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Economic and socioeconomic assessment of replacing conventional public transit with demand responsive transit services in low-to-medium density areas

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ABSTRACT

21 The emergence of demand responsive transport (DRT) services is restructuring mobility in the
22 urban universe. They provide a high level of service and in many cases compete with public
23 transportation modes. However, in less dense areas, where conventional public transit (CPT)
24 services such as buses are inefficient and costly, DRT services could be an alternative that is both
25 profitable and provides passenger satisfaction.

26 This paper investigates the economic and socioeconomic potential of replacing CPT with DRT
27 services. In particular, it focuses on the development and combination of two models. The first is
28 an agent-based model, which describes movements of vehicles and assigns them to passengers
29 according to a utility function. The assignment equilibrium problem is solved for demand that is

1 elastic to generalized cost alone. The second is an economic optimization model, based on a
2 simulated annealing algorithm, which aims to determine supply conditions that maximize the
3 benefit for the operator, the user, the environment, and society. Four economic problems are
4 discussed and formulated accordingly. In addition, supply optimization is carried out in particular
5 with respect to fleet size, trip fare, and vehicle capacity. Finally, these models are applied to a real
6 case in the Paris metropolitan area where a bus service has been replaced by a DRT system. The
7 results show that though this shift is not beneficial from a societal point of view, bus demand is
8 attracted by a DRT service consisting of 30 vehicles and charging a fare of €0.5. The operator
9 would aim to propose a taxi-service, with small-sized vehicles and higher fares, in order to increase
10 their profitability. User utility, on the other hand, would suggest that public authorities should
11 regulate fares and vehicle capacity (more than 6 seats). Fare regulation, in particular, will depend
12 on the fleet size, ranging linearly from €0 for 25 vehicles to €4 for 70 vehicles. Finally, we find
13 through the sensitivity analysis that thresholds exist for demand and fixed costs (respectively 85%
14 and 90% of reference values) beyond which the bus line is more beneficial to society than the DRT
15 service.

16

17

18 *Keywords:* Economic optimization, agent-based model, elastic demand, ridesharing, intermediate
19 transport modes

20

1. Introduction

In a metropolitan area, transit operators generally provide a range of mobility solutions to meet the needs of different areas and different population preferences. For instance, mass transit services are suitable for travelling longer distances while bus services are used as feeders on radial roads leading to metropolitan stations. In general, the speed and frequency of bus services makes them technically efficient in low-to-medium density areas. However, from an economic perspective, bus lines are sometimes costly for public authorities, in particular during off-peak periods, since they incur higher costs per passenger than in high-density zones (O'Shaughnessy, et al., 2011; Sørensen, et al., 2021). Demand is also decreasing because of the relatively poor quality of bus services: limited flexibility for passengers, with fixed routes and stopping points, preset schedules, and often complex and long transfer times to other bus routes (Koffman, 2004; Davison, et al., 2014; Papanikolaou, et al., 2017). At the same time, austerity policies have led to reduced transit coverage (Wang, et al., 2015). Finally, as Bar-Yosef et al. (2013) conclude, bus services in low-density areas may be entering a vicious cycle of low demand and declining service.

Given these difficulties, low-to-medium density areas are likely to provide opportunities for innovative and effective intermediate transport solutions to satisfy existing mobility demands, solutions such as ridesharing, bike sharing, carpooling, and taxi services (ENRD, 2020). In the absence of any public control, they are even likely to hasten the decline of bus services in low-to-medium density areas (Gentile, 2016). Demand Responsive Transit (DRT), which combines the regularity of bus transport with the flexibility of the taxi, has the potential to emerge as the most effective public mode in these areas (Takeuchi, et al., 2003; Koffman, 2004). Indeed, DRT would be more beneficial for passengers (e.g. greater flexibility and door-to-door transport), operators (e.g. lower operating costs), and local authorities (e.g. higher quality of service and fewer empty

1 kilometers, hence reduced negative externalities) alike.

2 In this paper, we propose an economic framework model that assesses the impacts of replacing
3 CPT (a bus network) with a DRT service in a suburban area. The economic framework notably
4 determines supply inputs (i.e. fleet size, vehicle capacity and fares) that maximize benefits for
5 passengers, operators and the public authorities. Passengers are sensitive in particular to fares and
6 quality of service (i.e. travel time and wait time). Operators are concerned with costs and revenues.
7 The public authorities want to maximize ridership, to improve user accessibility, and to reduce
8 environmental impacts while minimizing subsidy levels.

9 The economic framework is based on an agent-based model (2017) which simulates DRT
10 assignment strategies that maximize vehicle load while minimizing empty travel distances.

11 The assignment equilibrium problem is then tackled assuming elastic demand in generalized cost
12 only. Finally, economic and socioeconomic optimization problems are developed in order to
13 determine the operating conditions (fleet size, fares, and vehicle capacity) that maximize profit and
14 social welfare. The economic framework is applied to the real-world transport system in Palaiseau,
15 a municipality located in the outer suburbs of the Paris metropolitan area.

