Department of Computer Science

Economic Perspectives on Automated Demand Responsive Transportation and Shared Taxi Services

Analytical models and simulations for policy analysis

Jani-Pekka Jokinen

Aalto University

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Jani-Pekka Jokinen

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Abstract

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Abstract

The automated demand responsive transportation (DRT) and modern shared taxi services provide shared trips for passengers, adapting dynamically to trip requests by routing a fleet of vehicles operating without any fixed routes or schedules. Compared with traditional public transportation, these new services provide trips without transfers and free passengers from the necessity of using timetables and maps of route networks. Furthermore, automated DRT applies real-time traffic information in vehicle routing and in formulating trip offers with travel time promises, which enables differentiated pricing based on travel times and thereby tailored service provision for personal passenger needs.

This work considers the potential economic impacts of automated DRT and shared taxi services on urban transportation, and explores the effects of various transport policies on these new transport services as an integral part of urban transportation system. Analytical models are presented to define welfare optimal policies for these services, which have different trip production cost structures and external costs compared to conventional bus and taxi services. Moreover, simulation models are developed to analyse cost-effectiveness and regulation policies. Furthermore, alternative pricing models for these services are analysed from the viewpoint of transport companies, passengers and transport policy.

The publications presented in this dissertation provide theoretical foundations, models and insights based on empirical data for further policy analyses and empirical research on automated DRT and shared taxi markets. These markets are evolving due to the advances in intellingent transportation technologies adopted by innovative and even revolutionary companies, and due to the increasing political pressures for sustainable transportation.

Keywords demand responsive transportation, shared taxi, transportation economics, transport policy, pricing, regulation, crowdsensing, intelligent transportation, social welfare, public transport

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Tiivistelmä

Automatisoitu kysyntäohjautuva joukkoliikenne ja modernit jaetut taksipalvelut tarjoavat jaettuja kyytejä matkustajille makautuen dynaamisesti matkapyyntöihin reitittämällä operoivat ajoneuvot reaaliaikaisesti ilman ennalta määrättyjä reittejä ja aikatauluja. Verrattuna perinteiseen julkiseen liikenteeseen nämä uudet liikennepalvelut tarjoavat matkoja ilman vaihtoja ja vapauttavat matkustajat käyttämästä aikatauluja ja linjastokarttoja. Tämän lisäksi automatisoitu kysyntäohjautuva joukkoliikenne hyödyntää reaaliaikaista liikennetietoa ajoneuvojen reitityksessä ja muodostaessaan matka-aikalupauksia sisältäviä matkatarjouksia, mikä mahdollistaa matka-aikoihin perustuvan hintadifferoinnin ja siten yksilöllisemmän palvelutarjonnan matkustajien tarpeisiin.

Tämä työ tarkastelee automatisoidun kysyntäohjautuvan joukkoliikenteen ja jaettujen taksipalvelujen potentiaalisia vaikutuksia urbaanille liikenteelle sekä tutkii erilaisten liikennepolitiikkojen vaikutusta näihin palveluihin kiinteänä osana urbaania liikennesysteemiä. Työssä esitetään analyyttisiä malleja, joilla määritellään yhteiskunnan hyvinvoinnin optimoivia politiikkoja näille palveluille, joilla on perinteisiin bussi- ja taksipalveluihin verrattaessa erilaiset palvelutuotannon kustannusrakenteet sekä ulkoiskustannukset. Lisäksi työssä kehitetään simulointimalleja kustannustehokkuuden ja säännöstelypolitiikkojen analysointiin. Tämän lisäksi vaihtoehtoisia hinnoittelumalleja tarkastellaan liikenneyritysten, matkustajien ja liikennepolitiikan näkökulmasta.

Väitöskirjassa esitetyt julkaisut tarjoavat teoreettisen pohjan, malleja ja empiiriseen aineistoon pohjautuvia näkymyksiä automatisoidun kysyntäohjautuvan joukkoliikenteen ja jaettujen taksipalvelujen politiikkanalyysiin sekä empiirisen tutkimuksen tarpeisiin. Näiden uusien liikennepalveluiden markkinat ovat kehittymässä älyliikennneteknologioiden edistysaskelten ja niitä hyödyntävien innovatiivisten yritysten myötä sekä liikenteen kestävyyteen kohdistuvan kasvavan poliittisen paineen ja vaatimusten myötävaikutuksesta.

Avainsanat kysyntäohjautuva joukkoliikenne, jaettu taksi, liikennetaloustiede, liikennepolitiikka, hinnoittelu, säännöstely, joukkoaistiminen, älyliikenne, yhteiskunnallinen hyvinvointi, julkinen liikenne

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Preface

My studies in transportation economics and intelligent transportation services began in the Metropol project exploring the techno-economic prerequisites of automated demand responsive transportation. This multidisciplinary research project coordinated by the Helsinki University of Technology was launched by Prof. Reijo Sulonen. Two publications of this thesis were published during the project. Thereafter, my research continued in the TrafficSense project where I analyzed pricing policies and utilization of crowdsensing with demand responsive transportation and shared taxi services. Finally, I completed this thesis in the ongoing Living Lab Bus project, in which one goal was to explore means and possibilities to combine traditional public transportation and demand responsive transportation to offer attractive multimodal trip chain alternatives for passengers. This journey has been long, sometimes challenging but also very interesting and fruitful. I am grateful to all those people I have been working with during these years.

I would like to thank the Department of Computer Science of the Aalto University for the support and facilities. I also would like to thank the Finnish Funding Agency for Innovation, Ministry of Transport and Communications, Helsinki Metropolitan Area Council, Helsinki City Transport, International Business Machines Corporation, Aalto Energy Efficiency Program and City of Helsinki Innovation Fund for financial support and the Kutsuplus team in Helsinki Region Transport and Split Finland Ltd (previously Ajelo Ltd) for productive and enjoyable research collaboration.

I would like to thank Prof. Juha Laine for instructing me and for providing professional guidance and friendly support. I also would like to express my gratitude to Prof. Marko Nieminen for supervising this work and for providing invaluable support in challenging situations, and to Prof. Reijo Sulonen for encouragement and for providing an opportunity to work in this fascinating research field.

Moreover, I would like to thank my colleaques Mikko Heiskala, Dr. Esa Hyytiä, Dr. Lauri Häme, Teemu Sihvola, Dr. Markku Tinnilä and Timo Halko for scientific support, Prof. Robin Lindsey for being the opponent and Prof. André de Palma and Prof. Silvio Nocera for examining this dissertation and for providing insightful and useful comments. I also would like to thank Dr. Pia Lappalainen for language proofing and suggestions for improving the text.

Finally, I would like to thank my family and friends for loving and supporting me on this path. My Mom and Dad have always respected and supported my choices. My sister has been an important part of our family life and source of creativity and inspiration for me. My daughters always remind me of what truly matters. Children provide, in fact, an important motif to conduct research in this field and to pursue a sustainable and livable society. It's also important to foster the ability to see the world as children see it, that is, without prejudices and by genuinely wondering. The greatest thanks go to my dear wife for her loving support and for managing our daily family activities especially at the moments when this work demanded most of my time and energy. Heidi, thanks for sharing all my worries and joys during this journey and for standing by my side.

Helsinki, June 1, 2016
Jani-Pekka Jokinen

Contents

List of Abbreviations and Symbols

a	Average direct trip distance
b	Average detour
C	Total costs of operations (DRT)
c	Average increase in a route length due to an additional trip
c_0	Fixed cost per day
c_1	Cost of capital per seat kilometer
c_2	Cost of operations per seat kilometer
c_3	Distance-independent cost of passenger
c_4	Route-independent cost of passenger per kilometer
c_5	Cost of kilometer driven by an empty vehicle
DRT	Demand responsive transportation
d_i	Destination of trip
d_1	Demand elasticity of generalized cost
F	Quantity of capital
G	Average genaralized passenger cost
K	Number of vehicles (fleet size)
k	Average value of travel time cost
MC	Marginal cost
MPTT	Minimize passenger travel time (routing policy/algorithm)
O	Occupancy rate
o_i	Origin of trip
p	Ticket fare
p_{km}	Price per kilometer

q	Average value of waiting time cost
R	Quantity of operations
RTF	Ride time factor
SMC	Social marginal cost
s	Number of seats
TTR	Travel time ratio
t_i	Release time of trip request
U	Utilization rate of capital
W	Collective cross willingness to pay
WTP	Willingness to pay
τ_B	Travel time ratio of bus
τ_T	Travel time ratio of taxi

List of Publications

This doctoral dissertation consists of a summary and of the following publications which are referred to in the text by their numerals.

1. Jokinen, J. P. (2016). On the Welfare Optimal Policies in Demand Responsive Transportation and Shared Taxi Services. *Journal of Transport Economics and Policy (JTEP)*, *50*(1), 39-55.

2. Jokinen, J. P., Sihvola, T., Hyytiä, E., & Sulonen, R. (2011). Why urban mass demand responsive transport? In *Integrated and Sustainable Transportation System (FISTS), 2011 IEEE Forum on* (pp. 317-322). IEEE.

3. Jokinen, J. P., Häme, L., Hyytiä, E., & Sulonen, R. (2011). Simulation Model for a Demand Responsive Transportation Monopoly. In Kuhmo Nectar Conference on Transportation Economics, Stockholm, Sweden.

4. Heiskala, M., Jokinen, J. P., & Tinnilä, M. (2016). Crowdsensing-based transportation services—An analysis from business model and sustainability viewpoints. *Research in Transportation Business & Management*, *18*, 38-48.

5. Jokinen, J. P., Tinnilä, M., & Sulonen, R. (2014). Positioning and Pricing of Urban Mass Demand Responsive Transport: Case Study of Helsinki Metropolitan Area. In the 2nd UITP Taxi Conference, Doha, Qatar.

Author's Contribution

Publication 1: On the welfare optimal policies in demand responsive transportation and shared taxi services.

The article was written solely by the author.

Publication 2: Why Urban Mass Demand Responsive Transport?

The author was the main author of this article.

Publication 3: Simulation Model for a Demand Responsive Transportation Monopoly.

The author was the main author of this article.

Publication 4: Crowdsensing-Based Transportation Services - An Analysis From Business Model And Sustainability Viewpoints.

The author was the main author of sections 4 and 5.4, and co-author of the other sections.

Publication 5: Positioning and Pricing of Urban Mass Demand Responsive Transport: Case Study of Helsinki Metropolitan Area.

The author was the main author of this article.

1. Introduction

1.1 Challenges of urban transportation

Transportation has always played a crucial role in economic activities, primarily explaining the existence of cities, which enable increased productivity due to the shorter distances and lower transportation costs. These benefits, usually called economies of agglomeration, can be fully utilized as long as the capacity of the transportation system is sufficient. The increasing attractiveness of cities leads to the scarcity of land to be allocated to buildings, parks, parking places, road network, and other purposes. Thus, in urban areas, the capacity of the road network and other transportation infrastructures is always limited by the scarcity of land and other economic resources. Increasing demand for transportation together with limited road network capacity leads to congestions, and consequently to increasing travel time costs, fuel costs, air pollution, accidents and noise. See, for example, Verhoef (1994) and Litman and Doherty (2009) for detailed analysis of costs of urban transportation. Moreover, the increasing use of private cars requires more land for parking places near residents, workplaces and shopping centres causing urban sprawl and thereby longer travel distances and higher transportation costs.

Most of the above-mentioned transportation costs are closely dependent on the number of vehicle kilometers produced in the transportation system. Therefore, one measure to improve the efficiency of the urban transportation system is to increase the average occupancy of the vehicles. In private cars, the average occupancy is relatively low, for example 1.27 passengers per car in Helsinki in year 2008 (YTV, 2009), 1.54 passengers on average in the Western European countries in 2007, and respectively 1.8 passengers in the Eastern European countries (EEA, 2010). In public transportation the average occupancy is usually much higher, for example, the average occupancy rate of seats is 33% in the urban public transportation of the major cities in Finland (Finnish Transport Agency, 2015). Thus, increasing the modal share of public transportation could improve the efficiency of the transportation system and alleviate congestions and other urban transportation problems. However, private cars are the dominant mode of passenger transport both in Europe (EEA, 2015) and the US (Small and Verhoef, 2007), indicating private car attractiveness and competitiveness compared to public transportation.

Several factors increase the use of private cars, but probably one of the most essential ones explaining this trend is growing income and wealth (Pucher and Renne, 2003). The total vehicle stock is predicted to grow from about 800 million in 2002 to over 2 billion vehicles in 2030, and the growth will be fastest in countries like China and India, which are prospering and passing through the middle-income levels of $3,000 to $10,000 per capita (Dargay et al., 2007). Several studies have estimated that the valuation of travel time is on average 50% of the gross wage (Small and Verhoef, 2007). Therefore, increased income often leads to increased willingness to pay for faster trips, and private cars as enablers of faster trips have offered the most attractive transport mode, especially for regular use such as commuting, which is the primary reason for the morning and afternoon peaks and for the related congestions.

1.2 Automated demand responsive transportation and shared taxi services as potential solutions

Urban transportation problems could be potentially alleviated by decreasing the use of private cars through policies improving the competitiveness of public transportation. However, the traditional public transportation with fixed schedules and routes has not been capable of responding to the increased quality requirements of a growing number of passengers. Therefore, new innovative transportation solutions have been studied and developed by universities, transport authorities and companies (such as Aalto University, Helsinki Region Transport and Ajelo Ltd in Finland) to improve the competitiveness of public transportation by means of advanced technologies.

Demand responsive transportation (DRT) with automated dispatching and vehicle routing technology is one realization of this ongoing development of intelligent transportation technologies. In the present work, this transport mode is called automated DRT to distinquish it from the traditional DRT relying on human workers in vehicle dispaching and routing. The Automated DRT provides shared trips for passengers, and it adapts dynamically to trip requests by routing a fleet of vehicles operating without any fixed routes or schedules. The main advantages of automated DRT compared with traditional public transportation include its ability to provide trips without transfers and it frees passengers from the necessity of using timetables and maps of route networks. Furthermore, automated DRT utilizes real-time traffic information in vehicle routing and in formuling trip offers with travel time promises, which enables a differentiated pricing based on travel times and thereby a tailored service provision meeting personal passenger needs.

From the viewpoint of trip production, DRT (both the traditional and the automated one) and a shared taxi are similar as the trips are combined, and other passengers can cause detours and additional stops. Therefore, the technology developed for automated DRT can be utilized also in shared taxi services and other similar flexible transportation services offering shared trips. For instance, the algorithms developed for the automated DRT service called Kutsuplus in Finland has later been adopted by the Split Technology, Inc. for operating the service offering shared trips in Washington DC. There are currently several quite similar services offering shared trips such as CabCorner, Lyft Line, UberPool, and Via, which operate in the USA. Moreover, there are some services offering shared trips which are more closely linked with the traditional taxi industry. For example, Wecab offers both private and shared taxi services in Paris. Thus, the automated DRT and shared taxi services adopting advanced technologies are similar both from the viewpoints of service characteristics and technologies. In this work, we assume that the only difference between these two services is that shared taxi operators can also sell private taxi rides if there are vacant taxis. In Section 4 (Publication 3), we show that private taxi trips can be seen as a special case of trips with travel time promises in economic analysis. For simplicity, we hereon mention only DRT, but the results are also applicable to shared taxi services, unless we specify differences.

1.3 Transport policy and DRT (problem statement)

Consideration of urban transportation as a market reveals several market failures, i.e., transportation markets fail to allocate resources efficiently from the viewpoint of the whole society. The main reasons behind these failures include externalities and imperfect competition. These market failures have been extensively studied in transportation economics over one hundred years (Winston, 1985), and various policies have been suggested to achieve efficient transportation markets and thereby increase productivity and simultaneosly alleviate the problems of urban transportation.

Both theoretical economic analyses and empirical econometric research indicate that transport policies like price regulation, capacity regulation, subsidization, and public investments play an essential role in mitigating the inefficiency of transport markets and in solving problems of urban transportation. For comprehensive review of related literature and analysis, see, for example, Small and Verhoef (2007) and Polak and Heertje (2001).

The overall objectives of the work are (i) to consider potential economic impacts of the automated DRT and shared taxi services on urban transportation, and (ii) to study the effects of various transport policies on these new transport services.

The work addresses three main research questions:

1. How do automated DRT and shared taxi services differ from other public transportation services and how should these differenses be modelled in economic analysis?

2. Is the automated DRT cost-effective compared with a private car and a regular taxi service from the viewpoints of consumers and society?

3. How should the automated DRT and shared taxi services be priced and regulated to maximize social welfare?

1.4 Outline and key findings of the work

Section 2 reviews literature on DRT and releated research on bus and taxi services. The section considers the main differences between these transport modes and presents an analytical model addressing welfare optimal policies and unique cost structures of DRT and shared taxi service, as well as is presents simulation models of DRT.

In Section 3, the cost-effectiveness and external costs of the automated DRT is studied by simulation model and compared to the regular taxi service and private car. The results show that automated DRT can be a more cost efficient transportation mode than private car or taxi if the demand density is sufficient. Moreover, the results show that DRT tolerates unexpected demand peaks better than regular taxi service when the fleet sizes are fixed in both services. This is because the waiting times of the DRT service are more stable due to the efficient trip combining organized by the DRT operator whereas the regular taxi offers private trips and trips are combined only occasionally based on informal negotiation between customers.

Section 4 analyses a welfare optimal pricing of automated DRT for variable trip distances and travel-time promises. Moreover, alternative regulation policies for DRT monopoly are simulated with a model in which passengers make transport mode choices between DRT and other modes (bus and taxi) by comparing the offered prices and travel times. A new regulation policy enabled by fully automated vehicle routing, which utilizes real-time traffic information, is also introduced and studied. The results indicate that the new regulation policy enables significantly higher social welfare than the considered traditional regulation policy of taxi markets, i.e., regulation of the price and the fleef size. Furthermore, alternative pricing models are considered. The analysis of the empirical data collected from the Kutsuplus service and the review of the related literature forms the basis for the evaluation of the service positioning and alternative pricing models for the automated DRT.

Finally, Section 5 presents conclusions and suggestions for future research directions and transportation policies.

2. Economic Models for Automated DRT

2.1 Literature review

2.1.1 DRT research

DRT has been considered in several studies, mainly from the transportation engineering point of view focusing on dispatching and vehicle routing algorithms and system design, but the economic analysis of DRT markets has received less attention. Diana et al. (2006) provide a comprehensive review of related research, and they present a model for the fleet sizing of DRT for a given demand level where service quality is predetermined. The first studies on "many-to-many" DRT were conducted by Arrillaga and Medville (1974), Lerman and Wilson (1974), Flushberg and Wilson (1976), and Daganzo (1978). Arrillaga and Medville (1974) provided models to estimate demand, supply and costs of DRT, but since then, the economics of DRT have been less studied, until the new millennium evidenced growing interest in the automated DRT due to the technological advancements. Rodier et al. (1998) adopted the regional travel demand model to simulate the travel effects and consumer welfare effects of DRT and other advanced transit alternatives in the Sacramento region. The simulation of the scenario where both advanced transit information and DRT service was provided increased consumer welfare, although the other scenario, where only advanced transit information was provided, was economically even more beneficial. Brake et al. (2004) studied experiences with telematics-based DRT in the UK and they identified four aspects (regulatory, technological, service and system design, and sustainability) as the principal areas requiring attention in the future. Diana et al. (2007) studied emissions of DRT services. Kasibhatla and Benjamin (2009) studied alternative forms of cost function to estimate and predict the total operating costs of paratransit services. Häme et al. (2011) presented a network equilibrium model of DRT, which was further developed in Häme et al. (2012).

