Simulation Model for a Demand Responsive Transportation Monopoly

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Abstract

In this paper, we consider alternative regulation policies for a demand responsive transportation (DRT) monopoly, where public transportation is provided by a fleet of vehicles capable of quickly adapting to the constantly changing demand. On one hand, we are interested in the profit of the monopoly, and on the other hand, the level of service and the surplus the customers obtain. A combination of these, referred to as social welfare, serves as a well-defined one-dimensional objective to be maximized by means of regulation policies. 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 policies. Our main research question is: How regulation policies affect the DRT monopoly?

Keywords: Demand responsive transportation, Monopoly, Regulation policy, Simulation

1. Introduction

Demand responsive transportation (DRT) is a form of public transportation involving flexible routing and scheduling of small or medium sized vehicles, somewhere between bus and taxi which covers a wide range of transportation services ranging from less formal community transportation

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through to area-wide service networks[2] (Mageean and Nelson, 2003). Earlier work suggests that this type of transportation services has potential to become a socially and economically remarkable form of public transportation, see for example (Mulley and Nelson, 2009; Sihvola et al., 2010; Jokinen et al., 2011). Additionally, DRT service is more effective than a fixed route service in minimizing emissions of pollutants (Diana et al., 2007).

In this work, we study a sophisticated form of DRT service operating in an urban area with a high demand. The studied service is an instant-response DRT service, which means that customers are given *trip offers* immediately after requesting service. The bidding of trip offers and vehicle routing is fully automated, which is necessary in order to provide DRT service efficiently for a high demand market. An urban area is interesting for several reasons. Firstly, DRT services are often motivated by problems arising from the congestion of urban areas caused by the increasing number of private cars, i.e., DRT could be a competitive transportation mode for private cars and taxis in terms of quality of service and price, and thereby reduce the number of private cars (see for example Cortes and Jayakrishnan, 2001). Secondly, *high demand* in urban areas can enable considerable business opportunities for transport operators and economic benefits for society. Thirdly, *high demand density*[3] in urban areas enables effective use of vehicles in DRT, since the possibilities for trip combining without notable travel time increase are significantly improved (Sihvola et al., 2010).

As the present technology enables implementing the described advanced DRT service, the pilot projects are becoming reality soon. For our knowlege, the first pilot for highly automated public DRT service starts at Helsinki in 2012.

One fundamental question related to DRT is, how regulation policies affect an advanced DRT service with a real-time trip trading and vehicle routing. Can traditional regulation policies improve the *social welfare*? We define social welfare as the sum of profit and customer surplus, similarly as in, for example, (Yang et al., 2002) and (Yang et al., 2005). In this work, we use a simulation approach to study and compare different regulation policies for a monopoly of instant-response DRT service.

The DRT is studied as complementary service to conventional bus and taxi services, i.e., customers can always choose between these transportation modes. Demand for DRT is modeled as a linear function of price and level of service, describing potential customers' willingness to pay for different types of trips. We are interested in customers' travel mode choice decisions between DRT and other modes. As in widely used random utility choice models (see for example Polak and Heertje, 2001), customers are assumed to choose the utility-maximizing alternative. 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 if the expected surplus is positive.

Moreover, we consider total cost of service as a sum of fixed cost and variable cost. The fixed cost is a function of the number of vehicles and the variable cost is a function of total vehicle mileage. The quality of service is modeled by means of the ratio of the realized travel time to the direct ride time of the trip (more detailed definitions are given in Section 2.1).

[2]area-wide service = a transit service which gives a reasonably uniform level of service throughout an area.

[3]Demand density = number of trip requests per hour per square kilometer (Sihvola et al., 2010).

The rest of the paper is organized as follows. Section 2 describes the model of an instant response DRT service, describes the decision making process of customers and vehicle operators, and defines the studied regulation policies. Section 3 describes the simulation model and used parameters, and presents the simulation results. Section 4 concludes the paper with a discussion about future research directions.

2. Model

The model of an instant response DRT service studied in this work is governed by the following preliminary assumptions.

1. There are K vehicles available to transport customers requesting service within a certain operating zone A. For each pair of points a and b in A, the distance $d(a, b)$ and direct ride time $t(a, b)$ 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 a to a specific drop-off point b constituting a request for trip (a, b). 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. 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 maximizing the expected profit[4]. If an offer is accepted, the customer is assigned to the corresponding vehicle and its route is modified appropriately (see Figure 1).
6. There is a fixed fare structure. The price R of a trip is assumed to be dependent on the direct trip length $d(a, b)$ exclusively by means of the formula

$$R(a, b) = p \cdot d(a, b), \tag{1}$$

where p is the price per kilometer in relation to direct trip length[5]. The customers know the fare structure and the direct trip lengths of their trips beforehand.

[4]Calculating the expected profit for a trip proposal in a real-time DRT service is a complex task. See Section 3 for a description of the algorithm used in the simulation model.

[5]In this work we define the price per kilometer in relation to direct trip length, even though the realized trip length is normally greater than the direct trip. In practice, it might be reasonable to consider a sum of fixed initial price and a price per kilometer for each trip. For simplicity, we approximate this type of pricing by using a single price parameter.

