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Impacts of autonomous vehicle deployment on demand for line-based public transport services

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Abstract The maturing of autonomous driving technology in recent years has led to a number of pilot projects and the first integration of autonomous pods and buses into the public transport (PT) system. An upcoming field of interest is the induced demand level and potential changed demand patterns of PT systems. In this work a multi-objective optimization based multi-agent simulation framework is developed to study potential demand shifts from e.g. private cars to PT and the demand distribution when AV systems are deployed on fixed line networks. During the optimization process multiple deployment scenarios (vehicle types, capacity and frequency) are evaluated and optimized with respect to the operator cost and user cost of the system as well as the overall demand level. Different scenarios are studied (e.g. different operations costs for AV, policy and technology acceptance levels) to be able to gain a wide applicability of the proposed framework. The results will provide insights into the efficiency and potential increased ridership that will result from the deployment of AB in line-based PT systems.

Keywords Public transport · Automated Bus · Operational Costs · Demand Estimation · Multi-objective Optimization

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1 Problem statement & Research Objective

For the transition towards future mobility scenarios utilizing autonomous vehicles (AV) an understanding of system wide induced changes regarding the current transport system need to be gained. In this work insights of the changes in demand level and pattern are achieved. In [1] the changes in demand when operating autonomous mobility-on-demand (AMoD) systems are studied. The authors use a multi-modal simulation tool to compute the changed modal split and preferred mode of transport if AMoD systems are available for passengers. Another study, [2], predicts the changed of "mobility-service demand by considering changes in age compositions, age-related declines in individual travel needs, increasing rates of drivers license relinquishment, and regional factors including the level of service for alternative modes of transport". The authors also consider new mobility services employing AV yet they focus on shared taxi like mobility systems.

The goal of this work is to analyze the changes in demand level and demand pattern induced by the deployment of AV systems on fixed line PT networks. The focus is on the ability of autonomous buses (AB) to attract more travelers from e.g. private cars to PT. The research covers the impact of different bus deployment strategies, sequence of vehicle deployments and the different societal aspects (pricing, user acceptance). The purpose of the framework development is to be able to consult the planning and redesign of new and existing PT lines respectively.

The framework will be applied on a synthetic network as proof of concept and later centered around a case study in Barkarby, Stockholm, the first European pilot where AB are fully integrated into PT [3].

2 Methodological approach

To answer the research question as described above a multi-objective optimization model is developed where solutions are evaluated using a multi-agent mesoscopic simulation. The scheme of the framework can be seen in figure 1. The core of the framework is the multi-agent simulator. For this purpose BusMezzo (compare [4]) is used. In the simulation a predefined network and demand level/pattern will be evaluated. The demand is an input in form of an OD matrix. The network topology is defined by a set of links, routes and bus stops. The supply of the network is defined using the scenario descriptions and can be formulated as an input to BusMezzo. The tool is evaluating the given demand-supply setting based on the KPI like travel time per passenger, number of transfers, waiting time and others. Using these metrics both objectives are computed and updated. First, the user cost and operator cost can be computed using the extracted KPI and estimating the fleet size (see equation 2 for details). Second, the new demand level and pattern is computed based on elasticities values extracted from literature [5]. The elasticities, with respect to the decision variables (e.g. service frequency, number of transfers, total travel time), will be subject to sensitivity analysis to account for uncertainties in the data.