Recently, several studies have considered the current role of DRT and future possibilities in the UK. Wang et al. (2014) explored the effects of area-wide factors on the demand of DRT in Greater Manchester and found that the demand was higher in areas with low car ownership, low population density, high proportion of white people, and high levels of social deprivation. Ryley et al. (2014) studied the contribution of DRT to a sustainable local public transport system and simulated modal shares of DRT with mixed logit models and survey data collected from urban (Rochdale, Manchester) and rural (Melton Mowbray, Leicestershire) areas. Their study identified six market niches

(1. Rural hopper, 2. Shopping services, 3. Airport access, 4. Station access, 5. Employment shuttle, 6. Hospital access) and the simulation results indicated that the DRT services offering airport access or railway station access were most potential. Davison et al. (2014) explored the current provision of DRT in Great Britain and conducted a national survey of DRT providers to examine the design, performance, rationale and likely futures of DRT schemes. They concluded that cost and funding are the dominant concerns of the service providers. Recent funding reductions have resulted either in withdrawn of DRT service provision or in the replacement of conventional bus services when DRT is seen as a more cost-effective alternative to meet local needs for accessibility and geographical coverage of public transportation.

Shared taxi services have been also studied recently. Santi et al. (2014) present a method, which translates spatio-temporal sharing problems into a graph-theoretic framework providing efficient solutions. They apply the method for simulation of New York taxi trips and present potential benefits of the taxi sharing, such as reduction in cumulative trip length by 40% or even more. Paraboschi et al. (2015) studies also impacts of taxi sharing in New York taxi system by extending economic model of regulated taxi market, presented originally by Flores-Guri (2003), to include taxi sharing.

2.1.2 Models of bus and taxi as a basis for DRT modelling

A DRT is a transportation mode between the regular taxi offering private trips from door-to-door and the bus service with fixed routes and schedules. The economic significance and market shares of taxi and bus modes have traditionally been much higher than the market share of DRT services, and consequently, these more conventional transport modes have been studied more extensively in the economics of transportation. The economic model development of the bus service has been active since Herbert Mohring's and Ralph Turvey's articles in the 1970's, i.e., Mohring (1972), Turvey and Mohring (1975), and Mohring (1979). Ahn (2009) provides a review of studies on optimal bus frequency and bus fares.

Respectively, the model of cruising taxis presented in Douglas (1972) activated research and model development of taxi services (Beesley, 1973; De vany, 1975; Abe and Brush, 1976; Manski and Wright, 1976; Beesley, 1983; Frankena and Pautler, 1986; Arnot, 1996, Flores-Guri, 2003).

Many of the further developed economic models of bus and taxi services were useful for understanding and analysing the DRT service. Especially, the bus model presented by Pedersen (2003) provided a useful starting point for studying the differences between market characteristics of DRT and conventional public transportation. The major differences on the demand side are in the dependencies between time costs, demand, and trip production, which are considered in the following.

2.2 Analytical model for DRT (Publication 1)

We approach the first research question set in Section 1.3 (How do automated DRT and shared taxi services differ from other public transportation services and how should these differenses be modelled in economic analysis?) by formulating an analytical model describing the demand and supply of shared trips, and related welfare optimal policies. In the model, the demand for DRT trips within a limited geographical area is modelled by the decreasing function of the generalized costs, that is, as defined by an ordinary demand function:

$$X = D(G),\ \frac{dD}{dG} < 0 \tag{1}$$

where X is the number of passengers traveling by DRT during the considered time period (for example, one hour or day), and G is the average generalized costs, containing passenger's money and time costs (including travel time and waiting time costs). The average generalized costs of a passenger are defined by equation:

$$G = p + q + k \tag{2}$$

where p is the ticket fare, q is the average value of waiting time, and k is the average value of travel time in vehicle.

The passenger waiting time for a DRT trip is determined by the time the dispatched vehicle drives to the pick-up point, similarly to call taxes, but probably with more complex routing due to the simultaneously served customers with individual pick-up and drop-off points. An increase in the number of DRT vehicles operating in the service area decrease the expected distance between the dispatched vehicle and the pick-up point, and thereby decrease the average waiting time. Respectively, an increase in the number of passengers increases the expected route length to the pick-up point and the expected number of stops before the pick-up point, which consequently increases the average waiting time. These dependencies between the waiting time, number of vehicles and number of customers are modelled by defining the average value of waiting time, q, as a function of the trip production, R, and the demand, X:

$$q = Q(R, X),\ \frac{dQ}{dR} < 0,\ \frac{dQ}{dX} > 0 \tag{3}$$

Variable R measures trip production as the number of potential seat kilometers supplied in the considered time period. In the DRT service, the distinction between potential and actual seat kilometers is important, because a DRT vehicle is not necessarily moving if it is not (temporarily) dispatched to any trip request. In this sense, DRT operates similarly to taxi services, whereas regular buses drive their fixed routes based on the time table even though it is empty. We show later that the distinction between potential and actual seat kilometers is useful in the analysis of the cost structure of the DRT service.

In the DRT service, other passengers increase the value of travel time cost by increasing the route length and number of stops. In addition, other customers might cause discomfort like crowding and noise in the vehicle. These passenger travel time costs can be reduced by increasing the potential trip production level relative to the demand, which consequently also decreases the average occupancy of vehicles. Further, the average value of travel time depend on the average trip distance, a. Thus, we model the average value of travel time as a function of trip production, demand, and average trip distance:

$$k = K(R, X, a),\ \frac{dK}{dR} < 0,\ \frac{dK}{dX} > 0,\ \frac{dK}{da} > 0 \tag{4}$$

where the signs of the partial derivatives are based on the reasoning above.

In real transportation services, and especially in non-scheduled DRT services and shared taxi services, the dependencies between waiting time, travel time, route production and demand are complex, and the functions describing interdependence between waiting time, R and X or interdependence between travel time, R, a and X cannot be algebraically expressed for real systems. Therefore, we do not interpret the functions (3) and (4) as describing physical causality, but the knowledge of the social planner (or the operator) based on empirical data, which is modelled by some well-behaved (linear or non-linear) functions so that the derivatives in (3) and (4) can be computed.

We define the inverse demand function by inverting function (1) and using equation (2):

$$p + q + k = G = D^{-1}(X),\ \frac{dD^{-1}(X)}{dX} < 0 \tag{5}$$

Now, we can write the collective willingness to pay (WTP) of passengers during the considered time period by using equations (2)–(5):

$$W = \int_0^X D^{-1}(x)dx - [Q(R, X) + K(R, X, a)]X, \tag{6}$$

where the first term is the collective gross WTP as a function of the demand level, and the second term is the collective time cost of passengers.

We assume that the total costs of DRT operations, C, can be given by the linear function:

$$C = c_0 + c_1F + c_2R + c_3X + c_4(Xa + Xb) + c_5(Xc), \tag{7}$$

where c_0 is the fixed cost of the DRT operator, i.e., costs which are not dependent on the served passenger kilometers or on the capability to produce seat kilometers. The parameter c_1 is a cost of capital required for the capability to produce 1 seat kilometer during the considered time period, which is multiplied by the variable F measuring the quantity of the capital, respectively. The parameter c_2 is a cost of operations required for capability to produce 1 seat kilometer during the considered time period, which is multiplied by the variable R measuring the quantity of the operations, respectively. These first three terms in the cost function (7) are related only to the capability to serve passengers. A simple interpretation would be that the first term represents general costs incurred for the DRT operator, such as costs of premises and administration, and the second term represents capital costs of vehicles and the required equipment, and the third term represents costs of the driver's salary and costs related to the operations management and the ICT system during the considered time period.

The last three terms in the cost function are related directly to the number of passengers, X. The parameter c_3 is a distance-independent cost for an additional customer, i.e., costs incurred from dispatching and additional stops for boarding and alighting from the vehicle. The parameter a is an average trip distance where the distance is based on the shortest route between the pick-up and drop-off locations. Thus, the term Xa is the number of served passenger kilometers excluding detour kilometers, typical for DRT vehicle routing, from the term. The parameter b is an average detour on a trip. Thus, the term $(Xa + Xb)$ is the total kilometers travelled by passengers in vehicles, and the parameter c_4 is a route-independent cost of a passenger traveling 1 kilometer in DRT vehicle, i.e., increase in fuel consumption due to the extra weight, contamination, and abrasion of seats. The last term $c_5(Xc)$ is the costs of driven kilometers by DRT vehicles. The parameter c is an average increase in vehicle route length due to an additional trip, i.e., route change enabling pick-up and delivery. Multiplying c with the number of customers, X, gives the total kilometers driven by the DRT fleet. The parameter c_5 is the cost of kilometer driven by an empty vehicle. The cost of empty vehicle is used in this term, because the costs of the weight of customers are taken into account in the previous term, $c_4(Xa + Xb)$. A linear function was adopted in the cost function (7) because it provides a simple and illustrative way to present the cost structure of DRT and the differences compared to the cost structure of conventional bus and taxi services. Moreover, linear cost functions are seen to be good proxies for more advanced cost functions. See, for example, Pels and Rietveld (2000) and Jørgensen and Preston (2007).

A feasible level of operations required for potential seat kilometers, R, is constrained by the quantity of operator's capital, i.e., the fleet size and related equipment, measured by the variable F. We define this constraint by the following inequality:

$$R \leq UF, \tag{8}$$

where U is an upper limit for the utilization rate of capital, which will, in practice, be below 1 due to necessary pauses in service for refueling, maintenance, and breaks or changes of drivers.

A feasible level of served passenger kilometers, Xa, during the considered time period is constrained by capability to provide service, in our terms, by the level of operations required for potential seat kilometers, R. We define this constraint with the following inequality:

$$Xa \leq OR, \tag{9}$$

where O is an upper limit for the occupancy rate of vehicles (ratio of the occupied seat kilometers to the potential seat kilometers), which is normally distinctly below 1.

We define social welfare as the passengers' WTP, defined in equation (6), minus the transport operator's costs, defined in equation (7). An alternative and equal formulation for the objective is the maximisation of the sum of passengers' surplus and operator's profit (loss). In both of these formulations, the welfare effect of taxation to cover possible losses of transport operator is neglected.

The social planner's (can be interpreted as a public authority in charge of socially optimal transport policies and operations) objective is to maximise the welfare, with regard to X, R, and F, subject to the restrictions in (8) and (9). The Lagrangean function for the maximisation problem can be formulated as:

$$L = W - C - \lambda(aX - OR) - \mu(R - UF) \tag{10}$$

The following first-order conditions for optimal X, R, and F can be derived:

$$\frac{\partial L}{\partial X} = G - q - k - \frac{\partial Q}{\partial X}X - \frac{\partial K}{\partial X}X - (c_3 + c_4 a + c_4 b + c_5 c) - \lambda a = 0 \tag{11}$$

$$\frac{\partial L}{\partial R} = -\frac{\partial Q}{\partial R}X - \frac{\partial K}{\partial R}X - c_2 + \lambda O - \mu = 0 \tag{12}$$

$$\frac{\partial L}{\partial F} = -c_1 + \mu U = 0 \tag{13}$$

In equation (11), the term $\frac{\partial Q}{\partial X}X$ is the increase in the waiting time costs the passenger causes for other passengers. The term $\frac{\partial K}{\partial X}X$ is, respectively, the increase in the in-vehicle travel time costs the passenger causes for other passengers. This externality is normally higher in the DRT service than in conventional public transport services with fixed routes and schedules, because with DRT, a new passenger usually causes route changes, and consequently increases the travel time cost for other passengers significantly. In equation (12), the terms $\frac{\partial Q}{\partial R}X$ and $\frac{\partial K}{\partial R}X$ describe savings in travel time costs and waiting time costs due to a marginal increase in route production.

In modeling regular bus services with fixed routes and schedules, the social planner's maximisation problem can be analysed by separating the time span into three time periods (short, medium, and long run), where in the short run only the ticket price is a decision variable, whereas in the medium term, the route production can also be changed, while bus capacity can only be changed in the long run (Pedersen, 2003). Unlike DRT, in conventional bus services separation into potential and actual route production is not needed, because after deciding and publishing the timetables, the buses drive routes according to the fixed schedules regardless of actual demand in the short run.

In the DRT service, the distinction between decision variables and fixed variables in a certain time period is not as clear, and not necessarily even similar. The main difference is that DRT is not tied to fixed schedules, and therefore route production, R, can be increased relatively fast, even instantly, to match the supply for the sudden demand peaks, presuming that extra vehicles (measured by the variable F) and drivers are available. Depending on how the DRT service production is organised, the variable F might be fixed in the short run if, for instance, an increase in the fleet size requires bureaucratic decision making and procurement of vehicles and related equipment. Alternatively, more flexible organising forms of service production could be applied. For instance, the DRT operator could use charter transportation companies as subcontractors and agree on the option to request extra vehicles and drivers for the unexpected demand peaks, which would enable as fast changes in F as changes in p and R.

If capital and operations are fully utilized, the constraints (8) and (9) are equalities, and optimal p, R, and F can be deduced from equations (11)–(13):

$$p = \frac{\partial Q}{\partial X}X + \frac{\partial K}{\partial X}X + c_3 + c_4 a + c_4 b + c_5 c + a\frac{c_1}{OU} + a\frac{c_2}{O} + a\frac{\partial Q}{\partial R}\frac{X}{O} + a\frac{\partial K}{\partial R}\frac{X}{O}, \tag{14}$$

$$aX = \mathrm{OR} = \mathrm{OUF}. \tag{15}$$

Optimal price is equal to the marginal costs of operator (terms 3–8 in equation (14)) plus external costs to the passengers (terms 1–2) minus value of travel time savings from increased route production (terms 9–10).

The presented model and deduced optimality treats travel distances only as averages. Thus, the optimal price (14) can be interpreted as the optimal flat rate. Flat rates are often used in public transport pricing for political (equity and income distribution) and practical reasons (easy for implementation and payment). Thus, the presented optimality is interesting both theoretically and in practice. However, in many DRT services, pricing is based on the trip distance. Moreover, marginal costs of DRT trips are strictly dependent on trip distances, almost similarly to taxi trips. Therefore, a trip distance is an important element of socially optimal production and pricing policies of DRT services. Pricing policies based on trip distances are considered analytically in Section 4.

2.3 Simulation models

Publications 2 and 3 examine automated DRT with a simulation model adopted from (Hyytiä et al., 2010), where trip requests occur within a bounded region. Each trip request is defined as a triple, (t_i, o_i, d_i), where t_i denotes the time instance (release time) of the ith request, o_i and d_i denote the origin and the destination of the trip, respectively. Trip requests arrive according to a Poisson process with rate λ[trip/s], and for each trip request, both the pick-up and drop-off locations are uniformly distributed in a finite convex region with area A (i.e., the trip requests arrive according to a Poisson point process).

There are K vehicles each with *s* passenger seats providing DRT trips in an online fashion. We assume Euclidean distances between any two points and thus each vehicle follows the direct path between the waypoints that define the route. In addition, the ordering of waypoints is determined in a way that the route length is minimised. When a trip request arrives, it is immediately assigned to a single vehicle according to alternative policies and related algorithms. The chosen vehicle then, at some point of time, picks up the passenger for delivery to the corresponding destination point. With restriction s=1, the model can be used to simulate a regular taxi service and with s > 1 a DRT and shared taxi services, where several passengers can share a vehicle, which allows the system to combine trips and decrease the effort per passenger.

Moreover, there are some additional assumptions and specific parameter values in the simulation model in publications 2 and 3 in order to adapt the model for spesific context and research questions.

2.3.1 Simulation with fixed demand level (publication 2)

The first modification of the simulation model with a fixed demand levels (exogenious variable) is designed for cost efficiency and resiliency comparisons between DRT, taxi and private car. In the model, trip requests arrive to a 10 km × 10 km rectangular area. In this area, K vehicles operate, each capable of transporting at most 10 persons simultaneously, that is, s = 10. Vehicles have a constant speed of 10 m/s, they move freely in the given area (i.e., there is no road network), and each stop takes at least 30 seconds (including deceleration and acceleration). Moreover, there is a regular 250 m × 250 m stop grid laid over the service area. In all simulation experiments, we applied a 10-hour warm-up period that was followed by a 10-hour simulation period, during which the statistics were collected. In the numerical examples, the 10-hour simulation period is assumed to represent a one day busy period of operations, e.g., a demand density of 1 trip/km2/hour results in 1000 trips per day, and the demand densities varied between 1 and 50 in the simulations.

The simulated automated DRT system includes the following service promise, which is applied as the default unless otherwise stated: the maximum adjustment time is 15 minutes and the maximum waiting time 5 minutes. The maximum system time is 5 minutes plus 1.5 times the direct ride time of the trip. The factor 1.5 in the maximum system time is labeled as ride time factor (RTF). A service promise is also made in the taxi system so that the maximum time difference between the order time and pickup time is 15 minutes. Trip requests in the taxi system are immediate, i.e., customers are ready for the pickup at the order time. DRT trip orders, however, include a 5 minute pre-order time, which customers reserve for preparations and walking from trip origin to the pickup stop. Simulations are used for both taxi and DRT modes, while the simplicity of the model allows axamination of the private car mode analytically. A crucial element of the model (and of the real DRT services) is the policy defining the routes of the vehicles in response to trip requests. This (first) version of the simulation model utilizes a greedy heuristic policy referred to as minimise-passenger-travel-time (MPTT). MPTT assigns a new trip to a vehicle which can, according to the current information (cf. myopic control), deliver all current passengers, including the new one, with the smallest increase in the sum of the passengers (remaining) travel time. Thus, MPTT does not explicitly take into account the anticipated future requests (Ichua et al., 2006). For a more detailed description and analysis on MPTT and related heuristic policies, see, for example, Hyytiä et al. (2010), and Toth and Vigo (2001). The optimal control of the vehicle fleet is, in fact, a complicated problem in general, and one can indeed do better than what this heuristic policy can offer. However, the differences are not qualitative, and as the heuristic MPTT policy already provides on average a relatively good and robust solution, it satisfies the needs of the cost-effictiveness and resiliency comparison (presented in Section 3 and Publication 2).

2.3.2 Simulation with demand model (publication 3)

The second modification of the simulation model is designed for the analysis of the DRT monopoly market and related regulation policies. In this model, the deman level is defined by the demand model, where passengers compare prices and travel times and then choose the transportation mode between a DRT offer and other modes. Vehicle routes are defined similarly to the first modification, i.e., ordering of waypoints with minimised route length, but instead of MPTT policy in vehicle allocation, the monopolist compares all available proposals formulated by vehicles, and offers the customer a single proposal maximising the expected profit. If an offer is accepted, the customer is assigned to the corresponding vehicle and its route is modified accordingly. This version of the simulation model can be characterized as an agent-based simulation model, which simulates the behavior of independent agents (passengers and the monopolist), whose decicions are defined by certain rules in the complex system. For a more detailed introduction and review of agent-based models in transportation, see for example Bernhardt (2007) and Axelrod and Tesfatsion (2006).

