demand.

Future work utilizing the presented framework may improve its generalization by investigating a larger solution space with a larger possible 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. 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. Another direction of future research is investigating the impact of AB deployment on total travel demand, demand pattern and mode shifts which they may cause when introduced to a given PT network.

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