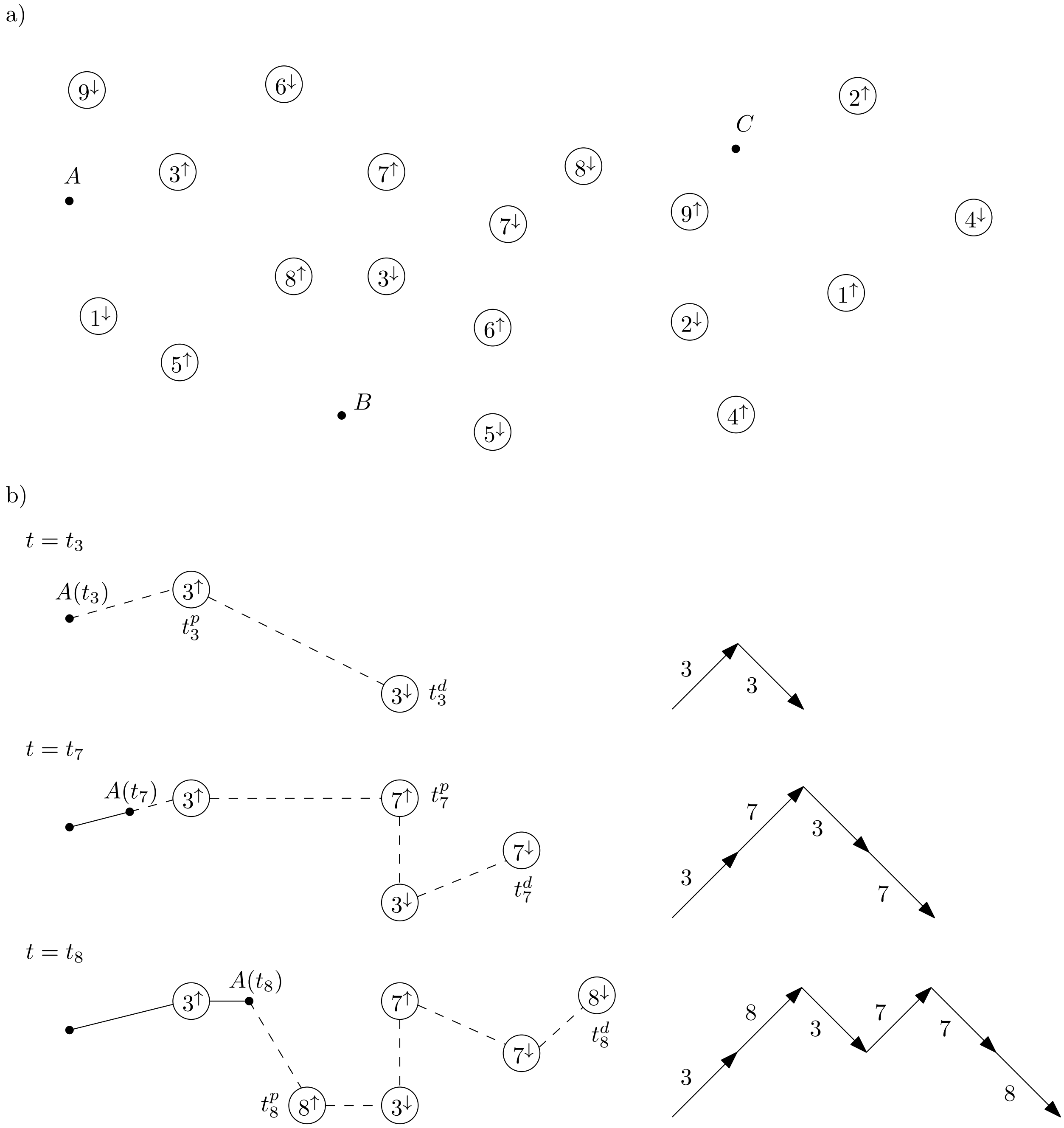

Figure 1: Formulating proposals. The top figure (a) shows the pick-up points (denoted by ↑-signs) and drop-off points (↓-signs) of nine customers and the initial locations of vehicles A, B and C. Each customer i requests a trip from $i^{\uparrow}$ to $i^{\downarrow}$ at time $t = t_i$, where $t_1 < t_2 < \ldots < t_9$. 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.

Note that due to the dynamic nature of the problem, the realized pick-up and drop-off times may differ from the expected pick-up and drop-off times due to the assignment of future customers. This means that the realized level of service may be worse than the expected in some situations. In this work, however, we are only interested in cases in which the average surplus of customers is positive (see Section 2.1). In other words, the realized level of service is better than what the customers are willing to accept most of the time.

In the following, we will elaborate the modeling of customer behavior, DRT monopoly and regulation policies in more detail.