The model is governed by the following six preliminary assumptions:

1. There are K vehicles available to transport customers requesting service within a certain operating zone A. For each pair of points o_i and d_i in A, the distance d(o_i, d_i) and direct ride time t(o_i, d_i) are known and equal for all vehicles.

2. At each moment, each vehicle is assigned a certain set of customers and a tentative route passing through all unvisited pick-up and drop-off points associated with these customers. In this work, we assume that the vehicles follow the shortest route with respect to known customers.

3. At any moment, a new customer may request a trip from a specific pick-up point o_i to a specific drop-off point d_i constituting a request for trip (o_i, d_i). In addition, each request is associated with a unit load (1 passenger/request).

4. As an instant response to each customer request, each vehicle formulates at most one proposal for transportation by means of the following procedure: a new route is determined, passing through the pick-up and drop-off points associated with already assigned customers and the new customer. The expected pick-up and drop-off times are calculated by means of this route, as depicted in Figure 1.

5. The monopolist compares all available proposals formulated by vehicles, and offers the customer a single proposal maximising the expected profit. If an offer is accepted, the customer is assigned to the corresponding vehicle and its route is modified accordingly (see Figure 1).

6. There is a fixed fare structure. The price, p, of a trip is assumed to be dependent on the direct trip length $\mathrm{d}(o_i, d_i)$ exclusively by means of the formula

$$\mathrm{p}(o_i, d_i) = p_{km} \cdot \mathrm{d}(o_i, d_i) \tag{16}$$

where p_{km} is the price per kilometer in relation to direct trip length. The customers know the fare structure and the direct trip lengths of their trips beforehand.

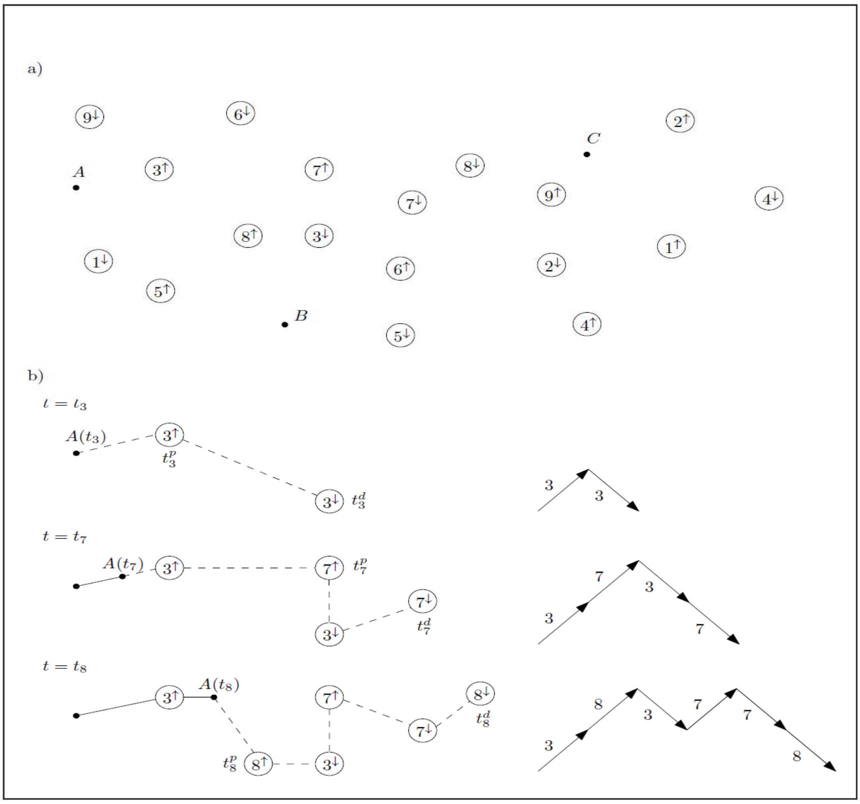

Figure 1. Formulating proposals. The top figure (a) shows the pick-up points (denoted by ↑-signs) and drop-off points (↓-signs) of nine customers and the initial locations of vehicles A, B and C. Each customer i requests a trip from $i^{\uparrow}$ to $i^{\downarrow}$ at time t = t_i, where $t_1 < t_2 < \ldots < t_9$. The bottom figure (b) shows the modifications in the route of vehicle A. At the time customer 3 requests a trip (t = t_3), the vehicle is located at A(t_3). A new route for the vehicle, namely ($3^{\uparrow}$, $3^{\downarrow}$), beginning from A(t_3) is calculated and the expected pick-up and drop-off times, t_3^p and t_3^d, are determined by means of the new route. Customer 3 accepts the proposal and the vehicle route is updated. Customers 7 and 8 are added to the vehicle route in a similar fashion. The figures on the right show the routes as so-called labeled Dyck paths (Cori, 2009; Häme, 2011), in which each pick-up $i^{\uparrow}$ precedes the corresponding drop-off $i^{\downarrow}$. After each step, a new path is formed due to the addition of a new customer. Clearly, the "height" of the path shows the number of customers aboard in different parts of the route.

In this model, the level of service is defined by means of travel time ratio, which is the ratio of travel time to direct ride time. Thus, a travel time ratio equal to 1 corresponds to the best possible level of service and a larger travel time ratio corresponds to a lower level of service. Since the fare structure for trips is assumed to be fixed, the only question a customer faces after requesting service is whether or not to accept the best trip offer in terms of the offered level of service. In other words, in this simulation model the fixed fare structure and the offered level of service define the generalized passenger cost of the trip. The level of service offered to a customer traveling from o_i to d_i is defined by means of expected travel time ratio:

$$\tau = \frac{t_d - t_r}{t(o_i, d_i)}, \tag{17}$$

where t_d is the expected drop-off time, t_r is the release time of the request and $t(o_i, d_i)$ is the direct ride time from o_i to d_i. Thus, τ describes the ratio of the expected travel time of a given trip offer to direct ride time. Clearly, since t_d-t_r $\geq$ $t(o_i, d_i)$, we have $\tau \geq 1$, and $\tau=1$ corresponds to the best possible offered level of service.

Due to modifications in the vehicle routes, the offered level of service may be different from the final outcome of the service. We define the realized travel time ratio τ' by means of the formula:

$$\tau' = \frac{t'_d - t_r}{t(o_i, d_i)}, \tag{18}$$

where t'_d is the realized drop-off time, that is, the point of time the customer actually reaches the destination, d_i.

We assume that potential DRT customers always have alternative transportation mode where the surplus is zero. Thus, a customer rejects the DRT trip offer if the expected surplus is negative and travel by some other transportation mode. In addition, we associate with each customer a certain willingness to pay, which describes the maximum price the customer accepts for a certain level of service. The three assumptions that hold for all passengers, and thus form the basis for the demand model, can be summarized as follows:

1. Denote the average travel time ratio of service provided by a conventional taxi by τ_T and the price per kilometer of a taxi by p_T. If the travel time ratio offered by the DRT service is greater than τ_T and the price per kilometer is greater than p_T, no customer accepts the DRT offer.

2. Denote the average travel time ratio of service provided by traditional bus transportation by τ_B and the price per kilometer by p_B. We assume that $\tau_B > \tau_T$ and $p_B < p_T$. That is, the average level of service (inverse on travel time ratio) and price per kilometer of traditional bus transportation are lower than those of a taxi. If the travel time ratio offered by the DRT service is greater than τ_B and the price per kilometer is greater than p_B, no customer is willing to accept the offer.

3. Finally, if the travel time ratio offered by the DRT service is less than τ_T and the price per kilometer is less than p_B, each customer accepts the offered DRT trip.

In this simulation model, we assume a linear demand model, in which the fraction of customers that are willing to accept a certain level of service for a certain price increases linearly from (τ_T, p_T) to (τ_T, p_B) and from (τ_B, p_B) to (τ_T, p_B). Thus, the three points $(\tau_T, p_T, 0)$, $(\tau_B, p_B, 0)$ and $(\tau_T, p_B, 1)$ define a linear demand model as a plane in R3, as presented in Figure 2.

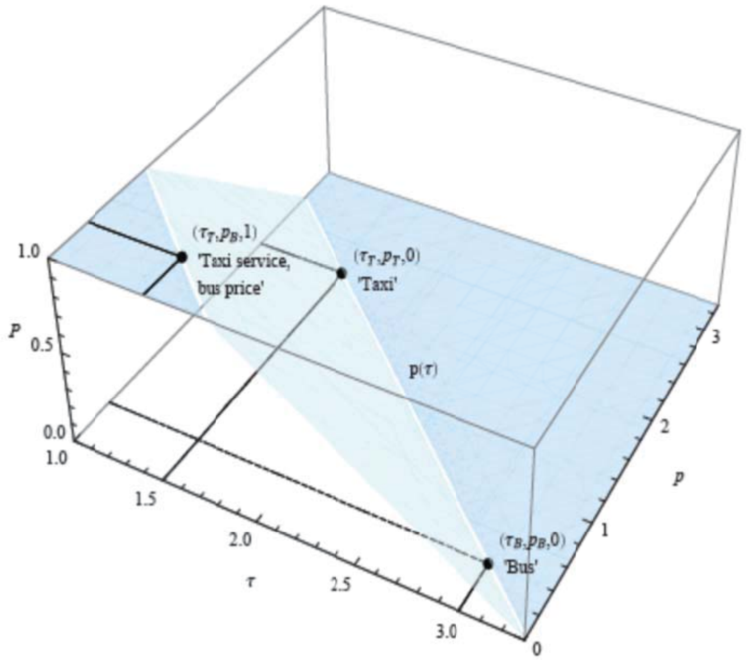

Figure 2. The acceptance probability function P(accept |τ, p) determined by τ_T=1.5, τ_B=3, p_T=2.3 and p_B=0.4. The linear function is specified by means of three points representing conventional bus and taxi services and a taxi-type service with the price of a bus.

The demand model can be expressed by means of a probability distribution P(accept | τ, p_{km}), which denotes the conditional probability that an arbitrary customer accepts a proposal with the expected travel time ratio τ and price per kilometer p_{km}. The proposed acceptance probability function P(accept | τ, p_{km}) is formally given by the equation:

$$P(accept \mid \tau, p_{km}) = \min\left(max\left(1 - \frac{p_{km} - p_B}{p_T - p_B} - \frac{\tau - \tau_T}{\tau_B - \tau_T}, 0\right), 1\right) \tag{19}$$

An example of the acceptance probability function with $\tau_T = 1.5$, $\tau_B = 3$, $p_B = 0.4$ and $p_T = 2.3$ is illustrated in Figure 2. Since the model is linear, we may equivalently think that with a certain price per kilometer, $p_{km} \in [p_B, p_T]$, the worst level of service that an arbitrary customer is willing to accept follows a uniform distribution. Similarly, for a certain offered level of service τ, each customer is willing to pay a certain maximum price per kilometer, which is also uniformly distributed. The upper bound $p_{km}(\tau)$ for the maximum price per kilometer over all customers is a straight line in the plane P = 0, see Figure 2. The equation of $p_{km}(\tau)$ can be written in terms of the two points (τ_T, p_T) and (τ_B, p_B):

$$p_{km}(\tau) = p_T - \frac{\tau - \tau_T}{\tau_B - \tau_T}(p_T - p_B) \tag{20}$$

Clearly, $p_{km}(\tau_T) = p_T$ and $p_{km}(\tau_B) = p_B$. We define the willingness to pay, WTP, with level of service τ as a real-valued random variable $W(\tau)$ by means of the uniform distribution

$$f_{W(\tau)} = U(p_{km}(\tau) - (p_T - p_B), p_{km}(\tau)) \quad (21)$$

The random variable $W(\tau)$ describes the price per kilometer that an arbitrary customer is willing to pay, when the level of service τ is known. For a trip (o_i, d_i), an arbitrary customer is willing to pay not more than the price $W(\tau) \cdot d(o_i, d_i)$, that is, WTP = $W(\tau) \cdot d(o_i, d_i)$.

The acceptance probability with the given service level and price per kilometer is equal to the corresponding cumulative distribution function:

$$P(accept \mid \tau, p_{km}) = P(W(\tau) \geq p_{km}) = \int_{p_{km}}^{\infty} f_{W(\tau)}(x)dx \quad (22)$$

For each realized trip (o_i, d_i) with the price per kilometer p_{km} and realized travel time ratio τ', the realized surplus S' is defined as the difference between WTP, that is, $W(\tau') \cdot d(o_i, d_i)$, for the realized level of service and the actual price paid for the trip $p(o_i, d_i) = p_{km} \cdot d(o_i, d_i)$, that is, $S' = WTP - R(o_i, d_i)$. If the customer does not accept the DRT trip offer, the realized surplus is zero as assumed previously. The expected surplus is thus given by

$$E[S|\tau, p_{km}] = P(W(\tau) \geq p_{km}) \cdot \left(d(o_i, d_i) \cdot E[W(\tau)|W(\tau) \geq p_{km}] - p(o_i, d_i)\right) \quad (23)$$

where $E[W(\tau)|W(\tau) \geq p_{km}]$ is the expected WTP on the condition that an offer with the expected level of service τ and price per kilometer p_{km} is accepted.

The DRT monopoly faces the trip demand defined by the demand model and decides the number of the vehicles and the price, and selects trip offers to maximise profits (as stated in the preliminary assumption 5). We provide a more detailed descrption of the decisions of the monopolist in Section 4.2, where this simulation model adopted to analyse impacts of regulation policies.

Table 1 summarizes the main parameters and differences between the two versions of the simulation model. The main difference in these models is that in the first version the trip demand is given (exogenious variable), whereas in the second version demand is defined by the demand model (endogenious variable). This and other differences in the versions are based on different research goals of the model versions, that is, the first version is designed for cost-effectivess comparison (Section 3) and the second for analysis of regulation policies and pricing (Section 4.2).

Table 1
The Basic Simulation Parameters of the Two Versions of the Simulation Model

Basic simulation parameters	Model version I	Model version II
trip request rate	0.03/s – 1.39/s	0.25/s – 1.00/s
simulation time	10 hours	12 hours
area	10 km × 10 km	disk with 5 km radius
speed of vehicles	10 m/s	10 m/s
capacity of vehicles	10	10
stop time	30 s	30 s
Fixed costs	230 € per vehicle per day	200 € per vehicle per day
Variable costs	0.16 € per vehicle km	0.5 € per vehicle km
Fleet routing policy	MPTT	3 policies: profit maximation and 2 regulation policies

2.4 Discussion on the presented models

This chapter has already given some answers to the first research question asking how automated DRT differs from other public transportation services and how these diffecenses should be modelled in economic analysis. Section 2.2 explained and formalized the main differences between DRT, regular bus and taxi services from the economic viewpoint (trip production, externalities) with the analytical model. Section 2.3 presented an alternative or complementary modelling approach. Instead of deriving analytically economic optimality conditions, the outcome of the complex transportation system can be also studied by simulation models where the behavior of agents (passengers, vehicles and operator) is defined by certain rules. This modelling approach usually cannot provide such a deep analytical or theoretical understanding of the studied phenomenom, but it enables examination of outcomes of complex systems which can be analytically untractable.

These two approaches can be taken simultaneously especially in the large multidiciplinay transportation research projects. Moreover, both approaches can utilize existing theory and results of transportation economics (and other diciplines like transportation engineering and operations research). In the first approach, the link to the existing theory is usually stonger, as in the model presented in Section 2.2, which can be seen as an extension or reformulation of the economic model of the bus service presented in Pedersen (2003). In contrast, the link to the theory also exists in the second approach, but is somewhat weaker, i.e. the behavior or decision rules of the agents are based on the theory of microenomics, but the market outcome is based on the computer simulations.

These approaches and models are adopted to analyse different policy issues in Sections 3 (cost-effectiveness) and 4 (pricing and regulation). In Section 5, we return to this methodological discussion related to the first research question after presenting the research results enabled by the models introduced in this section.

3. Cost-effectiveness analysis

This section studies and compares the cost-effectiveness of the most flexible (motorized) transport modes, that is, DRT, taxi, and private car. By cost-effectiveness we mean that the cost of satisfying a given traffic demand is small when compared with the alternative transport modes. Note that these flexible modes in the comparison cannot compete in cost-effectiveness with mass transport modes such as regular bus, train and metro in situations where the demand and occupancy rate are high and the destinations coincide sufficiently. However, these regular mass transportation modes cannot be adjusted dynamically based on the changing demand, and building a new train or metro line is a massive effort in terms of money and time. In contrast, DRT, taxi and private car can adapt to changes in demand extremely fast, even instantly.

In the cost-effectiveness comparison, we adopt simulation model I (Section 2.3.1) to study the services and realized internal and external costs at the various demand levels, which also enables us to consider the economies of scale of the transport modes.

3.1 Internal costs

We first consider internal costs only and then external costs in Section 3.2. Table 2 presents the values for the unit costs. The costs are classified to fixed costs, which are independent of the vehicle kilometers travelled, and to the variable costs, which are assumed to increase linearly with vehicle kilometers. We compare the costs of the alternative transportation modes for a one-day period. Therefore, the fixed costs are also calculated and presented for one day. Fixed costs for the taxi and DRT vehicles are defined as a sum of an ownership cost per day and a labour cost of a vehicle driver per day, whereas the fixed cost of a private car consists of ownership costs only.

We assume that each private car travels 2.9 trips per day based on the numbers presented in (Helsinki Region Transport, 2010), which describes passenger transportation in the Helsinki metropolitan area. We obtained values for the unit costs from (Litman and Dorethy, 2009). The variable costs are applied without any changes from the source, but for the fixed costs, we have made some adjustments. The second major component of the fixed cost after the labour cost is vehicle depreciation, which is estimated for 24 000 kilometers annual usage. Therefore, we adjusted the annual depreciation of taxi and DRT vehicles according to the realized vehicle kilometers, which was assumed to be 105 000 kilometers per year for a DRT vehicle and respectively 82 000 kilometers for a taxi. We used the average bus driver salary $16.14 per hour in the United States (Worldsalaries.org, 2008) as a labour cost, which is multiplied by 1.3 in order to take into account other related staff expenses. Finally, we added 10% to the DRT and taxi total costs to cover traffic system operation costs, which is based on our own estimate of the cost of the automated traffic system operation, where human labour is not needed in trip dispatching and selling, the only necessary human worker being a vehicle driver.