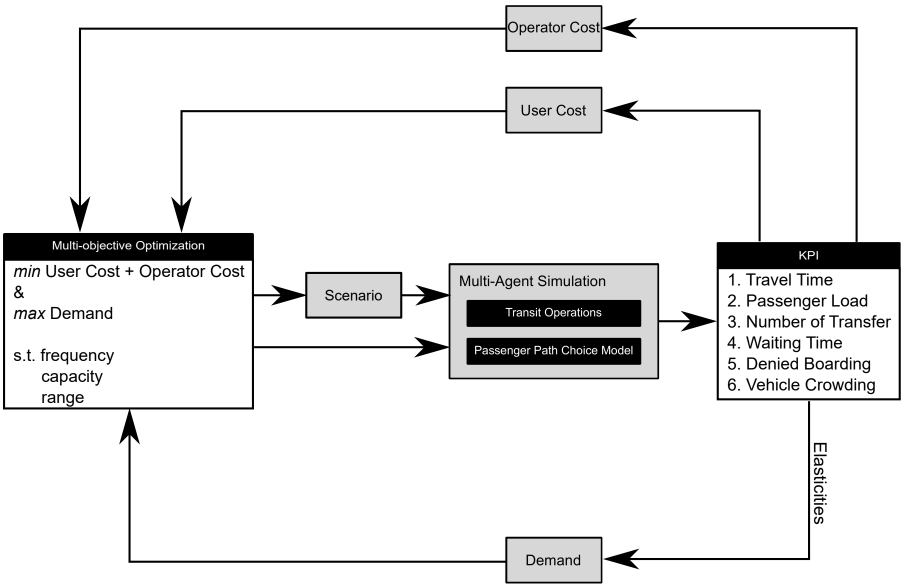

Fig. 1 Proposed optimization based simulation framework

Based on the operator cost and user cost a new scenario will be created and the new demand setting will be fed into the simulation tool. The goal of the multi-objective optimization is the minimization of operator and user cost respectively while maximizing the demand increase. The trade off between both objectives will be measured using the concept of Pareto front. For the computation of the optimal values a non-elitist multi-objective evolutionary algorithm or weighted sum method will be implemented.

The user cost (C_U) is computed using the perceived in vehicle time (T_{piv}), the Transfer Penalty (P), the total waiting time (T_w), the access and excess times (T_a and T_e) and the Denied Boarding waiting time (D).

- Perceived in Vehicle Time (T_{piv}): The time a passenger spends in a vehicle is multiplied with a factor which is representing the crowdedness of the vehicle. The more crowded a vehicle is the higher the perceived in-vehicle time is when traveling for the same absolute travel time.
- Transfer Penalty (P): Additional time is added to the waiting time a passenger is experiencing when transferring to a new vehicle. Transfers are perceived as very unattractive for passenger's route choice and travel experience; hence this penalty represents this matter.
- Waiting Time (T_w): The total time a passenger spends waiting between two connections.

- Access Time (T_a): The time a passenger spends to get from the house to his/her origin station.
- Egress Time (T_e): The time a passenger spends to get from the destination station to the final destination of his/her trip.
- Denied Boarding (D): The time added to the total travel time of a passenger due to being denied of boarding at a bus stop. This extra waiting time is seen as frustrating for passengers and therefore is represented with a higher cost term.

$$C_U = T_{piv} + P + T_w + T_a + T_e + D \tag{1}$$

The operation cost is computed using cost parameters β and η, which scale the cost regarding the vehicle type and the fleet size. The fleet size can be estimated either by using the frequency and trip time of a bus line or the headway and the trip time of the bus line.
$n = \frac{t \cdot f}{60} = \frac{t}{h}$

- Operating Cost (C_{oper}): Price for a vehicle per kilometer or a vehicle per hour including the expenses of the operator for stewards or bus driver and the maintenance costs
- Capital Cost (C_{cptl}): Purchase price for a vehicle depending on capacity and vehicle type

$$\begin{aligned} C_{oper,conv} &= n_i \cdot (k_{oper} + b_{oper} \cdot c_i) \cdot t_i/60 \\ C_{oper,auto} &= n_i \cdot ((1-\eta) \cdot k_{oper} + b_{oper} \cdot c_i) \cdot t_i/60 \\ C_{cptl,conv} &= n_i \cdot (k_{cptl} + b_{cptl} \cdot c_i) \cdot t_i/60 \\ C_{cptl,auto} &= n_i \cdot ((1+\beta) \cdot k_{cptl} + b_{cptl} \cdot c_i) \cdot t_i/60 \end{aligned} \tag{2}$$

where the parameters from table 1 (comp. [6]) are initially used.

Name	Parameter	Value
unit fixed operating cost	k_{oper}	334.60
unit fixed capital cost	k_{cptl}	14.24
unit size-dependent operating cost	b_{oper}	0.75
unit size-dependent capital cost	b_{cptl}	1.01
reduced fixed unit operating cost of AV	η	0.63
additional fixed unit capital cost of AV	β	0.5

Table 1 Operator Cost Parameter

3 (Expected) results

With the proposed framework we are able to study the induced changes in demand pattern and demand level for PT and therefore provide a better understanding of the impact AB systems have in the transport network. The transition to future mobility scenarios can then be designed to be optimal for users and operators and therefore maximize the utility of these systems. The main contribution of the work is the development of the proposed framework which is applicable to any network and capable of large-scale simulations and the computation of elasticity values for AB. Also, the framework allows for the analysis of different transport scenarios. The elasticity values can be adjusted to represent different user acceptances of AV technology, different fixed cost developments can be simulated by adjusting the operator cost parameter.

The authors expect a general increase in demand on the bus lines operated by AB since the reduced operational costs allow for a higher frequency and therefore offer a more attractive transport option for the passenger. However, the maximum passenger flow towards the new high frequency lines might not be sufficiently high to transport a lot of people to these lines. Therefore the surrounding lines need to be adjusted in frequency and capacity to match the newly introduced or redesigned AB lines. Due to the complexity of this problem, the system wide effects remain subject for investigation.

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