2.1. Behavior of customers

The level of service provided by various transportation modes is normally characterized in terms of travel time and its components (Talvitie and Dehghani, 1980). In this work, for simplicity, we model the level of service by means of *travel time ratio*, which describes the ratio of travel time to direct ride time. In other words, a travel time ratio equal to one 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 transportation offer in terms of the *offered level of service*. The level of service offered to a customer traveling from a to b is defined by means of *expected travel time ratio*

$$\tau = \frac{t_d - t_r}{t(a,b)}, \tag{2}$$

where t_d is the expected drop-off time[6], t_r is the release time of the request and $t(a,b)$ is the direct ride time from a to b. In other words, τ describes the ratio of the expected travel time of a given proposal to direct ride time. Clearly, since $t_d - t_r \geq t(a,b)$, 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 *realized travel time ratio* τ' by means of the formula

$$\tau' = \frac{t'_d - t_r}{t(a,b)}, \tag{3}$$

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

As previously stated, we consider the DRT as complementary service to conventional taxi and fixed-route bus services. We assume that potential DRT customers have always alternative transportation mode where surplus is zero. Thus, a customer rejects DRT trip proposal if the expected surplus is negative. That is, a customer that rejects a DRT offer is assumed to travel by some other means. In order to attract customers from these transportation modes, it is assumed that the offered level of service τ should be better than that of the bus, and the price per kilometer p

[6]The calculation of the expected drop-off time in a real-time DRT service is a non-trivial task, since the route may be modified during the trip. Here we assume that the service provider can estimate the expected drop-off time with sufficient accuracy.

should be lower than the price per kilometer of a taxi. 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 assumptions that hold for all customers and thus define the demand model can be summarized as follows.

1. Denote the average level of service provided by a conventional taxi by τ_T and the price per kilometer[6] 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 offer.
2. Denote the average level 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 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 DRT is less than τ_T and the price per kilometer is less than p_B, each customer accepts the offered trip.

Since the service studied in this work is hypothetical, no accurate information on customer behavior is available. We use a linear approximation, 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). In other words, the three points

$$(\tau_T, p_T, 0), (\tau_B, p_B, 0) \text{ and } (\tau_T, p_B, 1)$$

define a linear demand model as a plane in $\mathbb{R}^3$, Figure 2.

The demand model can thus be expressed by means of a probability distribution $\mathrm{P}(\text{accept} \mid \tau, p)$, which denotes the conditional probability that an arbitrary customer accepts a proposal with expected travel time ratio τ and price per kilometer p. The proposed acceptance probability function $\mathrm{P}(\text{accept} \mid \tau, p)$ is formally given by the equation

$$\mathrm{P}(\text{accept} \mid \tau, p) = \min\left(\max\left(1 - \frac{p - p_B}{p_T - p_B} - \frac{\tau - \tau_T}{\tau_B - \tau_T}, 0\right), 1\right). \tag{4}$$

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. The relation to alternative transportation modes is clarified in Figure 3, which shows the basic idea behind the demand model.

2.1.1. Willingness to pay and surplus

Since our demand model (4) is linear, we may equivalently think that with a certain price per kilometer $p \in [p_b, p_T]$, 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 $p(\tau)$ for the maximum price per kilometer over all customers is a straight line in the

[6] In this work we define the price per kilometer in relation to direct trip length for all transportation modes.