Table 2
Cost Items Applied in the Comparison

Cost item	Definition	Value $
Fixed cost of private car	Insurance per year, licence & registration, Depreciation (9320 kilometers/year), financing	15.33 per day
Variable cost of private car	Gas & oil, maintenance, tires	0.11 per km
Fixed cost of taxi	Same as private car + labour cost	15.33 + 210.00 per day
Variable cost of taxi	Same as private car	0.11 per km
Fixed cost of DRT	Same as private car + labour cost	19.92 + 210.00 per day
Variable cost of DRT	Same as private car	0.16 per km

Cost calculations based on simulation results, presented in Figure 3, indicate that DRT is a cost-effective transport mode compared to private cars and taxis. Costs per trip by private car (black line) are invariant at the various demand levels. The costs of taxi and DRT trips decrease as the demand level (demand density) increases, that is, both transport modes have economies of scale, which is a well-known feature of taxi services in transport literature, see for example Arnot (1996) and Small and Verhoef (2007). The average cost of a trip is lower with DRT than with the other modes at all presented demand levels due to efficient trip combining. However, efficient trip combing requires a sufficient demand level, and in the simulations, DRT is a cost-effective transport mode compared with the private car only if the demand level is over 1 000 trips per day.

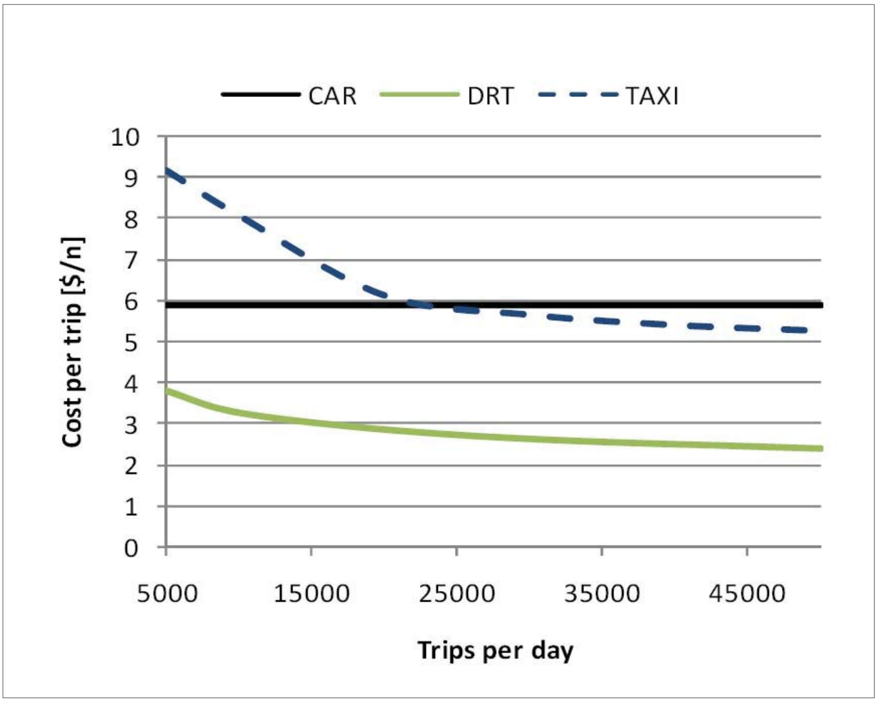

Figure 3. Estimated average cost per trip as a function of trips per day.

Table 3
Key Performance Figures

Quantity	Transport mode	Demand level (trips per day = 10 hour period)					
		5000	10 000	20 000	30 000	40 000	50 000
Number of vehicles	private car	1724	3448	6897	10345	13793	17241
	DRT	57	98	171	236	300	359
	taxi	173	302	446	611	776	943
Average occupation	private car	1.00	1.00	1.00	1.00	1.00	1.00
	DRT	1.86	2.20	2.62	2.85	3.00	3.18
	taxi	0.87	0.89	0.90	0.90	0.90	0.90
Mean travel time (minutes)	Private car	9.19	9.19	9.19	9.19	9.19	9.19
	DRT	18.05	17.77	18.11	18.10	17.90	18.05
	taxi	11.11	10.87	10.96	11.11	11.18	11.08

Table 3 presents the essential descriptive numbers from the simulations used in the cost comparisons. The fleet size required to satisfy a given demand is significantly lower in the DRT mode than in the other transport modes at all demand levels (5 000–50 000 trips per day). Moreover, the mean occupation of DRT vehicles is also higher, and it increases along with higher demand levels.

Note that we have not yet considered the travel time cost, which forms a significant part of the total travel costs of the passenger, that is, generalised passenger costs. For example in (Litman and Doherty, 2009), travel time costs represent 16.2% of all direct travel costs of a private car driver. It was a challenging task to estimate a passenger's value of time spent on traveling by automated DRT, because at the time the simulations for cost-effectiveness comparison was implemented (in 2011), the automated DRT service was not operating yet, and therefore, data for estimation was unavailable.

The new and useful service features of automated DRT, such as shared trips from origin to destination with travel time promises and without transfers and an exemption from using timetables and route information, most likely affect the passenger's value of time. In Section 4, we present empirical estimation of value of time based on the data collected in 2013 and 2014, but in the cost-effectiveness comparisons of this section (publication 2), we employed an estimate of a car driver's travel time value from (Litman and Doherty, 2009), which is $0.072 per minute (Orinally, the value was given as per mile, but we changed it as per kilometer and adjusted the cost value to match the travel speed applied in the simulations).

A trip by DRT takes approximately 9 minutes longer than by a private car, which means a $0.65 higher travel time cost. Figure 1 shows that DRT is the most cost-effective transport mode despite of the higher travel time cost, because the average cost difference between private car and DRT without time cost is over three dollars. This result is naturally depending on the adopted value of time, but it is valid also for significantly higher values and for the presented empirical estimates of travel time value averaging around 50% of the gross wage rate (Small and Verhoef, 2007). For instance, we used 0.17€ per minute (≈$0.19) for value of travel time in Publication 1. The value is approximately 50% of the average gross wage rate in Finland. With this higher value of time, the 9 minutes longer travel time means a $1.71 higher travel time cost for DRT compared to private car. Thus, DRT is clearly the most cost-effective transport mode also with the higher value of time adopted in Publication 1, because the difference in pecuniary costs is over three dollars.

The travel time of a DRT trip includes an adjustment time, that is, the time between customer-defined earliest pick-up time and the target pick-up time of a trip. As customers can spend the adjustment time at trip origin on other activities (personal or work-related), it is not necessarily accurate to use as high time value for adjustment time as for waiting time when estimating travel time costs.

3.2 External costs

As discussed in Section 1, the use of private cars creates external costs such as air pollution, noise, and travel time costs as a consequence of congestion on the road network. A DRT system naturally causes also external costs, but as the total vehicle kilometrage is reduced due to a higher mean occupancy of vehicles, significant external cost savings can be gained.

This section investigates the external costs of transportation in six scenarios, where a certain share of private car users (0%, 10%, 20%,..,50%), resulting in the total of 100 000 trips per day, change their transport mode to DRT or to taxi, and relinquish their private cars. We apply unit cost values for external cost from (Litman and Doherty, 2009). The unit cost values of a private car are adopted for private cars and taxis, and the unit cost values of a van with a capacity of 14 passengers for a DRT vehicle. The cost values were originally presented separately for urban peak hours, urban off-peak hours and rural travel.

In this section, we adopt the average external cost values of urban peak and off-peak hours, that is, considering only trips in the urban area, and we assume that half of the trips are made during peak hours. The external cost components are congestion, external crash costs, external parking costs, road facilities, land value, traffic services, transport diversity, air pollution, greenhouse gas, noise, resources, barrier effect, land use impacts, water and waste (see detailed descriptions from (Litman and Doherty, 2009)). The external cost for a private car and taxi is assumed to be $0.35 per kilometer and, respectively, $0.40 for a DRT vehicle.

As Figure 4 shows, the external costs decrease almost linearly as the share of DRT increases due to trip combining and related decrease in the total vehicle kilometers. In the 0%-scenario, where all trips are made by private cars, the external cost is approximately $181k per day. In contrast, in the 50%-scenario, where a half of the private car trips are changed to DRT trips, the external cost is approximately $127k per day, which corresponds to an about 30% reduction in external costs. As Figure 3 shows, replacing private cars with taxi increases the external costs to some extent. This is due to the fact that taxis often end up driving empty before the next passenger is picked up, which causes an increase in the total vehicle kilometers and the related external costs. However, the difference between taxi and private car modes must be interpreted causiosly, because the difference is relatively small, and because the value of external parking costs of private cars adopted for the all modes in the comparison most likely overestimate the external parking costs of DRT and taxi modes.

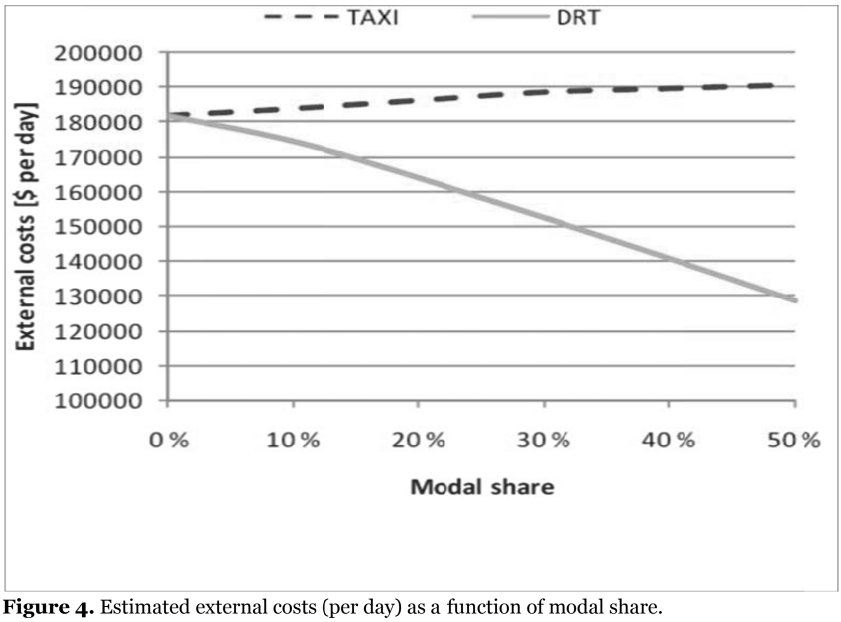

Figure 4. Estimated external costs (per day) as a function of modal share.

3.3 Simulations seen in the light of the recent empirical data

The presented simulation results show that DRT can be a cost-effective alternative compared to private cars if the scale, that is, both the demand and the supply, is high enough. In the simulated service area of 100 square kilometers (10 km × 10 km), a sufficient demand was 5 000 trips per day and sufficient supply was provided by 57 vehicles. On the lower demand levels, the cost-effectiveness of DRT was less obvious, and on the demand level of 1 000 trips or below, the results indicated poor cost-effectiveness compared with private cars. In the light of these results, it is understandable why DRT is typically seen as an expensive mode of transport, and why recently the modern automated DRT service in Finland (Kutsuplus) has required relatively high subventions, which have exceeded 80% of total costs during the first operating years of 2013 and 2014 in Helsinki (Helsinki Region Transport, 2015). The service area of Kutsuplus was somewhat larger (approximately 14 km × 9 km) than the area in the simulations, but the realized demand was on average 283 trips per day in September 2014 (Publication 1), and the number of the vehicles was 15. This means the scale has been far below the cost-effective levels of the simulations. For the first years, the relatively high subventions of Kutsuplus can be justified by the fact that the service is totally new and unique, and therefore the first years are challenging before the technology is matured, oparations optimized, and the passengers used to the new service. The first years are challenging and relatively expensive but enable learning and adaptation. Thus, the relatively high piloting costs can be seen as an investment in learning and development.

In the long run, significanly higher subvention rates compared to the traditional public transportation (approximately 50% in Helsinki) can be difficult to justify for the DRT service, except for special groups such as the elderly and handicapped. The optimal subsidization level is interrelated with pricing and regulation policies, and a more detailed consideration of this interrelationship is presented in Section 4. As a main conlusion drawn from the results presented in this section, DRT is a cost-effective mode compared with private car and taxi if the scale is sufficient high. Moreover, the presented simulation results of the DRT service indicate significant economies of scale, which is traditionally seen in the transportation ecomics literature as an argument for subsidization of public transportation in addition to aims for equal accessibility and reduced external costs.

4. Transport policies and DRT

This section considers the third main research question of the present work related to the welfare optimal pricing and regulation policies of the automated DRT and shared taxi services. A welfare optimal policy of public transportation, in general, is a wide research topic in transportation economics, and it can be divided into several sub-topics. One major distinction can be made between the first-best and second-best policy. In the first-best policy, the policy-maker has full information about preferences and technology and there are no restrictions on the set of policy instruments and on the set of economic agents to whom the instruments can be applied, whereas in the second best policy, some of these restrictions are prevailing or the information is imperfect (Gravelle and Rees, 1997). The analysis of the first-best policy is important for theoretical modelling and for understanding the economics of public transportation, and it also provides useful insights into real policy design. However, in reality there are typically many constraints prevailing related to the formulation of transport policy, and therefore the analysis of second-best policies can provide policy-makers with more practical and useful advices.

In this section, the main focus is on the first-best (pricing and production) policies of DRT services with alternative demand specifications. However, we also discuss the automated DRT and shared taxi services in a wider context as an integral part of public transport and the urban transportation system with many constraints on policy design. Moreover, we analyse alternative pricing models (fare structures) and related regulation policies.

4.1 Pricing

Tripwise marginal costs vary significantly in transportation services, and especially in the automated DRT and shared taxi services. These costs are allocated between transport operators, customers, and society with variable weighting depending on the market structure and transport policy. Socially optimal pricing sets the trip fare at the level of the marginal social cost. A complete schedule of marginal-cost prices would distinguish many trip characteristics, including distance, time of day, direction, and the density of loadings and boardings (Small and Verhoef, 2007). Section 2.2 presented the analytical model of the DRT service and derived the socially optimal price, which was equal to the marginal costs of the operator plus external costs caused for other passengers minus value of travel time savings from increased route production. This model and the derived optimal price takes into account only externalities for other DRT passengers. Thus, a more comprehensive definition of optimal price should include also the other social marginal costs, that is, the external costs for the other users of the road network (congestion costs and accident costs), and the external costs for the entire society (for example, air pollution, noise and CO2 emissions). Before discussing pricing policies and DRT in a wider context of urban transportation systems, this study focuses on analytical modelling of the specific characteristics of the automated DRT. More precisely, the analysis centres on the impacts of trip distances (Section 4.1.1), travel time promises (Section 4.1.2), and related marginal costs on pricing.

4.1.1 Analysis of distance-based pricing

To analyze the impact of trip distance on the optimal pricing policy, we reformulate the analytical model presented in Section 2.2 by defining demand for each trip distance, which are assumed to be integers for simplicity:

$$X_d = D_d(G_d), \frac{dD_d}{dG_d} < 0, \;\; d = 1,2, \dots n. \;\; n \in N. \tag{24}$$

We reformulate the cost function (7) by dividing operator costs into the distance-independent component (C_c) and distance-dependent component (C_d):

$$C_c = c_0 + c_1 F + c_2 R + c_3 X \tag{25}$$

$$C_d = c_4(X_d d + X_d b_d) + c_5(X_d c_d) \tag{26}$$

Equation (25) consists of the first four terms of the cost function (7) with the same interpretations of parameters. In equation (26), d is the direct trip distance, and b_d is the related detour, and c_d is an average increase in the vehicle route length due to the additional trip with a direct distance, d.

As in Section 2.2, the social planner's objective is to maximise welfare, but this time defined first for each trip distance, and then aggregated to define the total welfare as an objective function. The welfare maximisation problem can be formulated as:

$$L = \sum_{d=1}^{n}(W_d - C_d) - C_c - \lambda\left((\sum_{d=1}^{n} d\frac{X_d}{X})\, X - OR\right) - \mu(R - UF) \tag{27}$$

$$= \sum_{d=1}^{n}\left\{\int_0^{X_d} D^{-1}(X_d)dx - \left[Q_d(R, X_{1,\dots}X_n) + K_d(R, X_{1,\dots}X_n, d)\right]X_d - C_d\right\} - C_c$$

$$-\lambda\left(\left(\sum_{d=1}^{n} d\frac{X_d}{X}\right) X - OR\right) - \mu(R - UF),$$

where the value of waiting time cost, $Q_d(R, X_{1,\dots}X_n)$, and value of in-vehicle travel time cost, $K_d(R, X_{1,\dots}X_n, d)$, are functions of potential route production and demand levels for all trip distances. The potential route production and capital are utilised to produce trips simultaneously for all the distances, therefore the related constraints can be formulated as previously, except that the average trip distance is now a weighted average, $\sum_{d=1}^{n} d\frac{X_d}{X}$. Adoption of this weighted average in equation (27) requires assumption that all passenger kilometers consume vehicle capacity equally. Depending on the vehicle routing algorithm applied, it is possible that shorter trips have relatively higher consumption of vehicle capacity due to the higher ratio of the pickup kilometers to the passenger kilometers, which can be taken into account with weighted average $\sum_{d=1}^{n} d \frac{X_d c_d}{Xc}$. For simplicity, in the following text we adopt the assumption and the weighted average, $\sum_{d=1}^{n} d \frac{X_d}{X}$.

If potential route production and capital are fully utilized, then the optimal R, F, and p_d can be deduced:

$$p_d = \sum_{i=1}^{n} (\frac{\partial Q_i}{\partial X_d} X_i + \frac{\partial K_i}{\partial X_d} X_i) + c_3 + c_4 d + c_4 b + c_5 c_d + d\frac{c_1}{OU} + d\frac{c_2}{O}$$

$$+ \sum_{i=1}^{n} (d \frac{\partial Q_i}{\partial R} \frac{X_i}{O} + d \frac{\partial K_i}{\partial R} \frac{X_i}{O}) \tag{28}$$

$$\left(\sum_{d=1}^{n} d \frac{X_d}{X}\right) X = OR = OUF. \tag{29}$$

In the equation (28), the external travel time and waiting time costs of the trips are summarised over all trip distances. Respectively, the travel time savings for passengers due to the increased route production are summarised over all distances. Equations (28) and (29) define the socially optimal trip production and allocation of fleet capacity for variable trip distances.

One consequence of appying price p_d (28) instead of price based only on the average distance as defined in equation (14) is that passengers travelling longer distances pay higher prices, which is reasonable from the viewpoint of social marginal costs. As we mentioned in Section 2.2, there might be other political arguments for flat price, sush as equity and income distribution. The social planner choosing the pricing model between a flat rate (14) and a distance based pricing (28) needs to compare the value of political objectives requiring flat rates and value of increased efficiency due to the use of distance based pricing.

4.1.2 Analysis of pricing based on travel time

Consideration of travel time as the basis for the pricing model leads to an optimization problem similar to distance based pricing. To analyse the impact of travel time promises on optimal policies, we reformulate the model presented in Section 2.2. We assume that total demand is divided into the demands of two passenger groups with different values of travel time. Moreover, we assume that the DRT operator is capable of making reliable travel time promises with trip offers. We define the demand for DRT trips by the two passenger groups with the following demand function:

$$X = \sum_i X_i = D_i(G_i), \ \frac{dD_i}{dG_i} < 0, \ \ i = h, l, \tag{30}$$

where h stands for the passenger group with a high value of travel time, and l for a low value of travel time, respectively.

