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Determining the Optimal Allocation of Automated Buses

Jonas Hatzenbühler · Erik Jenelius · Oded Cats

Abstract This work proposes a framework for determining the optimal allocation of Automated Bus (AB) services in a multimodal public transit network. The proposed simulation and optimization framework considers the change in operator costs with AB systems and passenger flow distribution. For feasibility analysis the framework is first applied to a synthetic scenario, then a subsection of Stockholm area, where a pilot project is currently running, is assessed.

Keywords Public Transport · Automated Bus · Operational Costs · Route Choice

1 Introduction

This research is driven by the general need for affordable, frequent and convenient Public Transport (PT) solutions. Over the last years the advances in the sector of autonomous systems have triggered studies of their effect on PT [1, 2]. AB systems could contribute to a more efficient and profitable PT system by replacing humanly-driven vehicles. AB lower the operational costs due to the removal of labor costs, which in developed countries account for more than

J. Hatzenbühler
Division of Transport Planning, Economics and Engineering, KTH Stockholm, Sweden
E-mail: jonas.hatzenbuhler@abe.kth.se

E. Jenelius
Division of Transport Planning, Economics and Engineering, KTH Stockholm, Sweden
E-mail: erik.jenelius@abe.kth.se

O. Cats
Department of Transport and Planning, Delft University of Technology, The Netherlands
and
Division of Transport Planning, Economics and Engineering, KTH Stockholm, Sweden
Delft, The Netherlands
E-mail: o.cats@tudelft.nl

half of the overall operational costs. These lower operational costs are expected to lead to higher service frequencies. The introduction of more diverse vehicle sizes is then possible and economical which will allow the operators to target the user demand better than with a fixed sized vehicle fleet. In this study the term, social welfare of Public Transport Systems, is been used as a trade-off measure between the customer and operator costs [3]. By removing the bus driver in an AB, the bus fleet characteristics are more flexible and adaptable to changes in the user demand and bus fleet. A higher amount of buses and demand adjusted schedules will then ultimately result in lower overall passenger travel time and lower operation costs [4]. Hence, the interaction between vehicle capacity and AB fleet size will be consequential in the introduction of AB in PT systems. These variables have been investigated individually in the work of [5]. Unlike previous works, the combined costs of user and operator are used to determine the effects of deployed AB systems in existing PT networks. In this work we

- define an AV specific objective function
- integrate AV systems in a mesoscopic simulation framework
- extract KPIs for the economic employment of AB systems

Additionally, this work defines Key Performance Indicator which allow to predict the economic effect of applying AB systems in an existing Public Transit Network. Possible KPIs could be the passenger demand on specific route sections, the trip/route length or the AB vehicle-kilometers. On extracted interesting areas, we then can give an advise on how the AB fleet should be characterized in terms of vehicle capacity and overall AB fleet size.
This study aims at answering the following research questions:

1. How can AB systems be used to improve passenger and operator costs on existing lines?
2. What are the implications of the cost trade off in terms of the defined KPI?
3. Where is the deployment of AB systems most interesting in terms of social welfare?

2 Method

The implementation of the framework adopts an iterative approach. In figure 1 the approach is displayed. First the investigated area must be defined and important input values e.g. connected lines, existing bus routes, OD Matrix and the optimization cost parameters are extracted. The multi-agent simulation software (BusMezzo) [6] uses the networks routes and the optimization decision variables as input values. The simulation consists of 4 main modules. The traffic simulation, transit operations and control, dynamic path choice model and the real-time information generator. Subsequently the simulation is executed, and the filtered results will be handed to the optimization module. The objective function minimizes the overall cost which in this study is the