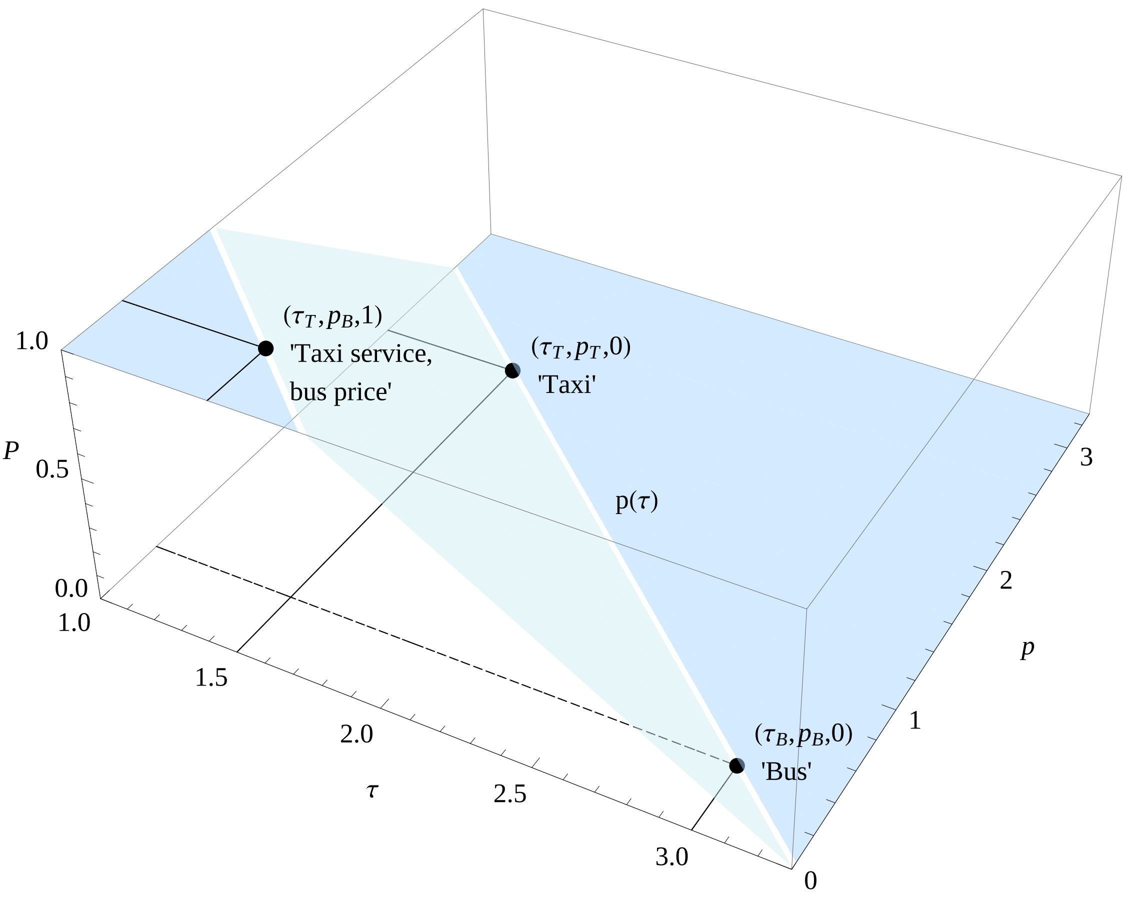

Figure 2: The acceptance probability function P(accept | τ, p) determined by $\tau_T = 1.5, \tau_B = 3, p_T = 2.3$ and $p_B = 0.4$. The linear function is specified by means of three points representing conventional bus and taxi services and a taxi-type service for the price of a bus.

plane $P = 0$, see figure 2. The equation of $p(\tau)$ can be written in terms of the two points (τ_T, p_T) and (τ_B, p_B), namely

$$p(\tau) = p_T - \frac{\tau - \tau_T}{\tau_B - \tau_T}(p_T - p_B).$$

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

$$f_{W(\tau)} = U\Big(p(\tau) - (p_T - p_B), p_\tau\Big). \tag{5}$$

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 (a, b), an arbitrary customer is willing to pay the maximum price $W(\tau) \cdot d(a, b)$.

The acceptance probability with given service level τ and price per kilometer p is equal to the

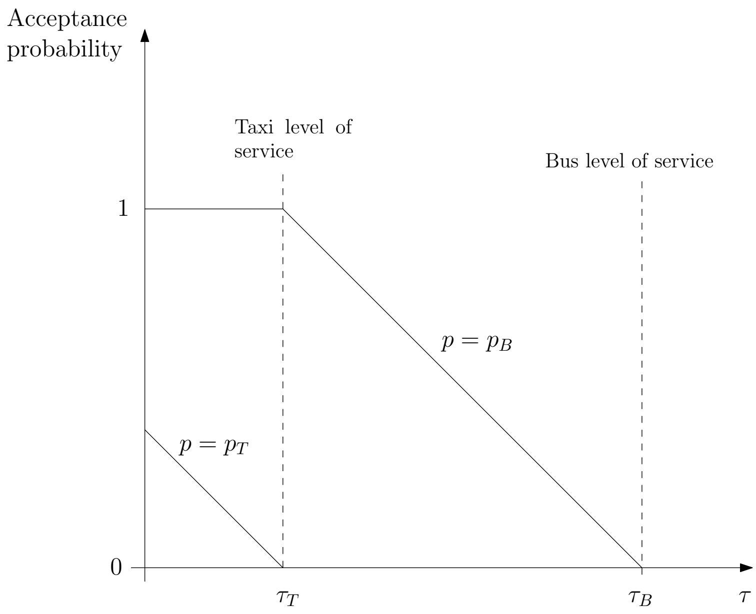

Figure 3: The acceptance probability function related to alternative transportation modes. If the level of service is as good as that of a normal taxi ($\tau = \tau_T$) and the price is equal to the price of a bus ($p = p_B$), any customer is likely to accept the DRT service. The fraction of customers willing to accept the service decreases with the level of service. If the price and level of service are equal to the taxi ($p = p_T$ and $\tau = \tau_T$), the acceptance probability is zero.

corresponding cumulative distribution function

$$\mathrm{P}(\text{accept} \mid \tau, p) = \mathrm{P}(W(\tau) \geq p) = \int_p^\infty f_{W(\tau)}(x)\, dx. \tag{6}$$

For each realized trip (a, b) with the price per kilometer p and realized travel time ratio τ', the *realized surplus* S' is defined as the difference between the willingness to pay $W(\tau') \cdot d(a, b)$ for the realized level of service and the actual price paid for the trip $R(a, b) = p \cdot d(a, b)$. If the customer does not accept the trip, the realized surplus is zero. The *expected surplus*, denoted by $\mathrm{E}[S \mid \tau, p]$, is thus given by

$$\mathrm{E}[S \mid \tau, p] = \mathrm{P}(W(\tau) \geq p) \cdot \Big(d(a, b) \cdot \mathrm{E}[W(\tau) \mid W(\tau) \geq p] - R(a, b)\Big), \tag{7}$$

where $\mathrm{E}[W(\tau) \mid W(\tau) \geq p]$ is the expected willingness to pay on condition that an offer with expected level of service τ and price per kilometer p is accepted. Note that the conditional expected willingness to pay satisfies $\mathrm{E}[W(\tau) \mid W(\tau) \geq p] \geq \mathrm{E}[W(\tau)]$.

2.2. Market mechanisms and regulation policies

First, in Section 2.2.1 we describe the long-run profit maximization decisions, i.e., decisions about the number of vehicles and the price per kilometer. The aim of the long-run decisions is to maximize the expected profit for each day, but these decisions cannot be changed during the day.

In Section 2.2.2 we describe daily decisions, i.e., the trip offering decisions which are made during the day.