In the origal cost function (7), all the cost components are presented as separated additional terms, but in this section, the modeling of the trip production costs with travel time promises requires some reformulations. Therefore, we define three cost functions: one for both types of travel time promises (C_l and C_h) and one for common costs (C_c):

$$C_c = c_0 + c_1F + c_2R + c_3X \tag{31}$$

$$C_l = c_4(X_l a + X_l b_l) + c_5(X_l c_l) \tag{32}$$

$$C_h = c_4(X_h a + X_h b_h) + c_5(X_h c_h) \tag{33}$$

The less tight travel time promises allow vehicles to serve more customers simultaneously by combining trips, which consequently increases detours in the trips. It is therefore reasonable to assume that an average detour is longer for trips with less tight travel time promises, that is, $b_l > b_h$. Furthermore, an average increase in the vehicle route length due to the additional trip is higher with tighter travel time promises due to the weaker trip combining possibilities. We therefore assume that $c_h > c_l$. For the same reason, the tight travel time promises decrease the average occupancy rate of vehicles, which must be taken into account in the constraint related to the level of operations required for potential seat kilometers, R. Therefore, we reformulate the constraint (9):

$$X_l a + X_h a \leq (O_l \frac{X_l}{X} + O_h \frac{X_h}{X})R \tag{34}$$

where O_h (O_l) is an upper limit for the occupancy rate if all trips have tighter (less tight) travel time promises. We assume that the upper limit for the total occupancy rate of the fleet is a weighted average of O_l and O_h, $\left(O_l \frac{X_l}{X} + O_h \frac{X_h}{X}\right)$. In practice, more accurate estimates for the total occupancy rate of the fleet could be estimated with collected travel data. In addition, the dependence between the total occupancy rate and O_l and O_h could be more complex than the presented weighted average. However, we assume that the presented weighted average provides a good approximation for various market conditions, and we adopt it in the following text.

As in Section 2.2, the social planner's objective is to maximize welfare, but this time defined first for both types of travel time promises, and then aggregated to define the total welfare as an objective function. The welfare maximization problem can be formulated as:

$$L = \sum_i (W_i - C_i) - C_c - \lambda\left(a\,X - \left(O_l \frac{X_l}{X} + O_h \frac{X_h}{X}\right)R\right) - \mu(R - UF) \tag{35}$$

$$= \sum_i \left\{\int_0^{X_i} D^{-1}(X_i)dx - [Q_i(R, X_l, X_h) + K_i(R, X_l, X_h, d)]X_i - C_i\right\} - C_c$$

$$-\lambda\left((d\,X - \left(O_l \frac{X_l}{X} + O_h \frac{X_h}{X}\right)R\right) - \mu(R - UF),$$

where the value of waiting time cost, $Q_i(R, X_l, X_h)$, and value of in-vehicle time cost, $K_i(R, X_l, X_h, a)$, are functions of potential route production and demand levels for both travel time promises. The potential route production and capital are utilized to produce trips simultaneously for both travel time promises, therefore the related constraints can be formulated as in Section 2.2, except that the upper limit for the occupancy rate is a weighted average of O_l and O_h, $\left(O_l \frac{X_l}{X} + O_h \frac{X_h}{X}\right)$.

As in Section 2.2, the optimal R, F, and p_i can be deduced:

$$p_i = \sum_j \left(\frac{\partial Q_j}{\partial X_i} X_j + \frac{\partial K_j}{\partial X_i} X_j \right) + c_3 + c_4(a + b_l) + c_5 c_l$$

$$+a \frac{c_1}{\left(O_l \frac{X_l}{X} + O_h \frac{X_h}{X}\right) V} + a \frac{c_2}{\left(O_l \frac{X_l}{X} + O_h \frac{X_h}{X}\right)} + \sum_j \left(a \frac{\partial Q_j}{\partial R} \frac{X_j}{\left(O_l \frac{X_l}{X} + O_h \frac{X_h}{X}\right)} + a \frac{\partial K_j}{\partial R} \frac{X_j}{\left(O_l \frac{X_l}{X} + O_h \frac{X_h}{X}\right)} \right), \quad (36)$$

$$aX = \left(O_l \frac{X_l}{X} + O_h \frac{X_h}{X}\right) R = \left(O_l \frac{X_l}{X} + O_h \frac{X_h}{X}\right) UF. \quad (37)$$

In the equation (36), the external travel time and waiting time costs of the trips are summarized over both travel time promises in the term $\sum_j \left(\frac{\partial Q_j}{\partial X_i} X_j + \frac{\partial K_j}{\partial X_i} X_j \right)$. Respectively, the travel time savings for passengers due to the increased route production are summarized over both travel time promises in the term $\sum_j \left(a \frac{\partial Q_j}{\partial R} \frac{X_j}{\left(O_l \frac{X_l}{X} + O_h \frac{X_h}{X}\right)} + a \frac{\partial K_j}{\partial R} \frac{X_j}{\left(O_l \frac{X_l}{X} + O_h \frac{X_h}{X}\right)} \right)$. Thus, equations (36) and (37) define socially optimal trip pricing and production, and allocation of fleet capacity for trips with variable travel time promises (or service classes).

Conventional private taxi rides can be interpreted as the fastest possible travel time promise (direct ride time), including the promise that other customers are not served simultaneously by the vehicle. Thus, shared taxi services offering both shared and private rides, such as Wecab in Paris, can be described by means of this model, in which case C_l stands for costs related only to the shared rides, and C_h for costs related only to the private taxi rides. In the private taxi rides, there are no detours caused by other passengers, therefore in the cost function (33), the term $X_h b_h$ is zero. Moreover, passengers travelling by private taxi rides cause time costs for other passengers only due to the increased waiting time costs, therefore the in-vehicle time cost term $K_i(R, X_l, X_h, a)$ takes the forms $K_l(R, X_l, a)$ and $K_h(R, a)$, and consequently the term $\frac{\partial K_j}{\partial X_i}$ in equation (36) is zero if i=h, or if j=h, that is , $\frac{\partial K_h}{\partial X_h} = \frac{\partial K_l}{\partial X_h} = \frac{\partial K_h}{\partial X_l} = 0$. In the formulation of an optimal pricing policy, it is important to note that, even though, the private taxi ride causes travel time costs for other customers only through waiting time cost, these costs are not, in general, the same as with shared taxi rides. They are, in fact, most likely much higher especially during demand peaks of taxi trips when demand typically exceeds the taxi supply level temporarily.

If the demand for shared rides is sufficient for efficient trip combining, as in the simulations of Section 3, the cost per shared ride is lower than the cost per private ride, and the optimal price for shared ride is lower than the optimal price for private ride. In this situation, the market share of private rides depends on passenger willingness to pay for privacy and faster trips, which is mainly determined by the passenger's value of travel time savings.

4.1.3 Numerical examples

We have modelled socially optimal pricing and production policies for flat rates (alternatively interpreted as constant distance), variable distances, and travel time promises. The following numerical examples illustrate the adoption of the presented models for empirical analyses of service production and pricing policies. We collected empirical data from the DRT service (Kutsuplus) operated by the Helsinki Region Transport in Finland. The data were collected during 16 weekdays both in September 2013 and in September 2014 from the automated trip trading system. The data consist of 4 852 trips and provide values for variables defining generalized costs of the demand, that is, prices, waiting and travel times. Unfortunately, the data on the cost side of the DRT service were available only on the aggregate level. Therefore, we adopt the cost estimates presented in literature, complemented with reasonable assumptions.

We specify demand, X, as the log-linear function of generalized cost, G:

$$X = d_0 G^{-d_1}. \tag{38}$$

Following Jørgensen and Preston (2007), we assume the value of the demand elasticity with respect to generalized cost as 1.5, that is, d_1=1.5. With the assumed demand elasticity and data on the average daily demand and generalized costs, we estimate the parameter d_0 of the demand function. The parameter values and empirical values of the variables are presented in Table 4.

Table 4
Values of Parameters Based on Estimations, Literature and Reasonable Assumptions and Base Values for Variables Based on Empirical Data from Helsinki

Parameters / Variables	Values
Demand (empirical base value), per day	283
Elasticity, d_1	1.5
d_0	9 453
Value of time (€ per minute)	0.17
Average waiting time	7.21
Average value of waiting time, q	1.20
Average in-vehicle time	22.81
Average value of in-vehicle time, k	3.80
Average price (empirical base value), p	5.37
Average distance (km)	7.14
Marginal waiting time externality, $\frac{\partial Q}{\partial X}$	0.003
Marginal in-vehicle time externality, $\frac{\partial K}{\partial X}$	0.0009
Marginal waiting time external effect of fleet capacity, $\frac{\partial Q}{\partial R}$	-0.00008
Marginal in-vehicle time external effect of fleet capacity, $\frac{\partial K}{\partial R}$	-0.000007
Utilization rate of capital, U	0.8
Occupancy rate, O	0.06
Production costs	
Fixed cost per day, c_0	3 504
Cost of capital per seat kilometer, c_1	0.006
Cost of operations per seat kilometer, c_2	0.098
Distance-independent cost of passenger, c_3	0.016
Route-independent cost of passenger per kilometer, c_4	0.005
Cost of kilometer driven by an empty vehicle, c_5	0.146

The value of time is estimated as 50% of average wage, which is in Finland approximately 20 € per hour leading to the value of 0.17 € for minute and, for simplicity, it is assumed to be equal for waiting time and in-vehicle time. The values of the demand, waiting time, in-vehicle time and price in Table 4 are based on the mean values of the data from year 2014. This means that the base values roughly describe the autotomate DRT service (Kutsuplus) in September 2014.

The fleet size was increased from 10 vehicles in year 2013 to 15 vehicles in year 2014. Thus, the combined data from 2013 and 2014 enable estimating the effects of variable fleet capacity and demand level on travel times. The increase in the waiting time cost the passenger causes for other passengers, $\frac{\partial Q}{\partial X}$, and the decrease in the waiting time cost due to increased fleet capacity, $\frac{\partial Q}{\partial R}$, are estimated by means of the linear regression model, where the dependent variable is the waiting time and the explanatory variables are the fleet capacity and the number of customers in the service at the time of the trip request. Similarly, $\frac{\partial K}{\partial X}$ and $\frac{\partial K}{\partial R}$ are estimated with the linear regression model where the dependent variable is the in-vehicle time and the explanatory variables are as in the first regression model. Thus, the estimates of $\frac{\partial Q}{\partial X}$, $\frac{\partial K}{\partial X}$, $\frac{\partial Q}{\partial R}$ and $\frac{\partial K}{\partial R}$ in Table 4 are regression coefficients multiplied by the value of time based on the data from 2013 and 2014.

The utilization rate of capital, U, is assumed to be 0.8, and the occupancy rate, O, is assumed to be 0.06. This is based on the observed maximum occupancy rate during morning peak hours in September 2014, that is, the average produced seat kilometers during the peak hour (193) divided by the potential seat kilometers of the fleet per hour (3 240).

The value of the fixed cost per operating day, c_0, is based on the annual general costs of the Kutsuplus service (841 037€ in year 2014) announced in Helsinki Region Transport (2015). The other parameter values of the cost function in Table 4 are based on estimates presented in literature, complemented with reasonable assumptions. The value of parameter c_1 (0.006) is based on our rough estimate that the annual capital cost for a DRT vehicle is 10 000€, resulting in 27.4€ daily costs, which is divided by the daily vehicle capacity to produce seat kilometers (4 590). The capacity is calculated by multiplying the seat number (9), the average speed (30 km/h) and the number of the operating hours (17), i.e., 9×30×17 = 4 590 and 27.4/4 590 ≈ 0.006. The value of parameter c_2 (0.098) is based on the driver's salary (15 €/h) for 17 operating hours plus additional operating costs totalling 360€ daily costs, which is divided by the daily quantity of operations measured by potential seat kilometers (R) per vehicle (R=U×F=0.8×4 590=3 672), i.e., 360/3672 ≈ 0.098. The value of parameter c_3 (0.016) is based on the assumed fuel price (1.5 €/L) and idle fuel consumption (1.6L/h), and on the average dwelling time of 11.84 seconds presented by Dueker et al. (2004), i.e., 2×11.84×1.5×(1.6/3 600) ≈ 0.016. The value of parameter c_4 (0.005) is based on the assumed passenger total weight (70 kg) and fuel price (1.5 €/L), and on the result that on average every 100 kg weight reduction yields a 0.39L/100 km reduction in fuel consumption (Cheah, 2010), i.e., 0.39/100×(70/100)×1.5 ≈ 0.0041, which is increased to 0.005 to take into account other costs related to the parameter (see Section 2.2). The value of parameter c_5 is based on the estimated variable vehicle operating costs (an average of urban peak and off-peak) of van/light track presented by Litman and Doherty (2009).

The values presented in Table 4 are applied in numerical simulations of the presented model and its variants with different pricing policies, i.e., flat rate pricing, distance based pricing and pricing based on service classes with travel time promises. Table 5 presents the simulation results for the three cases and empirical base values based on data from September 2014.

Table 5
Simulation Results for Three Cases: Flat Rate Pricing, Distance-based Pricing, and Service Classes with Travel Time Promises

Variables	Empirical base values	Flat rate	Distance-based	Service classes
Demand, X	283	96	99	110
X, 3.00 km	25	-	12	-
X, 7.14 km	233	-	79	-
X, 9.00 km	25	-	8	-
X, economy class	229	-	-	87
X, normal class	54	-	-	23
Average waiting time, WT	7.21	25.23	25.41	25.45
WT, economy	8.57	-	-	26.04
WT, normal	5.72	-	-	23.19
Average value of waiting time, Q	1.20	4.20	4.23	4.24
Average in-vehicle time, TT	22.81	23.81	23.28	25.26
TT, 3.00 km	15.28	-	15.71	-
TT, 7.14 km	22.81	-	23.83	-
TT, 9.00 km	28.12	-	29.14	-
TT, economy class	24.89	-	-	25.89
TT, normal class	21.85	-	-	22.85
Average value of in-vehicle time K	3.80	3.97	3.88	4.21
Price (flat/ weighted average), P	5.37	13.12	12.47	12.22
P, 3.00 km	3.88	-	5.71	-
P, 7.14 km	5.37	-	13.10	-
P, 9.00 km	6.04	-	16.43	-
P, economy class	5.37	-	-	12.18
P, normal class	6.71	-	-	12.39
Quantity of capital, F	68 850	14 274	13 990	16 360
Quantity of operations, R	55 080	11 419	11 192	13 088
Total costs, C	9 564	4 816	4 797	5 007
Total revenue	1 520	1 260	1 234	1 345
Social welfare	-2 173	541	514	887

As Table 5 shows, in all the three cases, the optimal values for R and F are significantly lower and prices higher compared with the base values, which leads with clearly longer waiting times and somewhat longer in-vehicle times to the lover demand levels than with the base values. In the simulations of variable trip distances, we selected one short distance (3 km) and one long distance (9 km) with an approximately equal market share in the data. We then made a simplifying assumption that the rest of the trips have the average distance, allowing us to restrict the analysis to the three distances. In the case of distance-based pricing, the price of the long-distance trip is relatively much higher than in the base values, and respectively the share of long-distance trips (9 km) is lower than short-distance trips (3 km). In the case of service classes with travel time promises, the price difference between the service classes decreases and the share of the normal class trips increases. These numerical results are as expected based on our analytical results, that is, longer distances increase costs and optimal prices, which reflects on demand. The relatively small price difference between the service classes can be explained by the low occupancy rate, which causes that the realised travel times of the service classes differs only marginally.

In all the three cases, the total costs are much lower compared with the base value. A straightforward social welfare comparison between the cases based on the figures in Table 5 is not reasonable because the demand functions are specified differently in each simulation. In the case of flat rate pricing, the demand function is specified for trips with the average distance, whereas in the case of distance-based pricing, the demand functions are specified for the three distances, and in the case of service classes, the demand functions are specified for two service classes. Moreover, the social welfare estimated for the base values is also based on flat rate pricing, whereas the real pricing model of the DRT service is more complex, including group discounts, starting fees, distance-based pricing, and service classes with travel time promises.

However, the social welfare comparison of the pricing policies is an important issue and relates closely to the third main research question of this work. Therefore, to illustrate the use of the model for welfare comparison between pricing policies, we simulated the optimal flat rate pricing policy with the demand functions for the three distances as in the case of distance-based pricing, which resulted in a 6% decrease in the share of short-distance trips and a relatively small decrease in the (daily) social welfare from 514 € to 499 €. More detailed modeling of distances would increase the number of the different trip distances, and consequently, the welfare differences would also be higher between the pricing policies. Furthermore, inclusion of external costs of vehicle kilometers for other than DRT passengers (Section 3.2) in the model would increase the difference between the pricing policies.

4.1.4 Exploratory analysis of pricing models and principles

The presented numerical examples illustrate how the analytical model, presented in Section 2.2, and its variants, presented in this section, can be adopted to define optimal prices and trip production for DRT services with alternative pricing models. Moreover, the numerical examples show that the selection of the pricing model affects social welfare. This is in line with the economic theory of the socially optimal prices, which states that prices should be equal to the social marginal costs. This condition is usually difficult to fulfill completely in pricing transportation services, but some pricing models can satisfy the condition more completely than others, which also depend on the prevailing market conditions and the transportation system. The variety of alternative pricing models (or fare structures) for transportation services is basically unlimited, for instance, public transit operators often adopt relatively complex pricing models, including the combination of several ticket types, nighttime tafiffs, special group discounts and zone pricing. We conducted exploratory analysis of alternative pricing models and principles in transportation services to identify the most applicable models for the automated DRT based on the principle of marginal cost pricing and other criteria.

In the analysis, we define *pricing model* as a concrete system that defines prices for different trips, whereas *pricing principles* are general principles that can be applied to pricing models to modify them to better respond to the requirements and objectives of the customers, transport operators, and society. A pricing principle in itself does not define any concrete pricing model. The presented pricing models and principles are mainly identified through literature review and observation of pricing models adopted by operators (Publication 5). Moreover, the analysis is based on data and experiences from the Kutsuplus service. The main purpose of the analysis is to evaluate the suitability of the pricing models and principles for the automated DRT service.

We have identified four main criteria for the pricing models based on the general policy objectives to increase the attractiveness of public transportion and efficiency of urban transportation systems, and on the spesific features of the automated DRT. The main criteria for the suitability of pricing models are:

1. Fast growth: The pricing model is compatible with a fast growth strategy.

2. Competitiveness: The pricing model enables exploitation of the competitive advantages of the automated DRT in different customer segments.

3. **Compatibility:** The pricing model for automated DRT can easily be integrated into the pricing models of other public transport services.

4. Marginal cost pricing: The pricing model enables fulfilling the condition that trip prices are equal to the social marginal cost.

The first criterion, that is, the need to support fast growth at an early phase of the service launch is based on the supply and demand side scale economies of the automated DRT. In a pricing model selection (or formulation), it is reasonable to emphasize the first criterion at the service launch, and later, at a more mature phase when a sufficient market share and related scale economies are achieved, the pricing model can be modified to more effectively attend to the other criteria. This type of pricing model modification, which evolves dynamically over time, is not typical for public transport, but for the automated DRT it can be justified by the need to first increase the market share and then attend more accurately to the emerging customer needs and other policy objectives.