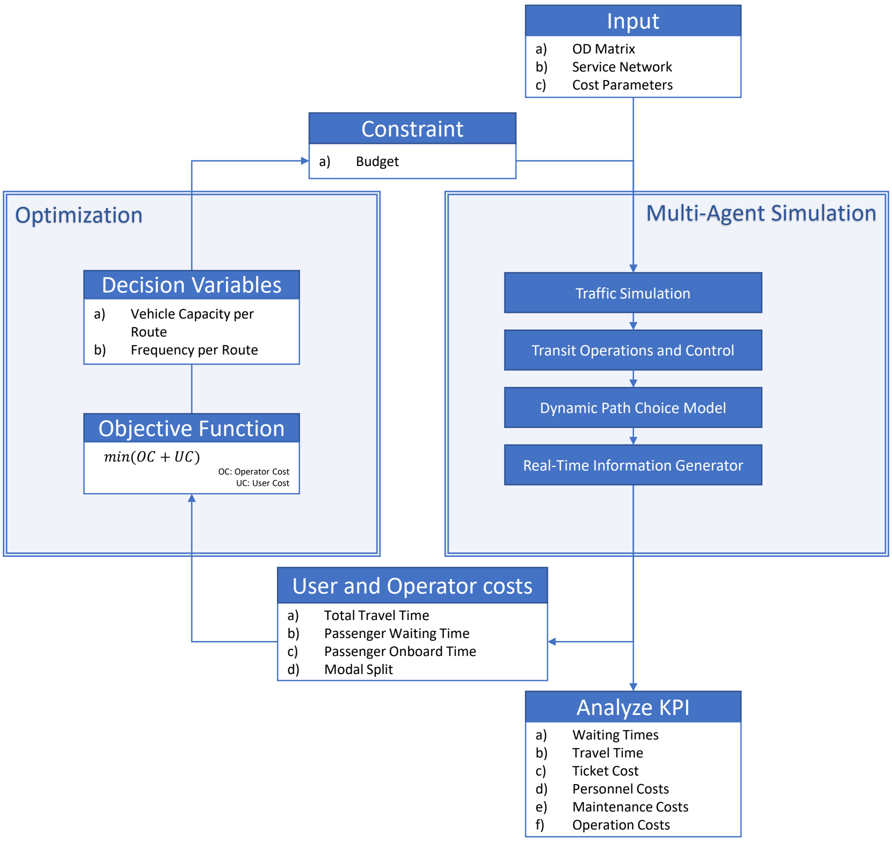

Fig. 1 Simulation Framework

sum of operator costs (personnel costs, maintenance costs, operation cost) and user cost (travel time, waiting time, ticket cost). The output of the optimization step determines the value of the decision values. This loop is executed until a defined break out point is reached (minimal accepted social welfare). From there on the KPIs will be analyzed.
The decision variables for the optimization module are the vehicle capacity and the frequency per route.

The analysis is performed as a simulation-based optimization which allows a general approach and drawing widely applicable results. For the simulation of the proposed model the simulation tool BusMezzo is used. The optimization is conducted using a mixed-integer programming model [7] with a branch-and-price-and-cut algorithm [8] and a Generic Algorithm [9] for scenario creation and scenario comparison. For the interpretation of the results, Key Performance Indicator (KPI) have been defined. For the customer waiting times, travel time and ticket cost is analyzed. For the operator personnel costs, maintenance costs, operation costs (energy consumption, down time) are considered.

3 Application and Outlook

The proposed model will be applied to a case study in the area of Kista in Stockholm, Sweden. An on-going pilot of an actual AB system runs in Kista. Passenger flow data collected during the project phase will be used as a reference when analyzing the proposed framework results. Table 1 summarizes the characteristics of the Kista pilot. The values in table 1 represent the current route of the AB service in Kista. This framework however will investigate the impact of AB systems in the entire Kista area with connected metro systems, regional trains and over regional bus services. In addition, the optimization model will be applied on a synthetic network which helps to analyze the properties of the proposed method. To show the general applicability of the proposed approach for larger scale problems.

Table 1 Case Study Kista

	Kista
Number of Buses	2
Length of Bus Route	approx. 1.2km
Number of Bus Stops	3
Capacity of Buses	max. 12
Connections	Metro, Commuter Train, Bus
Shuttle	Service Feb 2018 – Jul 2018
Customer	office workers, tourists, shopping and visitors

Scenario design and sensitivity analysis include the investigation of the effect of uncertainties in the input variables (e.g. cost parameters, changes in supply or demand). We will then generally conclude on the relations between the input values and KPIs as shown in fig. 1. Possible applications of the proposed methodology is as a tool for identifying the most promising areas for introducing AB, test beds and first pilot areas as well as a measurement for the economic impact of AB Systems on PT. Potential extensions of the model include the study of the transition process to AB systems for all bus lines in a given network and the fleet composition of special AB zones in high user demand areas.

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