We consider two types of traditional regulation policies which are focused on the long-run decisions and used simultaneously: 1. price regulation and 2. vehicle number regulation. In addition, we consider a novel new regulation policy which is focused on the monopolist's daily trip offer-making decisions. The new regulation policy is explained more detailed in Section 2.2.2. In all regulation policies the aim is to maximize social welfare defined as the sum of profit and surplus.

2.2.1. *Long-run decisions*

A monopoly operator controls all available vehicles. Number of vehicles, denoted by K, and price per kilometer (length of trip is measured from direct trip), denoted by p, are determined in a way that the daily profit is maximized. The optimal number of vehicles and price are given by

$$(K^*, p^*) = \arg\max_{K,p} D_s\bar{R} - KC_F - C_V, \tag{8}$$

where D_s is the number of sold trips ($D_s <$ potential demand), $\bar{R}$ 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 depend on driven kilometers), during one day. $D_s, \bar{R}$ and C_V are functions of K and p.

2.2.2. *Daily decisions*

At any instant, each vehicle is restricted to follow the route that minimizes the total route length with respect to the customers assigned to the vehicle. In addition, a trip offer for a customer x is generated by means of the shortest tour with respect to x and the existing customers assigned to the vehicle. The shortest tour is chosen for two reasons: Firstly, it is the most efficient way of providing service for known customers. Secondly, it guarantees a certain fairness of service since all customers are treated equally (no customer may be favored by proposing an unreasonably good trip at the expense of other customers). In this work, we study two different methods for generating proposals at the time a customer request is released:

1. Monopoly market mechanism: In order to maximize the total revenue, the monopolist aims to formulate a single proposal in a way that the additional cost of providing the service is minimized and the probability that the customer accepts the proposal is maximized. In other words, the monopolist chooses for each trip (a, b) the vehicle in a way that the expected profit

$$\mathrm{E}[\pi] = \mathrm{P}(\text{accept} \mid \tau, p) \cdot \Big(R(a, b) - \mathrm{E}[\Delta C]\Big) \tag{9}$$

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

2. Real time regulation for monopolist: As in the former case, a single proposal is presented for each customer requesting service. Instead of expected profit, the vehicle is chosen in a way that the expected social welfare

$$\mathrm{E}[L] = \mathrm{P}(\text{accept} \mid \tau, p) \cdot \Big(R(a, b) - \mathrm{E}[\Delta C]\Big) + \mathrm{E}[S \mid \tau, p] \tag{10}$$

is maximized, where $\mathrm{E}[S \mid \tau, p]$ is the expected surplus defined by (7).

3. Simulation

We consider a model for DRT adopted from (Hyytiä et al., 2010), where trip requests occur within a bounded region in a plane. Each trip request is defined as a triple, (t_i, a_i, b_i), where t_i denotes the time instance (release time) of the ith request, a_i and b_i denote the origin and the destination of the trip, respectively.

We assume that trip requests arrive according to a Poisson process with rate λ [trip/s], and that 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 request arrive according to a Poisson point process).

There are K vehicles each with c passenger seats to support the given transportation demand in online fashion. We assume Euclidean distances between any two points and thus each vehicle uses the direct path between the waypoints that define the route. In addition, as already stated, the ordering of waypoints is determined in a way that the route length is minimized. When a trip request arrives, it is immediately assigned to a single vehicle with probability $\mathrm{P}(\text{accept} \mid \tau, p)$ as discussed in section 2.1. The chosen vehicle then, at some point of time, picks up the passenger for delivery to the corresponding destination point. With $c > 1$, several passengers can share a vehicle, which allows the system to combine trips and decrease the effort per passenger.

For analysis, we assume a constant velocity v (e.g., 36 km/h) and a constant minimum stop time of t_{st} (e.g., 30 s) for each vehicle. After the minimum stop time, passengers can enter and exit the vehicle until it starts moving again. The minimum stop time is assumed to include the time needed for deceleration and acceleration. Note that in our trip demand model (Poisson point process), each stop corresponds to exactly one passenger entering or exiting the vehicle at a time, i.e., passengers do not share the stops (cf., door-to-door vs. stop-to-stop service). The basic parameters used in the simulation are presented in table 1.

We simulate a period of time representing one day. The simulation starts with all vehicles idle and ends when the last customer is dropped off at the destination. The simulation time in table 1 corresponds to the period of time during which customers request trips. After the simulation time has expired, the remaining accepted customers are still processed.

3.1. Real-time optimization

Calculating the additional cost of providing service for a new customer in a real-time transportation service is generally seen to be a challenging task (Psaraftis, 1995). In this work, the expected increase in the cost of the vehicle route $\mathrm{E}[\Delta C]$ in (9) and (10) is estimated by taking into account i) the immediate cost increase caused by the increase in route length and ii) the expected additional cost due to the allocated vehicle capacity. The latter is calculated by means of the average realized profit rate of a seat in a vehicle as follows. Letting t_0 denote the beginning of the simulation period and t_i denote the release date of a new customer i, the average realized profit rate R_{t_i} of a seat in a vehicle at t_i is calculated by dividing the total price of realized trips until t_i by the total vehicle seat hours until t_i, namely $Kc(t_i - t_0)$. The expected additional cost due to the allocated vehicle capacity is given by $r_i \cdot R_{t_i}$, where r_i is the tentative ride time of the customer. In other words, each served customer occupies a single seat in a vehicle between the pick-up and drop-off. Thus, when customer x accepts a trip offer, the possibilities of making profit in the future are reduced since the seat occupied by x cannot be used to transport new customers when customer x is in the vehicle.

trip request rate:	1/s
simulation time:	12 hours
area:	disk with 5 km radius
velocity of vehicles:	10 m/s
capacity of vehicles:	10
stop time:	30 s
Fixed costs:	200 euros per vehicle per day
Variable costs:	0.5 euros per vehicle kilometer
τ_T:	1.5
τ_B:	3
p_B:	0.4 euros
p_T :	2.3 euros

Table 1: Basic simulation parameters. The values for the costs and the prices describe roughly the Finnish price and cost level.