The second criterion is related to the potential competitive advantages of the automated DRT in relation to private cars, which are the lower costs especially in the long run due to the capital costs of private cars, ease of use, and environmental friendliness (if a sufficient average occupancy rate is achieved). In Section 3, we showed by simulations that at a sufficient demand level, the automated DRT is more cost-effective than private car, which enables competitive price setting. By ease of use, we mean that automated DRT relieves private car users from the need e.g. to search for parking spaces, overhaul their vehicles, refuel, and scratch ice off the windows. In the long run, current private car users probably represent the greatest potential customer segment for the automated DRT, but especially in the launch phase, other public transportation users also represent an important customer segment. The automated DRT service can be a particularly attractive service for public transportation users who need to transfer frequently and suffer from uncertain connections. Thus, the second criterion means that pricing models should enable exploitation of these sources of competitiveness, which varies with customer segments.

The third criterion is also related to competitiveness, and is based on the transport policy objective for the development of the automated DRT (discussed in Section 1) to increase attractiveness of public transportation as a whole compared with private car. Thus, the third criterion means that pricing models should foster cooperation between public transport modes to fulfill passengers' daily varying and constantly changing travel needs.

The fourth criterion is based on the previously discussed condition that trip prices are equal to the social marginal cost. In practice, it is impossible to fulfill this condition completely with a simple pricing model such as flat rate. On the other hand, a pricing model which could capture social marginal costs, that is, both the production costs and external costs such as pollution and congestion for other modes, perfectly would probably be too complex to understand for customers.

The four main criteria were adopted for the analysis of the five pricing models: (1.) *flat rate pricing model, (2.) fixed kilometer price with a fixed starting fee, (3.) fixed minute charging with a fixed starting fee, (4.) fixed term pricing model, and (5.) zone pricing model,* which were identified as typical models for transportation services.

The flat rate pricing model is simple and therefore easy to understand, and it is commonly adopted pricing model for transport services. Therefore, the flat rate pricing model makes the decision whether to test or to use the automated DRT occasionally easy. It also supports the fast growth strategy during the launch phase, provided the trip price is also set at a competitive level. On the other hand, it may not be attractive for regular users in contrast to, for istance, 30-day tickets of public transportation. Moreover, the flat rate model treats all customers similarly, but not necessarily equally, because it prices trips similarly without considering the variable marginal costs of trips. For instance, the flat rate model favors customers making long-distance trips at the expence of short distance passengers. Thus, we can conclude that the flat rate model fulfills criteria 2 and 4 poorly or not at all.

The second pricing model is based on a *fixed kilometer price with a fixed starting fee*, which is typical for taxi services. In automated DRT, the kilometer price should be based on a direct trip length, to avoid charging of additional kilometers (detour) due to new customers. From the viewpoint of our criteria, this model is somewhat similar to the flat rate model. Customers are familiar with it thanks to their experiences with taxi services and find it easily understandable. One difference compared to the flat rate model is that a customer cannot typically determine the exact price of the trip beforehand or before the trip request. The other difference is that it takes trip length into account in price determination, which enables adoption of marginal-cost pricing for the trip to a certain extent, but still enables capturing the incurred marginal costs before the pick-up only as an average.

The third pricing model is based on a *fixed minute charging with a fixed starting fee*. This pricing model is typically adopted when a taxi is asked to wait for a customer in a certain location, or when the speed of taxi cabs is low on congested roads. In automated DRT, this pricing model causes notable uncertainty for customers, because travel time is usually more difficult to estimate than trip distance. One advantage of this model from the efficiency viewpoint is that it creates an incentive for customers to avoid travelling during peak periods. The model adoption for automated DRT in its basic form, that is, positive values for per-minute price and starting fee, would contradict with the second criterion (competitiveness), and with the policy objective to increase attractiveness of public transportation, because a longer travel time, that is, lower quality of service, for a certain trip means higher price. Travel time is an essential element in the pricing of the automated DRT, but the pricing model should take travel time into account conversely, by pricing faster trips at a higher price, because faster trips based on travel time promises cause higher production costs and external travel time costs for other DRT passengers, as explained in Section 4.1.2.

The fourth pricing model is the *fixed term pricing model* (season ticket), which allows unlimited travelling with a certain fixed price during a certain time period, typically, for example, a day or a month. This model is common in conventional public transport and it normally applies a nonlinear pricing principle, which means, for instance, that one 30-day ticket is cheaper than 30 one day tickets. The pricing model is attractive for regular users such as commuters and students, and therefore can support the objective of fast growth. In contrast, the model creates risks for the supply side, because it is difficult to predict the trip demand if passengers have an unlimited right to use the service. Therefore, some form of constraining the daily traveling per passenger should be considered with the model. In principle, this model can be integrated into public transport ticketing systems even if some limits on the usage of the automated DRT are applied. One weakness in the fixed term pricing model (in the basic form) is that marginal costs can be captured only as an average.

The fifth pricing model is the *zone pricing model*, in which a trip price is based on zones travelled or on the zone borders crossed. This model is basically a combination of flat rate and distance-based pricing. The trip price of is always a fixed sum, increasing stepwise as the zone borders are crossed. For passengers, the model is rather easy to understand and they can determine the trip price in advance if the origin and destination zones are known. In automated DRT, however, partitioning of the service area into zones can be a complex task if the marginal-cost principle is applied even with a low accuracy. Denser partitions would enable a more refined determination of the price as a function of trip length to improve capturing the marginal costs. Table 6 summarizes the analysis of the pricing models. As can be seen from the table, none of the analyzed pricing models fullfil completely all the four criteria.

Table 6
The Analyzed Pricing Models
(+ indicates that a pricing model fulfills the numbered criterion)

Pricing model	Description	Suitability of pricing model according to the four criteria	Illustrative example
Flat rate / fixed pricing for single trip	All kinds of trips with fixed price	1. (Fast growth): + 2. (Competitiveness): 3. (Compatibility): 4. (Marginal cost pricing):	Single bus ticket with a fixed price
Fixed kilometer pricing	Fixed starting fee + fixed kilometer price, based either on driven trip or direct trip distance	1. + 2. 3. 4. +	Typical taxi pricing scheme
Fixed minute pricing	Fixed starting fee + fixed minute fee	1. 2. 3. 4. +	Congestion-related element in taxi pricing
Fixed term pricing / season ticket	Fixed price for unlimited travel within a time period	1. + 2. 3. 4.	Typical frequent passenger or commuter price scheme, typically monthly pricing for a certain service area
Zone pricing	The price is determined based on zone borders crossed	1. + 2. 3. 4. Depends on density of partitioning	Greater Copenhagen pricing scheme

Next, we present the seven pricing principles identified from literature and existing transportation services. These principles can be applied to the modifications of the analyzed five pricing models to impove their suitability for automated DRT.

The first principle is the *time dependent pricing*, in which a trip price can vary according to the time of the day. This principle is applied, for example, in bus ticket pricing in Helsinki, where the ticket price is higher at nighttime, and the same applies to taxi starting fees. In automated DRT, this principle can serve many objectives. For instance, a price reduction for off-peak hours could attract passenger groups with a lower WTP (or valuation of travel time), such as students, retired and unemployed, that is, improving competitiveness in certain customer segments (criterion 2). The principle could also intensify fleet management by lowering prices for off-peak hours to shift demand from peak to off-peak hours, and thereby enable more steady utilization of the fleet capacity and even alleviate congestions. This principle was also applied in the pricing of the Kutsuplus service in 2015, but the impacts have been unanalyzed thus far. However, this objective of the fleet management can contradict with the congestion reduction objective if the price reduction for off-peak hours leads to increased prices for peak hours (to maintain the budget balance), which consequently can lead to increased use of private cars during peak hours by travellers whose schedule is inelastic anyway. This issue was considered by Glaister, who found that under plausible market conditions, the external costs of private car use are so high that reverse peak-load pricing of public transportation can be reasonable, that is, leading to reductions in social costs (Glaister, 1974).

The second principle is *the discount for preordered trips*. A discount may depend on the length of the interval between the order time and the requested pick-up time. This principle is common for airlines, which give discounts for early preordered trips. In automated DRT, the principle could be applied so that customers would be allowed to preorder a trip by defining the desired pick-up time for hours, days or even weeks beforehand. Preorders may provide valuable information about the future trip demand, enabling a more effective use of vehicle capacity due to better routing and trip combining. In the long run, the preorder information could enable more reliable predictions of the daily and hourly demand, which would intensify fleet management even more, and thereby reduce costs of the automated DRT operator. Therefore, it would be reasonable to give discounts for the preordered trips. From the viewpoint of customers, the trip preorder can be seen as a guarantee of service availability. One concern related to the preorder option is that it can decrease the instantly vacant vehicle capacity, and thereby deteriorate the perceived quality of service (availability and waiting times) for those customers who want to use the service instantly. However, this concern can be addressed by adjusting fleet capacity based on the preorder information.

The third principle is *nonlinear pricing*. In its basic form, this means reduced prices for frequent users. As we previously stated, this principle is often applied for season tickets of public transport (the fourth pricing model). Another example from airlines is frequent flier plans with reduced prices. These examples illustrate two common means to use nonlinear pricing. The first is to reward a customer making a considerable advance purchase (e.g., 30-day ticket) with a discounted price. The advance payments improve the liquidity position of the service provider through a positive cash flow. The second approach to using nonlinear pricing is to reward frequent users with further discounts or other privileges. Nonlinear pricing can be an effective tool to attract customers for frequent use and to grow the market share of the automated DRT. On the other hand, automated DRT can have conflicting objectives. Purely from the viewpoint of business objectives, that is, profit maximization, nonlinear pricing can be easily justified. From the viewpoint of the policy objectives set in this work, however, the use of nonlinear pricing for automated DRT is a more complicated issue, because the objective of improving the attractiveness of public transport as a whole and the objectice of maximizing the number of (profitable) DRT trips are somewhat contradictory. The other possible conradiction is that nonlinear pricing can encourage customers to make "needless" trips, more precisely, a social marginal cost of a trip can exceed the marginal benefit for the passenger who still makes the trip, if the additional fee is relatively low due to the nonlinear pricing. This would be a serious (efficiency) problem especially for automated DRT, because a new trip immediately incurs significant marginal costs, unlike in conventional public transport with fixed routes and schedules where the marginal costs are usually lower.

The fourth principle is *bundling*, which means selling and pricing products and associated services together as a bundle. In transportation services, bundling can be used to create attractive multimodal travel offers, e.g., a door-to-door trip that takes place first through a DRT trip from the origin, followed by train travel, and finally by a DRT trip to the destination, which can provide a competitive alternative to private cars in terms of travel time and price. Trip bundling can reduce customer effort to potentially complex and time-consuming trip combining. A challenge in bundling transport services is the complexity of collaboration between several transport operators. For instance, in a train plus automated DRT bundle, it is not clear to what extent the customer's WTP for the bundle can be attributed to automated DRT and train service. Moreover, the cost structures of transport modes are different. Marginal costs for automated DRT are significant, whereas (short-run) marginal costs for a train are almost zero, but the sunk costs of the railway investments are significant. Thus, it is no trivial issue how earnings should be shared. Furthermore, conceivable arguments such as additional value for customers (for example, travel time savings and convenience) and costs of service are not easily measurable when the whole multimodal trip chain is considered. For instance, the valuation of travel time can vary in different parts of the trip chain, and some of the transport modes with spesific features (such as proper working space with internet connection in a train) can be critical for the selection of the whole multimodal trip chain instead of using private car.

The fifth principle is *pricing based on fulfilled service*, which means that the trip price is not fixed before the trip ends. This means that there is an initial price based on a pricing model, but the passenger can change the route while travelling, which changes also the price. For instance, taxi services typically use this principle. As mentioned earlier, taxi services typically adopt a pricing model in which the starting fee and the kilometer price are fixed, and then apply the fifth principle, that is, customers are allowed to change the destination during the trip. In automated DRT, this principle would enable flexibility for the customers and bring service quality closer to that of a private car and taxi. Most likely, passengers would use this option only rarely (depending on the extra fee for trip canges), but it can have a crucial option value, that is, a customer can rely on that she can change the route if her personal plans change. To enable decent flexibility and still maintain an effective vehicle routing, it should be possible to use other DRT vehicles or even taxi cabs to complete changed trips.

The sixth principle is *pricing based on quality of service*. A perceived quality of transportation service depends on several factors such as waiting times, travel times, reliability of the promised travel times, safety, and comfort of the travel experience. Quality factors that can be controlled and communicated to customers can be used as a basis for pricing. This principle is rarely adopted in conventional public transport, whereas in airlines, it is quite common, that is, direct air connections are typically more expensive than flights with intermediate landings and extra comfort is offered in more expensive business classes. The possibility to flexibly adjust the automated DRT trip quality with travel time promises (linked to the routing algorithm) and related service classes enables the service positioning of automated DRT to be competitive against different types of transportation services and an attractive tranport mode for customers with variable quality requirements. When a customer makes a trip request, the automated DRT system can not know beforehand what type of a combination of quality and price the customer currently prefers. Therefore, it would be beneficial to give several offers with variable quality and price, thereby increasing the probability that the customer will choose the automated DRT service now and in the future even though the quality requirements and WTP are changed.

The seventh principle is *price discrimination*, which means that different buyers are charged different prices for the same good. Pigou (1938) defined three degrees of price discrimination. In the first-degree price discrimination each buyer pays the price equal to her (personal) WTP. It provides a theoretical benchmark as a maximal discrimination often referred also as perfect price discrimination. In the second-degree price discrimination different prices are set for customer groups segmented according to the WTP. In the third-degree price discrimination prices are also set for several customer groups, but the segmentation is based on "some practicaple mark", that is, verifiable customer characteristic. The third-degree price discrimination is common for public transportation services. For example, students, the unemployed, and pensioners receive discounts for a bus ticket price. The main argument for this type of price discrimination in public transportation is usually social justice or equity, but it can also be justified as revenue maximization because some customer segments, like pensioners and students, have usually lower WTP than customers with a job. For automated DRT, especially the third-degree price discrimination opens possibities to integrate the pricing model with conventional public transportation, for instance, by offering discounts to owners of transit season ticket. Moreover, discounts for chidren would increase the attractivess of automated DRT for families.

For clarity, we mention that the principles 1, 3 and 6 (time-dependent pricing, non-linear pricing, and pricing based on quality of service) are often also seen as discriminatory pricing practices, but these principles are not based on verifiable customer characteristic but rather on customers own choices (Anderson and Renault, 2011). Therefore, these principles cannot be seen as third-degree price discrimination. Anderson and Renault (2011) note with several references that economists often call these principles as second-degree price discrimination, even though these principles differs from Pigous' original definition. Table 7 summarizes the analysis of the pricing principles.

Table 7
Analyzed pricing principles
(+=use of pricing principle foster to fulfill the numbered criterion)

Pricing principle	Description	Suitability of principle according to the four criteria	Illustrative example
Time-dependent pricing	Different prices according to time of day	1. + 2. + 3. 4. +	Taxis have higher starting fees at night and during the evenings
Discounts for preordered trips	Reduced price if the trip is preordered. Reduction may be dependent on the time span between the order and the trip	1. 2. + 3. 4.	Airlines typically give reduced prices for preordered trips
Nonlinear pricing (basic form), volume-based pricing	Reduced prices for one-time payment of several trips or for frequent users	1. ++ 2. + 3. 4. +	Frequent flier plans of airlines with reduced prices or upgraded service
Bundling	Bundle of services consisting of travel/trips and other products and services. Combined bundle of connected services	1. + 2. + 3. + 4.	Train + bus bundles, i.e., train for main routes and bus to smaller locations
Pricing based on fulfilled service	Preliminary pricing based on a certain scheme, but the passenger can change the route while traveling, which changes pricing	1. 2. + 3. 4. +	The total price of taxi trip is based on realized kilometers and/or travel time
Pricing based on quality of service	A trip price is proportional to the quality aspects of the trip such as comfort and travel time	1. + 2. + 3. 4. +	Trips by fast intercity trains are more expensive than by regular trains
Price discrimination	Different buyers are charged different prices for the same service	1. + 2. + 3. + 4.	Students get discounts for a bus ticket price

Our target has been to evaluate alternative pricing models and principles for automated DRT. The automated DRT system enables a wide variety of different dynamic pricing models and real-time trading mechanisms. Important constraints in the adoption of these models are related to customer requirements, that is, the pricing model and trading system should be understandable and easy to use.

The other important constraints and requirements are related to the system itself. The automated DRT system is dynamic, that is, temporarily and spatially variable demand can lead the system into different states, unlike in a conventional public transportation system with fixed schedules and timetables. Therefore, the adopted pricing model should foster a balance between demand and supply and reduce uncontrolled variability of service quality. With these constraints and requirements and the four main criteria, we started to identify alternatives to an adequate pricing model for automated DRT.

Firstly, it was obvious that none of the five pricing models in their basic form would fulfill all four criteria, as Table 6 depicts. Criterion 2 (exploiting the competitive advantages of automated DRT in different customer segments) is weakly fullfilled in all the five pricing models. By combining the five basic models, however, we can formulate 31 models, including the five basic ones (2^5-1=31, where -1 is for an empty set in combinations). Some of these model combinations are relevant and common for public transport services. For instance, in Helsinki, bus ticket pricing is based either on the flat rate pricing model for a single ticket or on the fixed term pricing model for a season ticket. However, some of the combinations seem strange and irrelevant. For instance, selling trips simultaneously for a flat rate and a fixed kilometer price or a fixed minute price seems unreasonable (unless the flat rate is considered a quaranteed price ceiling).

By applying the seven pricing principles to the models, over 35 billion alternative pricing models can be formulated (the number would be even higher without the simplifying assumption that there is only one way to apply each pricing principle). For instance, pricing models which combine two of the five basic models form 10 alternatives that all consist of two components (e.g., flat rate and season ticket). Now, for one component, seven principles can be applied in 2^7=128 different ways. Finally, there are 10×128×128=163 840 alternative pricing models of two components. Thus, as the number of alternatives for a pricing model is so high, it was obvious that some other research strategy than systematic analysis of all alternatives should be chosen.

We proceeded in the analysis by first identifying the most promising and simple alternatives. Then, the problems with these models were improved by adding new components and formulating models by applying some of the pricing principles until all four criteria were fulfilled. In the analysis of automated DRT, it is important to note that trip trading between a customer and the DRT system is assumed to be implemented by a mobile device. This enables relatively simple trading for the customer, e.g., the customer makes a trip request and then receives an offer, which she can choose to accept or reject. Simultaneously, the pricing model determining the price for the offer can be defined by complex algorithms and utilize real-time information on demand and traffic. Therefore, the complexity of the pricing model is not necessarily as harmful a feature for automated DRT as it would be for transportation services with traditional ticket sales.

From the viewpoint of the four criteria, the most suitable of the five pricing models was a fixed starting fee with a fixed kilometer price, which is based on a direct trip length. This pricing model is familiar from taxi pricing and therefore understandable. The model enables capturing marginal costs to some extent. However, the model still leaves many criteria weakly or not at all fulfilled. To improve the competitiveness of automated DRT for different customer segments (criterion 2), we applied the pricing principle based on quality (travel time promises) of service. The DRT system does not know customers' acute needs beforehand regarding travel times. Therefore, providing alternative offers with different promised travel times can be recommended as already explained with the sixth pricing principle. To keep the trading system simple and usable for passengers, we propose that the system should give no more than three alternative offers simultaneously. Now, we have defined a relatively simple trading mechanism and pricing model that enables marginal costs and different customer preferences to be taken into account.

The proposed model can be formulated further to better respond to market-specific requirements by applying adequate pricing principles without significant or any changes to the trading mechanism. We identified four feasible options for the further formulation of the proposed pricing model. Firstly, a kilometer price or a starting fee can vary according to the time of day if there is a need to balance travel demand between hours. Secondly, nonlinear pricing could be applied to trip requests of groups, which can be justified by the fact that passenger groups that have the same trip origin and destination enable more effective trip combining. Thirdly, concessionary fares should be considered for children, otherwise a private car would often be a more cost-effective alternative for families. Fourthly, customers should have the option to request travel bundles of conventional public transport services and the automated DRT service, that is, multimodal trip offers, if the objective is to improve the competitiveness of the entire public transport compared to a private car.

The pricing model of the Kutsuplus service, which operated (fully) during years 2013 – 2015, applied many similar features and principles with our proposal. It also applied kilometer pricing with a fixed starting fee and offered alternative service classes and group discounts. However, the pricing model of the Kutsuplus service offered no concessionary fares for children (or for any special group). Moreover, the price was the same during peak and off-peak hours, except in 2015. The Kutsuplus service was a service pilot of a new and unique transport mode. Therefore it is understandable that the pricing model was relatively simple rather than "optimal". However, the distribution of trips (presented in Publication 5) indicates that time-dependent pricing should be considered if automated DRT or other similar services such as shared taxi services reach a more mature phase of the service in order to spread the demand peaks.

Data on passengers' choices between alternative transportation services or offers can provide useful insights into the selection of relevant components for the pricing model. We analysed passenger choice data collected from the Kutsuplus service, the automated trip ordering system of which provides simultaneous and alternative trip offers based on the service classes with variable prices and travel times. The data collection period extended from 1.9.2014 to 22.9.2014 (16 workdays). The total number of trip requests was 12 593, and 4 531 offers were accepted. The average acceptance percentage was 36, and the highest acceptance percent (44%) was for trips requested before 7 AM. A discrete choice logit model was adopted to study passenger choices between the alternative offers i (service classes), and more precicely, to analyse the impacts of the price,P_i, the travel time estimate, T_i (announced in the trip offer), and the promised maximum delay, D_i, for the choices between the economy class and the normal class. The estimated utility function for an offer i is:

$$V_i = -0.0131 * P_i - 0.1458 * T_i - 0.0490 * D_i,$$

$$(0.001) \qquad (0.021) \qquad (0.036)$$

where the standard errors of the coefficient estimates are given in parentheses. The logit model includes the three decision variables of the DRT system (price, travel time estimate, maximum delay) as explanatory variables, which also defines the trip offers.

The ratio of coefficients of the estimated travel time and of the price,that is, the marginal rate of substitution, is 11.1 (-0.1458/-0.0131). A straightforward interpretation would be that the value of travel time savings for passengers is 6.6 euros per hour, which is approximately 45% of the average after-tax salary in Finland. Thus, the value of travel time for Kutsuplus passengers seems to have been quite similar to the typical level. The ratio of coefficients of the promised maximum delay and of the price is 3.7 (-0.049/-0.0131). Thus, it seems that the customers of the Kutsuplus service are willing to pay at most 0.037 euros to reduce the maximum delay by one minute. The estimate of the coefficient of the promised maximum delay should be interpreted cautiously, because the statistical significance of the variable was only 0.176 whereas the other variables of the model (price and travel time) were statistically highly significant. From the viewpoint of the pricing model formulation, the presented data and estimations confirm, as expected, that the travel time promise or reliable estimate (in offers) can be a relevant component of the pricing model. The data indicate the same interpretation also for the promised maximum delay, even though, less evidently.

4.2 Regulation policies and pricing

Public transportation services, including taxi services, have been typically regulated by the public autohorities. Regulation of transport can take several forms, such as the economic regulation of prices, output, entry and exit, regulation of product quality, safety, and environmental standards (Savage, 2006). This work considers only economic regulation of prices and output on the monopoly market. Optimal pricing is influenced also by regulation policies other than price regulation. Therefore, it is meaningful and important to study pricing and other regulation policies in conjunction.

We use the simulation model II to study alternative regulation policies for the monopoly market of the automated DRT. On one hand, we are interested in the profit of the monopoly, and on the other hand, the level of service and the customer surplus. We define social welfare as the sum of profit and customer surplus, similarly as in, for example, Yang (2002) and Yang (2005). We study impacts of traditional price and output regulation policies on the social welfare. Moreover, we propose a new type of real-time regulation policy, enabled by fully automated vehicle dispatching, yielding a significantly higher social welfare than the considered traditional regulation policy.

In this section, the automated DRT is studied as a complementary service to conventional bus and taxi services, that is, customers can always choose between bus, taxi, and DRT. For simplicity, we assume that potential DRT customers always have an alternative transportation mode where the surplus is zero, which means that a customer chooses the DRT service for a given trip only if the expected surplus is positive, forming a necessary but not sufficient condition for trip offer acceptance. As described in Section 2.4.2, the demand for DRT is modeled as a linear function of price and level of service, which is expressed by means of a probability distribution P(accept | τ, p_{km}), which denotes the conditional probability that an arbitrary customer accepts a proposal with theexpected travel time ratio τ and price per kilometer, p_{km}.

A monopoly operator controls all the available vehicles with the dispatching and routing algorithm. The number of vehicles, denoted by K, and price per kilometer (length of trip is measured from direct trip), p_{km}, are determined in a way that maximizes the daily profit. The optimal number of vehicles and price are given by

$$(K^*, p_{km}^*) = \arg\max_{K,p_{km}} D_s p - KC_F - C_V \tag{39}$$

where D_s is the number of sold trips, p is the average price of a trip, C_F is the fixed cost of vehicle, and C_V is the variable cost of vehicles (which depends on driven kilometers), during one day. D_s, p and C_V are functions of K and p_{km}.

As assumed in the fifth preliminary assumption in Section 2.4.2, the monopolist aims to formulate for each trip request a single offer which maximizes the expected profit. In other words, the monopolist chooses for each trip (o_i, d_i) the vehicle so that the expected profit

$$E[\pi] = P(accept \,|\tau, p_{km}) \cdot (p(o_i, d_i) - E[\Delta C]) \tag{40}$$

is maximized, where $P(accept \,|\tau, p_{km})$ denotes the acceptance probability with level of service τ and price per kilometer p_{km}. $E[\Delta C]$ denotes the expected increase in the cost of the vehicle route caused by the new potential customer.

Thus, the monopolist has two types of decisions, that is, long run decisions defining the fleet size and price per kilometer (equation 39), and daily decisions instantly defining trip offers (equation 40). The traditional regulation policy regulates the long run decisions by defining the price and the fleet size (potential output) to maximize the social welfare. The new regulation policy, the real-time regulation, regulates the daily decisisions. Thus, instead of expected profit, the vehicle is chosen so that the expected social welfare

$$E[SW] = P(accept \mid \tau, p_{km}) \cdot (p(a,b) - E[\Delta C]) + E[S \mid \tau, p_{km}] \tag{41}$$

is maximized, where $E[S \mid \tau, p_{km}]$ is the expected surplus defined by equation (23).

The simulation model II is adopted to compare the optimal number of vehicles and kilometer price in three cases: 1) monopoly (maximizing profit), 2) regulated monopoly (price and fleet size regulation), and 3) real-time regulation , that is, price and fleet size regulation with regulation of vehicle selection defined by equation (40). The results of the simulations are summarized in Table 8. The table shows the optimal price per kilometer and the optimal number of vehicles for each case (market mechanism) together with the corresponding total profit, realized customer surplus, and social welfare. Moreover, the number of served customers, the average realized travel time ratio, and the relative driven distance are given for the each case. The average travel time ratio is determined by dividing the total travel time of customers by the sum of direct trip ride times. Thus, it describes the average level of service experienced by the customers. The relative driven distance is calculated by dividing the total driven distance of vehicles by the sum of direct trip lengths. Thus, it describes how efficiently the vehicles are utilized. The average values in the table were calculated over 100 simulation runs with the parameter values listed in Table 1 (model II). The average number of requested trips was 43 253 in each case.

Table 8 shows that the monopoly yields the highest profit and almost zero customer surplus as expected. By regulating the kilometer price and the number of vehicles of the monopoly to maximize social welfare (case 2), the total customer surplus, number of served customers, the average level of service and number of vehicles increase slightly, but the optimal price remains the same. It seems that price regulation of the DRT monopoly is relatively ineffective compared to fleet size regulation, because the monopolist can react to regulated lower price by dropping the service level in daily dispatching decisions, and consequently, the generalized price remains almost at the same level. Referring to the relative driven distance, it can be seen that the monopoly without regulation is slightly more efficient than the regulated monopoly.

The real-time regulated monopoly (case 3), is a novel attempt to transform the monopolist from a profit maximizer to a social welfare maximizer. The monopolist's regulation is focused both on the long-run decisions (price and fleet size) and on the daily trip offering decisions to maximize the expected social welfare of each trip request, which results in substantially higher social welfare than with the other mechanisms. The result suggests that the automated DRT and other similar type of new ICT-enabled transportation services, in which the vehicle routes are not fixed beforehand, and in which decisions on routing and trip offers are delegated from the driver to the automated system utilizing real-time information and routing algorithms, enables the social planner to adopt new regulation policies that can be much more efficient than when adopting only traditional regulation policies such as regulation of price and output.

Table 8
Simulation of Regulation Policies

The first columns of the table show the optimal number of vehicles and price per kilometer for the three studied cases. The remaining columns show the corresponding average values of surplus, profit, social welfare, number of served customers, realized travel time ratio and relative driven distance calculated over 100 runs with the parameter values in Table 1. The lower part of the table shows the margin of error of the mean of the studied quantities at a 95% confidence level.

Market mechanism	Number of vehicles, K	Price/km, p	Surplus	Profit	Social WF	Served customers	Travel time ratio	Relative distance
1) Monopoly	210	1.65	417	94535	95429	21213	1.688	0.613
2) Regulated monopoly	240	1.65	5089	91799	96888	22180	1.642	0.626
3) Real time reg. monopoly	320	1.40	31162	81488	112650	29387	1.585	0.660

Margin of error at a 95% confidence level:

Surplus	Profit	Social WF	Served customers	TTR	Relative distance
150	180	200	20	0.0011	0.00029

4.3 Crowdsensing and policy objectives (publication 4)

In this section, we consider connections between the automated DRT and crowdsensing-based traffic services expecially from the viewpoint of policy objectives for sustainable transportation systems. We focus on crowdsensing services, in which real-time travel information can be collected from smartphones and utilized in creation of an accurate state description of the current transportation system, which can be delivered further to road users in different forms, such as general traffic information services, or as more personal trip and route advices. Such services form a platform for two-sided markets (Eisenmann et al., 2006) where both the costs and revenues come from both sides (travellers and service providers), as both sides have customers, that is, travellers can sell their private data and buy (transportation and information) services produced with aggregated and refined data.

All the parties involved in the two-sided market of the crowdsensing-based traffic information (consumers, service providers, and a platform operator) are influenced by policies targeting for the sustainability of the transportation systems and by technological advancements of the intelligent transportation, which we identified as the critical external drivers fostering the utilization of traffic-related crowdsensing. In addition to external drivers, there are various external obstacles, such as national legislation and regulation possibly limiting the utilization of the crowdsensing and different technical standards and interfaces of the related digital services (like maps and transport route and schedule information) slowing or even temporarily preventing transferring the crowdsensing-based traffic services to new countries. Such obstacles may be critical in the short-run, whereas the external drivers can be seen influencing more in the long-run. In the following, we focus only on the external drivers.

As explained in Section 1.2, the automated DRT and shared taxi serices have been deleloped to increase the attractiveness of public transportation and thereby respond to the policy objectives of sustainability. Crowdsensing-based traffic services can provide accurate and detailed real-time traffic information also for authorities planning and implementing transport policies. For instance, detailed traffic information can be used to optimize congestion charges, and to optimize pricing and allocation of subsidies for alternative public transportation modes. Moreover, public transportation operators could utilize the real-time traffic information to improve the service level by offering more accurate information to passengers and by offering seamless multimodal trip chains, where dynamic fleet management and real-time information can be utilized to increase the reliability of connections and travel times. This is especially crusial for travel time promises and related service classes of the automated DRT. Furthermore, discounts for congestion charges could be applied to cars with several passengers to foster ride sharing and shared taxi trips, which could be verified with crowdsensing technologies.

We analysed three crowdsensing-based services from business model and sustainability viewpoints in Publication 4. The analysed services are Waze, Moovit and TrafficSence.

Waze is a navigation service based on crowdsourcing providing real-time traffic information mainly for private car drivers. It provides typical navigation information about roads and crossings, but informs also about travel times, and route-related information. The service is owned by Google and has been taken into use in many countries and cities. The main difference between Waze and traditional navigation services is the reliance on crowd-based information. It gathers and complements the data with traffic information provided by users. The service is free of charge for travellers, but they are required to provide personal traffic information for the service. Users can also manually report accidents, traffic jams and bottlenecks, update roads and other map data. Additional services are provided, such as information about the cheapest fuel station near the user or along the route. Waze collects information from users by anonymously collecting traveller speed and location and it has adopted some gamification features to involve users more deeply and to encourage them to provide more information.

Moovit is a public transport planning service, which features arrival and departure times, updated schedules, local station maps, and service alerts. The service offers real-time public traffic information by relying on location information, and it provides a digital map with a view of stops and stations and planning based on real-time data of public transport trips. The service is based on crowd-sourced information connecting public transit data from transport operators to real-time data from crowdsourcing. Travellers send passively and anonymously their speed and location data to Moovit, which then connects the data with public transit schedules to improve trip planning of travellers. In addition to passively sharing data, travellers can also actively send reports about traffic delays and quality of service.

TrafficSense is a pilot service being developed in a research project of Aalto University. The envisioned two key features of the service are (1) transportation mode and route recognition, and (2) learning and prediction of regular (and frequent) routes and destinations. Thus, the service can learn and predict individual moving entities' (private individuals, professional drivers, and vehicles) regular and frequent routes and destinations. Combining this prediction capability of individual travel intentions with the crowdsensed awareness of the current situation of a transportation system facilitates the creation of the anticipated state of the transportation system by offering trip advices, which takes into account both individuals needs and systemic effects. In contrast, the current system level predictions are based on models utilizing real-time traffic data and historical data of traffic on roads without any interventions by trip advices.

The analysed three crowdsensing-based services have various potential societal and environmental impacts. TrafficSense provides more accurate information on the current traffic system enabling possibilities for transport authorities to improve transport policies (e.g. optimize congestion charges, taxation, and subsidies) and for public transportation operators to improve the efficiency of fleet management and operations. Both TrafficSense and Moovit services can increase the usability and attractiveness of public transportation modes, which consequently can decrease the negative externalities of transportation if the public transportation mode is selected instead of private car and respectively increase economies of scale of public transportation both on the supply and demand side due to the higher occupancy rates in the buses and shorter average waiting times on the stops if the bus frequency is increased as a response to the increased demand.

The societal and sustainability impacts of Waze are two-fold. Waze helps drivers to find the best routes and to avoid congestions, which can immediately reduce the fuel and travel time costs of drivers, and thereby improve the efficiency and sustainability of transportation systems at least in the short run. However, the long-run impacts on transportation systems are less obvious, because Waze can improve the attractiveness of private cars compared with public transportation, leading to increased ownership and use of private cars. The overall outcome depends on which type of sustainability impacts dominate, positive or negative. One way to strengthen the positive impacts of the service could be to put efforts to the development and marketing of the ridesharing feature of the service, which could increase the occupancy rates of cars.

The other way could be to develop features improving park & ride options in co-operation with public transportation operators. For instance, car drivers heading to the congested city centrum from suburban areas could be informed by the service about the fastest train connections and the nearest train stations with free parking places or, alternatively, the fastest feeder service (for example, bus or DRT) to the train station if the parking place is already found elsewhere.

Thus, these crowdsensing-based services open many possibilities to foster the sustainability objectives in the transport policy. Technology-driven change on transportation market increases a multitude of alternatives for (exclusively) use of private car. The crowdsensing-based services can help travellers to find the best travel options easily from this multitude, which could otherwise be a difficult task due to the tight schedules of the transportation services and of the travellers themselves. For instance, service offers of the automated DRT and shared taxi services with travel time promises for passengers can be valid only for short time-windows. As mentioned, the trip advices based on crowdsensing data and prediction of intentions can be adopted to direct the transportation system to the anticipated state. For the same reason, these advices can be given also to taxi and DRT fleets, and even utilized in the real-time regulation of the automated DRT described in Section 4.2.

5. Conclusions and Disscussion

The first main research question of this work, “How do automated DRT and shared taxi services differ from other public transportation services and how should these differenses be modelled in economic analysis?” was considered by taking several complementary methodological approaches, first by means of analytical economic modelling in Section 2.2 and its extensions in Sections 4.1.1 and 4.1.2 (Publication 1), then by adopting two simulation models introduced in Section 2.3. The main difference of DRT compared with regular bus services is the lack of fixed schedules and routes, and when compared with regular taxi service, the main difference is that the rides are shared, that is, the automated DRT and shared taxi services combine trips. The automated dispatching system enables responding to the trip requests instantly based on real-time information of vehicle location, routes, and traffic situation even with high demand levels and large DRT fleets, which also forms the main distinction between the automated DRT and traditional DRT offered typically to special customer groups or on rural areas with low demand levels.

The trip combining in DRT potentially increases the travel time externalities due to route changes required to serve a new passenger. The average travel time cost of DRT trip (k) depends on the prevailing levels of trip demand (X), trip production (R), and average trip distance (a). This dependence was described by the function $k = K(R, X, a)$, and the related travel time externality the new passenger causes for other DRT passengers was expressed by $\frac{\partial K}{\partial X} X$. Respectively, the related travel time saving induced by the increase in trip production was expressed by $\frac{\partial K}{\partial R} X$. From the possibility for route changes follows that the externality $\frac{\partial K}{\partial X} X$ can be much higher in DRT than in bus services. On the contrary, an increase in route production decreases the required route changes. Thus, the possibility for route changes is an essential difference between DRT and regular bus service, which naturally reflects on the analytical models of these transportation modes, for example in Pedersen’s model of public transportation, route production is not included to the travel time function (Pedersen, 2003), which is well-founded if the routes are fixed.