3.2. Long-run optimization

The simulator is used to find the optimal number of vehicles K and price per kilometer p in three cases: 1) monopoly, 2) regulated monopoly, 3) real-time regulated monopoly. In non-regulated monopoly, the objective is to maximize profit as defined in Equation (8). In the regulated cases 2 and 3, we seek to maximize social welfare defined as the sum of surplus and profit. The optimal values K^* and p^* are determined for each case by running the simulator with different values of K and p and choosing the best combination with respect to the objective. We use increment 5 for the number of vehicles and 0.01 for the price per kilometer.

3.3. Confidence analysis

Since we are interested in daily operations of a DRT service, the simulation time is fixed for each run. In order to eliminate noise from the results, we calculate the mean values of quantities over several runs using the same parameter values. Let us study the width of the 95% confidence interval for mean social welfare as a function of the number of simulation runs. More precisely, we examine the relative margin of error m defined by means of the formula $m = r/\bar{l}$, where r is the radius of the confidence interval and $\bar{l}$ is the observed mean social welfare. In other words, the difference between the observed mean from the simulation model and and the true mean is at most r with probability 95%. The relative margin of error expresses the ratio of r to the observed mean. Figure 4 shows the relative margin of error for mean social welfare in the monopoly mechanism as a function of the number of runs with $K = 210$ and $p = 1.65$.

Referring to Figure 4, we note that the margin of error is relatively small even if only a few runs were performed. With 10 runs, the margin of error is approximately 0.8%. With 100 runs, the margin of error is only order of 0.2%. As will be seen in the following section, the accuracy achieved by 100 runs is sufficient to identify the main differences between the studied regulation policies.

We determine the optimum (K^*, p^*) for each mechanism by means of a local search as follows: At first, an approximate optimum (K_1^*, p_1^*) is determined by performing an initial run for each

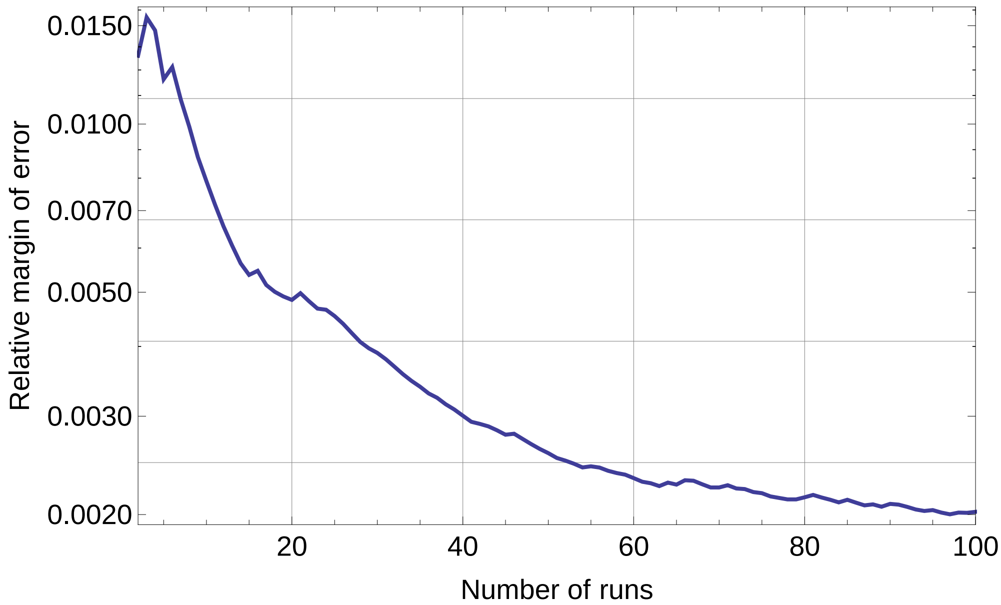

Figure 4: Relative margin of error at a 95% confidence level for the mean social welfare in the monopoly mechanism as a function of the number of runs, on a logarithmic scale, with $K = 210$ and $p = 1.65$.

$(K, p) \in \{100, 110, \ldots, 800\} \times \{0.4, 0.45, \ldots, 2.3\}$ (see figure 5). Then, a second optimum (K_2^*, p_2^*) is obtained by calculating the average over 10 runs for each point in the neighborhood grid of (K_1^*, p_1^*) consisting of 81 points, namely $\{K_1^* - 40, \ldots, K_1^*, \ldots K_1^* + 40\} \times \{p_1^* - 0.2, \ldots, p_1^*, \ldots, p_1^* + 0.2\}$. The new optimum (K_3^*, p_3^*) is given by calculating the average over 100 runs for nine points in the neighborhood of (K_2^*, p_2^*). If $(K_3^*, p_3^*) \neq (K_2^*, p_2^*)$, we set $(K_2^*, p_2^*) = (K_3^*, p_3^*)$ and repeat the last step until the equality is valid. Since our search space is finite, the above local search procedure obviously converges to some point.