The average waiting time cost of DRT trip (q) was described with function $q = Q(R, X)$. An increase in R, that is, an increase in the number of vehicles operating in the service area decreases the average distance between the dispatched vehicle and the pick-up point, and thereby decreases the average waiting time. Respectively, an increase in the number of passengers increases the average route length to the pick-up point and (expected) number of stops before the pick-up point, which increases the average waiting time. In contrast, the waiting time of the bus service with fixed routes is affected basically only by route production (or more precisely, by bus frequency on fixed routes) and the effect of the demand level is insignificant except in case buses are full and part of the passengers cannot hop in the first arriving bus they are waiting for. Therefore, the waiting time in bus services is modeled usually as a function of trip production, but not as a function of the demand level, whereas in the models of taxi services, a waiting time is modelled often somewhat similarly to our waiting time function, that is, as a function of demand and vacant vehicles (see, for example, Yang et al. (2010) and Yang & Yang (2011)). However, the mechanism of other passengers influencing the waiting time of taxi service is simpler than in automated DRT and shared taxi services, because once a vacant call taxi is dispatched to the customer, it can normally drive the shortest possible route to the pick-up point. Moreover, our simulation studies (Publication 2) indicated that a waiting time in the DRT service is more stable than in the taxi service if the demand level suddenly increases.

We also analysed the cost structure of DRT (in Section 2.2), which resenbles the cost structure of the taxi service, but is somewhat more complex, once again, due to the trip combining and related route changes. Moreover, the costs of DRT were examined with simulation models. In Section 3, the simulations showed that the automated DRT can be more cost-effective than private car and regular taxi, if the scale of the trip production is sufficiently high. Thus, the answer to the second main question of the work (Is the automated DRT cost-effective compared with a private car and a regular taxi service from the viewpoints of consumers and society?) is a “conditional yes” on the condition that demand density and fleet size are sufficient. However, these conditions can be challenging to fulfill especially for public transportation operators simultaneosly facing both political requirements, for instance, related to the service area and budget constraints limiting the fleet size. We presented empirical data on the Kutsuplus service in Section 4 (Publications 1 and 5), whith the average occupancy rate being relatively low and subsidization rate high, which can be interpreted, based on our simulation results, that both the demand and supply levels, that is, the scale level has been too low for efficient trip combining. In Section 4.1.4 (Publication 5) we proposed integrated pricing models of the automated DRT and other public transportation modes to increase the attractiveness of public transportation in general and to raise simultanaeously demand for the automated DRT.

The third main research question, “How should the automated DRT and shared taxi services be priced and regulated to maximize social welfare?”, was considered first by the analytical models and exploratory analysis focusing on pricing policies in Section 4.1. The pricing and other regulation policies were then explored in conjuction with the simulation model in Section 4.2. In all the three versions of the analytical model, the optimal price level for trips is equal to the marginal costs of operator plus external travel time and waiting time costs to the passengers minus value of travel time and waiting time savings from increased route production (demand side scale economies), and the optimal trip production is equal to the potential trip production multiplied by the upper limit of the occupancy rate, which was exogeniously given, and based on empirical data from the Kutsuplus service in the numerical examples. The modelling of the occupancy rate as an endogenious variable would be one interesting direction for the future model development, and empirical dependence between the scale and the occupancy rate is an important issue for policy design. Our simulations indicate that this dependence is strong in the automated DRT and consequently enables the supply side scale economies. Moreover, optimal capacity decisions were defined for variable demand levels with a fairly detailed cost function. However, an extension of the model by adding costs of instantaneous adjustments in the fleet size would be useful for evaluating benefits of dynamically flexible fleet size compared to fixed fleet size as in the Kutsuplus service.

The analytical models defined the first-best pricing policies, which provide a basis for the wider consideration of the automated DRT and shared taxi services as a part of the urban transportation system where many contraints typically prevail. For instance, one contraint with high relevance for transport policies is the lack of congestion pricing in congested cities, leading to the under pricing of private car use during peak hours, which is one common argument for subsidization of public transport in addition to the scale economies. Small and Verhoef (2007) derive these two sources of second-best public transport subsidies when private car toll is fixed at zero, and they conclude that insofar as lowering public transport price is effective in reducing congestion costs by drawing away private car users, it is desirable to use subsidies for that objective. This result, in general, is valid also for automated DRT and shared taxi services, but opens also some relevant follow-up questions, such as, whether these new transport services can be more effective in reducing congestion costs than conventional public transport for certain segments of private car users, and whether the effectiveness of subsidies increased by combining these new services and the traditional public transport modes? The second-best analysis of these questions remains for future research.

However, we have identified potential benefits of the mode combining from the passenger viewpoint and suggested pricing models for the implementation of the mode combining. Thus, the mode combining is realizable (even though it requires substantial technical preparations) and can be recommended for consideration especially in cities where a significant proportion of passengers suffer from too many transfers in public transport or avoid using transit because of transfers and uncertain connections. Related to the policy design of these new services, we underline that the automated routing and dispacthing algorithms utilized in these services enable also new regulation policies such as the real-time regulation policy, which improved social welfare in our simulations of Section 4.2 (Publication 3). Furthermore, adoption of crowdsensing-based services provides possibilies to intensify these policies even more.

In addition to the second-best analysis and empirical modelling of occupancy rate, there are other important directions for future research. Modelling and measuring the degree of product differentiation of automated DRT, shared taxis, and other transport modes would improve our knowledge on the impacts and possibilities of these new services for urban transport systems. Moreover, stochastic aspects of demand, effects of crowding (Palma et al. 2015) and heterogeneity of passengers with respect to trip purpose and demographic variables should be taken into account, especially in empirical demand models of these services. Improved demand models would enhance more efficient demand and fleet capacity management and pricing policies, which would also reduce uncertainty in waiting and travel times induced by variances in spatial stochastic demand levels. Furthermore, acceptability issues, both from the viewpoints of customers and taxi industry, are important when designing and analysing these new services and related policies.

Nobel laureate Paul Krugman visioned in 1996 the future of the urban transportation: "Today the roads belong mainly to hordes of share-a-ride minivans, efficiently routed by a web of intercommunicating computers" (Krugman, 1996). The literature reviewed in this work show that similar visions of future transportation have been presented earlier in the field of transportation science, and related mathematical and technical problems have been studied in diciplines of transportation engineering and operations research. The present-day automated DRT services resemble in many ways Krugman's vision, except that roads do not belong *mainly* to minivans. The market share of all motorized trips has still been quite small, but, for instance, the daily trip numbers of the Kutsuplus service increased relatively fast during the pilot period of years 2013 – 2015. Respectively, taxi companies are currently developing and testing shared taxi services, which also resembles closely the vision of the share-a-ride minivans. Moreover, the globally operating transportation network company, Uber, announced in 2014 a new service called UberPool, which enables unfamiliar passengers to share a ride and split the bill by using a mobile application to call a ride. Currently, Uber, Lyft, and Split Technologies, which utilizes the same algorithms as the Kutsuplus service, are competing for markets of shared rides in Washington D.C.

Thus far, the long-run market shares of new ride sharing services like Split and UberPool remain an open question. In addition, it is yet unclear which kinds of forms of these services will succeed commercially, and how these services are combined with traditional public transportation services. However, their potential to solve globally critical urban transportation problems by increasing the average occupancy rate of vehicles in the urban areas can be significant, especially in the future, due to the development of driverless vehicles, which can enable substantial cost and price reductions.

The publications presented in this dissertation contribute to this field of research by presenting simulation models, empiral studies, and analytical models providing theoretical foundations for further policy analysis and empirical research on the automated DRT and shared taxi markets which continually evolve, owing to the advances in intellingent transportation technologies and increasing political pressures for sustainable transportation.

References

Abe, M. A., & Brush, B. C. (1976). Regulation of price and service quality: the taxicab problem. *Quarterly Review of Economics and Business*, *16*(3), 105-111.

Ahn, K. (2009). Road pricing and bus service policies. *Journal of Transport Economics and Policy (JTEP)*, *43*(1), 25-53.

Anderson, S. and R. Renault (2011). Price discrimination. *In* de Palma, A., R. Lindsey, E. Quinet & R. Vickerman (eds.) 2011, A *Handbook of Transport Economics*, Edgar Elgard.

Arnott, R. (1996). Taxi travel should be subsidized. *Journal of Urban Economics*, *40*(3), 316-333.

Arrillaga, B., and D.M. Medville (1974). Demand, supply and cost modeling framework for demand-responsive transportation systems. Transportation Research Board Special Report, 147, 32–47.

Axelrod, R., and L. Tesfatsion (2006). A Guide for Newcomers to Agent-Based Modeling in the Social Sciences. In *Handbook of Computational Economics, Vol. 2: Agent-Based Computational Economics* (L. Tesfatsion and K. L. Judd, eds.). Handbooks in Economics Series, Elsevier/North-Holland, Amsterdam, Netherlands.

Beesley, M.E. (1973). Regulation of taxis. The Economic Journal 83 (329), 150–172.

Beesley, M.E., Glaister, S. (1983). Information for regulation: the case of taxis. The Economic Journal 93 (370), 594–615.

Bernhardt, K. (2007). Agent-based modeling in transportation. *Artificial Intelligence in Transportation*, *72*.

Brake, J., Nelson, J.D., Wright, S. (2004). Demand responsive transport: towards the emergence of a new market segment. Journal of Transport Geography 12, pp. 323–337.

Cheah, L.W. (2010): Cars on a Diet: The Material and Energy Impacts of Passenger Vehicle Weight Reduction in the U.S., Massachusetts Institute of Technology.

Cervero, R. (1997): Paratransit in America: Redefining Mass Transportation, Westport, CT: Praeger.

Cori, R., (2009). Indecomposable permutations, hypermaps and labeled dyck paths. Journal of Combinatorial Theory, Series A 116, 1326–1343.

Daganzo, C.F. (1978). An approximate analytic model of many-to-many demand responsive transportation systems. Transportation Research 12 (5), 325–333.

Dargay, J., Gately, D., & Sommer, M. (2007). Vehicle ownership and income growth, worldwide: 1960-2030. *The Energy Journal*, 143-170.

Davison, L., Enoch, M., Ryley, T., Quddus, M., & Wang, C. (2014). A survey of demand responsive transport in Great Britain. *Transport Policy*, *31*, 47-54.

De Palma, A., Lindsey, R., Monchambert, G (2015). The Economics of Crowding in Public Transport. <hal-01203310>

De vany, A.S. (1975). Capacity utilization under alternative regulatory constraints: an analysis of taxi markets. Journal of Political Economy 83 (1), 83–94.

Diana, M., Dessouky, M.M., and N. Xia (2006). A model for the fleet sizing of demand responsive transportation services with time windows. Transportation Research Part B 40, 651–666.

Diana, M., Quadrifoglio, L., Pronelloa, C. (2007). Emissions of demand responsive services as an alternative to conventional transit systems. Transportation Research Part D: Transport and Environment 12, 183–188.

Douglas, G.W. (1972). Price regulation and optimal service standards: the taxicab industry. Journal of Transport Economics and Policy 6 (2), 116–127.

Dueker, K.J., Kimpel, T.J., Strathman, J.G., and S. Callas (2004). Determinants of Bus Dwell Time. Journal of Public Transportation, 7, 21-40.

EEA, 2010. Occupancy rates of passenger vehicles (TERM 029), European Environmental Agency.

EEA, 2015. SOER 2015: Cross-country comparisons, Transport – passenger transport demand and modal split, European Environmental Agency.

Eisenmann, T., Parker, G., & Van Alstyne, M. W. (2006). Strategies for two-sided markets. *Harvard business review*, *84*(10), 92.

Finnish Transport Agency, Information Department. Public Transport Performance Statistics 2013. Helsinki 2015. Statistics of the Finnish Transport Agency 3/2015. 46 pages and 4 appendices. ISSN-L 1798-811X, ISSN 1798-8128, ISBN 978-952-317-083-4.

Flores-Guri, D. (2003). An economic analysis of regulated taxicab markets. Review of Industrial Organization 23 (3–4), 255–266.

Flusberg, M., and N.H.M. Wilson (1976). A descriptive supply model for demand responsive transportation system planning. In Proceedings of the 17th Annual Meeting of the Transportation Research Forum, pp. 425–431.

Frankena, M.W., Pautler, P.A. (1986). Taxicab regulation: an economic analysis. Research in Law and Economics 9, 129–165.

Glaister, S. (1974). Generalised Consumer Surplus and Public Transport Pricing. *The Economic Journal*, *84*(336), 849–867.

Gravelle H. and R. Rees (1997). Microeconomics, second edition, Addison Wesley Longman Publishing, New York.

Helsinki Region Transport (2010). Helsinki metropolitan area mobility survey 2008.

Helsinki Region Transport (2015). Financial Statements 2014.

Hyytiä, E., Häme, L., Penttinen, A., Sulonen, R. (2010). Simulation of a large scale dynamic pickup and delivery problem, in: Proceedings of SIMUTools 2010.

Häme, L., (2011). An adaptive insertion algorithm for the single vehicle dial-a-ride problem with narrow time windows. European Journal of Operational Research 209, 11–22.

Häme, L., Jokinen, J.P., and R. Sulonen (2011). Modeling a competitive demand responsive transport market. In Kuhmo Nectar Conference of International Transportation Economics Association, Stockholm, Sweden.

Häme, L., and J.P. Jokinen (2012). A stochastic network model for demand-responsive transport. In Kuhmo Nectar Conference of International Transportation Economics Association, Berlin, Germany.

Ichoua, S., Gendreau, M., & Potvin, J. Y. (2006). Exploiting knowledge about future demands for real-time vehicle dispatching. *Transportation Science*, *40*(2), 211-225.

Jørgensen, F., and J. Preston (2007). The Relationship Between Fare and Travel Distance. Journal of Transport Economics and Policy, 41, 451–468.

Lerman, S.R., and N.H.M. Wilson (1974). Analytic model for predicting dial-a-ride system performance. Transportation Research Board, Special Report 147, 48–53.

Litman, A. T., and E. Doherty (2009). Transportation Cost and Benefit Analysis, Techniques, Estimates and Implications. Victoria Transport Policy Institute, second edition.

Kasibhatla, K., and J. Benjamin (2009). Cost Function Estimation of a Paratransit System. In TRB 88th Annual Meeting.

Krugman, P. (1996). White collars turn blue. The New York Times Magazine.

Manski, C.F., Wright, J.D. (1976). Nature of equilibrium in the market for taxi services. Transportation Research Record 619, 296–306.

Mageean, J., Nelson, J.D. (2003). The evaluation of demand responsive transport services in europe. Journal of Transport Geography 11, 255–270.

Mohring, H. (1972). Optimization and scale economies in urban bus transportation. *The American Economic Review*, *62*(4), 591-604.

Mohring, H. (1979). The Benefits of Reserved Bus Lanes, Mass Transit Subsidies and Marginal Social cost Pricing in Alleviating Traffic Congestion. *Current Issues in Urban Economics. Mieskowosky, P. y Straszheim M. editors*.

Mulley, C., Nelson, J.D. (2009). Flexible transport services: A new market opportunity for public transport. Research in Transportation Economics 25, 39–45.

Paraboschi, A., Santi, P., and C. Ratti (2015). Modeling Urban-level Impact of a Shared Taxi Market. CUPUM 2015.

Paxson, V., Floyd, S. (1995). Wide area traffic: the failure of poisson modeling. IEEE/ACM Transactions on Networking 3, 226–244.

Pedersen, P.A. (2003). On the optimal fare policies in urban transportation. Transportation Research Part B, 37, 423–435.

Pels, E., and P. Rietveld (2000). Cost Functions in Transport, in Hensher, D. A. and K. J Button (eds) Handbook of Transport Modelling, Elsevier Science, Oxford.

Polak, J.B., Heertje, A. (2001). Analytical Transport Economics: An International Perspective. Edward Elgar Publishing Ltd.

Psaraftis, H. (1995). Dynamic vehicle routing: status and prospects. Annals of Operations Research 61,143–164.

Pucher, J., & Renne, J. L. (2003). Socioeconomics of urban travel: evidence from the 2001 NHTS. *Transportation Quarterly*, *57*(3), 49-77.

Rodier, C.J., Johnston, R.A., and D.R. Shabazian (1998). Evaluation of advanced transit alternatives using consumer welfare. Transportation Research Part C, 6, 141–156.

Ryley, T. J., Stanley, P. A., Enoch, M. P., Zanni, A. M., & Quddus, M. A. (2014). Investigating the contribution of Demand Responsive Transport to a sustainable local public transport system. *Research in Transportation Economics*, *48*, 364-372.

Santi, P., Resta, G., Szell, M., Sobolevsky, S., Strogatz, S. H., & Ratti, C. (2014). Quantifying the benefits of vehicle pooling with shareability networks. *Proceedings of the National Academy of Sciences*, *111*(37), 13290-13294.

Savage, I. (2006). Economic Regulation of Transport: Principles and Experience, Published in Michael Crew and David Parker (eds.) *International Handbook on Economic Regulation*. Cheltenham, UK: Edward Elgar.

Sihvola, T., Häme, L., Sulonen, R. (2010). Passenger Pooling and Trip Combining Potential of High-Density Demand Responsive Transport. Presented at the Annual Meeting of the Transportation Research Board, Washington D.C.

K. A. Small and E. T. Verhoef (2007). The Economics of Urban Transportation, Routledge, New York.

Talvitie, A., Dehghani, Y. (1980). Models for transportation level of service. Transportation Research Part B: Methodological 14, 87–99.

Turvey, R., & Mohring, H. (1975). Optimal bus fares. *Journal of Transport Economics and Policy*, 280-286.

P. Toth and D. Vigo, editors. The Vehicle Routing Problem. Society for Industrial and Applied Mathematics (SIAM), Philadelphia, USA, 2001.

Verhoef, E. (1994). External effects and social costs of road transport. Transportation Research Part A. Vol. 28A, No. 4, pp, 273–287.

Wang, C., Quddus, M., Enoch, M., Ryley, T., & Davison, L. (2014). Multilevel modelling of Demand Responsive Transport (DRT) trips in Greater Manchester based on area-wide socio-economic data. *Transportation*, *41*(3), 589-610.

Winston, C. (1985). Conceptual Developments in the Economics of Transportation: An Interpretive Survey. Journal of Economic Literature Vol. XXIII (March 1985), pp. 57–94.

Worldsalaries.org (2008). The International Average Salary Income Database, Bus Driver Salaries - International Comparison.

Yang, H., Wong, S., Wong, K. (2002). Demand-supply equilibrium of taxi services in a network under competition and regulation. Transportation Research Part B 36, 799–819.

Yang, H., Ye, M., Tang, W.H.C., Wong, S.C. (2005). A multiperiod dynamic model of taxi services with endogenous service intensity. Operations Research 53, 501–515.

H. Yang, C. W. Y Leung, S. C. Wong, and M. G. H. Bell (2010). Equilibria of bilateral taxi-customer searching and meeting on networks. *Transportation Research Part B*, 44:1067–1083.

Yang, H. and T. Yang (2011). Equilibrium properties of taxi markets with search friction. Transportation Research Part B 45, 696–713.

YTV Helsinki Metropolitan Area Council (2009). Origin-destination survey of Helsinki metropolitan area in 2008.

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