3.4. Results

The results of the simulations are summarized in Table 2. The table shows the optimal price per kilometer and the optimal number of vehicles for each market mechanism together with the corresponding total profit, realized customer surplus and social welfare, i.e. the sum of the profit and surplus. In addition, the number of served customers, average realized travel time ratio and relative driven distance are given for 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 distance driven by vehicles by the sum of direct trip lengths. Consequently, it describes how efficiently the vehicles are utilized. The average values in the table were calculated over 100 runs with the parameter values of Table 1. The average number of requested trips was 43253 in each case.

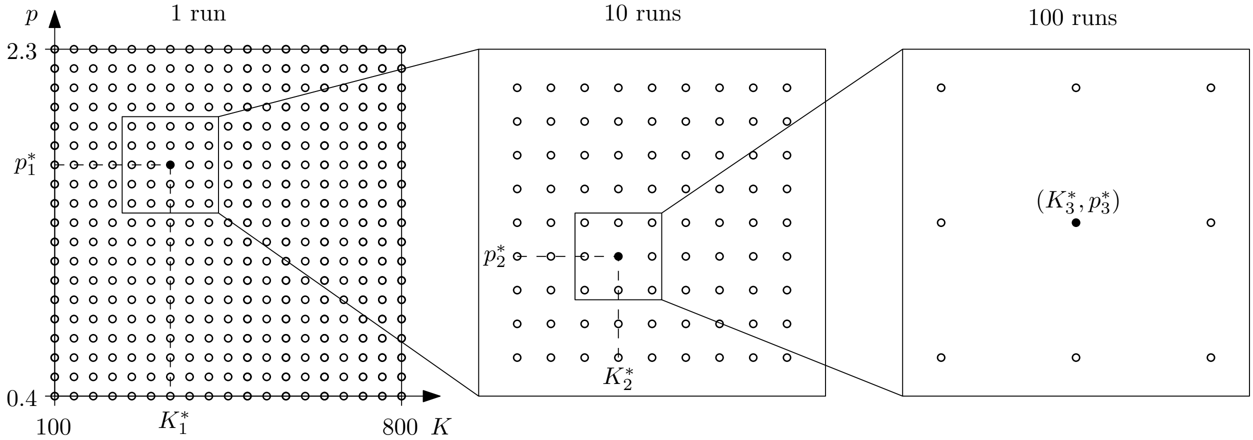

Figure 5: Determining optimal number of vehicles K and price per kilometer p by means of simulation. At first, an initial run is executed for each $(K, p) \in \{100, 110, \ldots, 800\} \times \{0.4, 0.45, \ldots, 2.3\}$. Then, the optimum (K_1^*, p_1^*) is updated by narrowing the parameter space to 81 points chosen from the neighborhood of the optimal point and performing 10 runs for each point, yielding (K_2^*, p_2^*). Finally, a new optimum is determined by performing 100 runs for nine points in the neighborhood of the previous optimum. The last step is repeated until convergence.

Market mechanism	Number of vehicles K	Price/ km p	Surplus	Profit	Social welf.	Served cust.	Travel time ratio	Relative dist.
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 welf.	Served cust.	Travel time ratio	Relative dist.
150	180	200	20	0.0011	0.00029

Table 2: Simulation results. The first columns of the upper table show the optimal number of vehicles K and price per kilometer p 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 of table 1. The lower table shows the margin of error of the mean of the studied quantities at a 95% confidence level.

3.4.1. Monopoly

From table 2, one can observe that while the monopoly (1) yields the highest profit, focusing only on profit will wither the total customer surplus. By regulating the kilometer price and the number of vehicles of the monopoly in order to maximize social welfare (2), the total customer surplus, number of served customers, average level of service and number of vehicles increase a bit, but the optimal price remains the same. It seems that price regulation of DRT monopolist is relatively ineffective compared to vehicle regulation, because the monopolist can react to regulated lower price by dropping service level in daily dispatching decisions. Referring to the relative driven distance, it can be seen that the monopoly without regulation is slightly more efficient than regulated monopoly.

We studied scale economies of DRT by simulating the monopoly market mechanism with different levels of potential demand. The results in Table 3 indicate significant economies of scale,

Demand (requests / s)	Number of vehicles K	Price/km p	Surplus	Profit	Social welfare	Served customers	Travel time ratio	Relative distance
0.25	65	1.57	46	17808	17854	5356	1.746	0.757
0.5	120	1.58	433	41960	42393	11089	1.724	0.672
0.75	165	1.63	267	68301	68569	16528	1.717	0.627
1	210	1.65	416	94535	95414	21213	1.688	0.613

Table 3: Economics of scale. The table shows the outcome of the monopoly mechanism with different demands (0.25,0.5,0.75,1 requests /second).

which can be seen from decreasing relative distance due to the higher demand. This means that on a higher demand level, less vehicle kilometers are needed to produce the same number of trips. This is a natural consequence of improved possibilities to combine trips. The other interesting result is the positive effect of scale on the level of service, which can be seen from the decreasing travel time ratio.

3.4.2. Real-time regulated monopoly

The last market mechanism in comparison, i.e. real-time regulated monopoly market mechanism (3), is a novel attempt to transform the monopolist from profit maximizer to social welfare maximizer. The monopolist's regulation is focused both on long run decisions (price and vehicle number) and on daily trip offering decisions to maximize expected social welfare of each trip request, which results in clearly higher social welfare than the other mechanisms. This is a very interesting result for two reasons. Firstly, this mechanism is a "winner" of the comparison, because it leads to highest social welfare with pretty fair allocation of utility between profits and customers surplus. Secondly, the result suggests that this type of new ICT enabled transportation service, where the vehicle routes are not fixed beforehand and routing decisions are delegated from the driver to the computer and trip offers are also automated, enables the social planner to use new regulation policies that can be much more efficient than traditional regulation policies such as price- and entry-regulations.

3.5. Discussion on the validity of the results

In this paper, we have compared various market mechanisms for the DRT service with automated trip proposals and fixed fare structure by means of simulations. This includes designing an appropriate model for the task that captures the important phenomena and neglects the rest. One can identify simplifications related (i) to the DRT service model, and (ii) to the anticipated DRT market as we see it. In the following we try to justify the modeling assumptions and argue that they have negligible effect to the validity of the comparison.

The used model for DRT service is elementary, i.e., trip requests arrive according to a Poisson process with a constant rate, the pick-up and drop-off locations are uniformly distributed, each trip request corresponds to exactly one passenger, there is no road network, and vehicles move at a constant velocity. Poisson process is a widely used model, e.g., for telephone calls and generally it models well many activities a large human population generates. However, some caution is still in place. For example, a packet arrival process in communication networks is typically considerably more bursty than what a Poisson process suggests (Paxson and Floyd, 1995). Similarly, spatially the trips in reality are hardly uniformly distributed, e.g., some destinations are more popular at certain time of day than others. We believe that such differences affect mainly the absolute level of performance, i.e., the relative performance between the market mechanisms remains the same. Similarly, the road network and velocity aspects are unnecessary details in this respect. Also, the assumption of single passenger per trip request is merely a scaling factor, as long as the occupancy in the vehicles remains below the capacity (seats per vehicle), as typically was the case in our experiments.

Moreover, there are three simplifying assumptions on the customer behavior: (i) Customers may accept a trip proposal immediately after receiving the proposal, (ii) Customers perceive quality of service by means of travel time index (Section 2.1), (iii) Customers accept a trip proposal if expected surplus is positive (Section 2.1). The first assumption is obviously unrealistic, bacause a customer typically needs at least few seconds to make desicion. However, one can expect that "thinking times" have negligible influence to the comparison of the market mechanisms, and thus can be omitted. Regarding (ii), we acknowledge that the perceived quality of service is a complicated issue itself, but argue that the travel time is the most important factor with this respect. The third assumption ignores the fact that not only the expected travel time but uncertainty about travel time, i.e., the variance of travel time is also an important criterion for passengers, see for example (Small and Verhoef, 2007). However, the variance of travel time is quite similar in all compared market mechanisms. Thus, the third simplifying assumption is harmless in the context of the study.

4. Conclusions and future research

In this paper, we have analyzed and compared alternative regulation policies for a monopoly of a DRT service by using a simulation model. In particular, we studied three versions of monopoly market mechanisms, i.e., non-regulated, price and vehicle number regulated, and real-time regulated monopoly. Social welfare is highest in the real-time regulated monopoly mechanism. Moreover, our results indicate that DRT service has positive economies of scale and a positive effect of scale on the level of service.

We studied market mechanisms with fixed fare structure. Fixed fare structures are a widely used form of pricing in transportation services. Therefore, the studied mechanisms are relevant alternatives for the demand responsive transportation services in practice. A fixed fare structure is beneficial for the customer, because she knows the price of the trip before the trip request. However, market mechanisms where fares are not fixed beforehand can result in a much higher social welfare, because trip proposing is less limited and therefore a customer has a higher probability to get an offer with a positive expected surplus. For the vehicle operator, a market mechanism with variable fares means that it is reasonable to make many offers for the customer, i.e., fast trip offers at a higher price and slower trip offers at a lower price, because the operator usually has no information on customers' preferences and acute needs beforehand. We see that this is an important future direction of research.

The other important research topic related to the market mechanisms of DRT is externalities. As we mentioned earlier, DRT is often motivated by problems arising from the congestion of urban areas caused by the increasing number of private cars. There are positive externalities if private car users or taxi users change their transportation mode to the demand responsive transportation, whereas change from bus to the DRT can have negative externality. Studying relationships between market mechanisms, pricing, regulation policies and externalities requires comprehensive data on consumers' transportation needs, preferences and a more detailed modeling of consumers' trip mode decisions.

Understanding the effects and possibilities of market mechanisms with real time pricing presumably provide means to improve DRT service and externalities of DRT naturally must be estimated and taken into account in regulation policies. The regulation policies considered in this study provide relevant baselines for the other regulation policies and market mechanisms and the results point out for policymakers that traditional regulation policies alone are not optimal for a modern demand responsive transportation service.

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