16 The rest of this paper is organized as follows. Section 2 reviews previous work on the assessment
17 of DRT systems. Section 3 presents the three main layers of the economic framework model: (1)
18 the agent-based model, (2) the assignment equilibrium problem, and at the top (3) the economic
19 optimization model. We describe the assumptions as well as the formulation of the optimization
20 problems. The economic model is then applied to a real case in Section 4, with the aim of assessing
21 its performances. Finally, the simulation results are presented and discussed.

22

2. Related Studies

1 2. **Related Studies**
2 Research on DRT systems has become available in recent decades. It initially focused on
3 optimizing dial-a-ride systems based on centralized dispatching and phone reservation (Gustafson
4 & Navin, 1973; Roos, et al., 1971). With technological progress and the emergence of several types
5 of intermediate mobility solutions, research has attempted to provide a definition of DRT.
6 According to Wang et al. (2015), DRT is “a service that is available to the general public, provided
7 by low capacity road vehicles such as buses, vans or taxis, that responds to changes in demand by
8 either altering its route and/or its timetable, and for which the fare is charged on a per passenger
9 and not a per vehicle basis”. Mehran et al. (2020) define the DRT service as “a form of transit
10 service where the vehicle deviates from its fixed route and enters into narrow local routes to serve
11 passenger demand for their distinct pick-up or drop-of location”.

12 Bellini et al. (2003) propose a broader definition of DRT systems with a classification into four
13 operational levels: (1) with fixed itineraries and stops, (2) with fixed itineraries and stops and
14 possible detours, (3) with unspecified itineraries and predefined stops, and (4) with unspecified
15 itineraries and unspecified stops.

16 Levels 1 and 4 are more common since they are closer to existing conventional transport modes
17 (CPT). In particular, the first level resembles a conventional transit service, except that users have
18 to prebook the service since it is on-demand. The fourth level, on the other hand, mostly closely
19 resembles a conventional taxi service. These two configurations have been widely studied in the
20 economic literature in recent decades, for instance CPT in (Douglas, 1972; De Vany, 1975; Manski
21 & Wright, 1976; Cairns & Liston-Heyes, 1996), and taxi services in (Wong, et al., 2001; Wong &
22 Wong, 2002; Yang, et al., 2005; Yang, et al., 2010; Wong, et al., 2015; Zhang & Ukkusuri, 2016).
23 Intermediate levels 2 and 3 combine the extreme characteristics of levels 1 and 4. Level 2 thus

1 corresponds to what is now called a flexible transit systems. Itineraries and timetables are partially
2 fixed but can be changed at the request of users with the possibility of detours within certain fixed
3 limits, thus incorporating optional stops into the total itinerary (2003). A small number of studies
4 have attempted to describe the technical characteristics of these services and to simulate their
5 interaction with passengers (Carotenuto, et al., 2011). However, much work remains to be done on
6 issues relating to operational and economic optimization, and to the interaction – in a multimodal
7 context – with other existing modes.

8 Finally, the third operational level proposes itineraries that are flexible but have fixed stops that
9 mainly correspond to public hubs such as park-and-ride interchanges, train stations, etc. They are
10 based on information on real-time demand and auxiliary data (Häme, 2013; Wang, et al., 2014).
11 These services often propose a ridesharing option since they are considered as feeders into mass
12 transit modes. Agatz et al. (2012) and Furuhata et al. (2013) reviewed various forms of ridesharing
13 and outlined the challenges associated with the development of such systems. Also, several recent
14 studies have sought to simulate and assess the technical and economic performances of this type
15 of DRT service, mostly using agent-based models (Jung, et al., 2013; Ikeda, et al., 2015; Biswas,
16 et al., 2017; Li, et al., 2018; Zellner, et al., 2016). Their aim has been to optimize routing and
17 ridesharing matching algorithms (Jung, et al., 2013; Biswas, et al., 2017; Li, et al., 2018; Agatz, et
18 al., 2011; Santi, et al., 2014; Tafreshian, et al., 2020; Ikeda, et al., 2015; Narayan, et al., 2020), to
19 assess the effect on public transit (Babar & Burtch, 2020; Zhu, et al., 2020; Ma, 2017; Li, et al.,
20 2018), to explore competition with taxi services (Berrada, 2019), to design a last-mile pricing
21 strategy (Chen & Wang, 2018; Wang, et al., 2016), or to analyze the spatiotemporal behavior of a
22 real-world DRT service (Sörensen, et al., 2021). They have all looked at DRT as an additional
23 transport mode which supports the high-capacity fixed route network.

24 A very small number of studies have investigated the impact of replacing a CPT with DRT, through

1 the analysis of real data (Becker, et al., 2013), by formulating and applying analytical models
2 (Zheng, et al., 2018; Mehran, et al., 2020), or by running simulation models (Quadrifoglio & Li,
3 2009; Diana, et al., 2009; Navidi, et al., 2018). Becker et al. (2013) discussed the operational results
4 of implementing twenty-one DRT systems in Denver, Colorado, two of which had replaced existing
5 CPT lines. Mehran et al. (2020) proposed a decision support tool based on operating cost models
6 to determine the volume of demand that would justify a switch from CPT to a DRT system. They
7 assumed that the DRT is given a flexible schedule along the fixed bus route and a limited number
8 of fixed stops. Zheng et al. (2018) proposed relaxing the constraint on routes and stops by
9 respectively allowing route deviation and/or point deviation. They then identified the switching
10 point between these two strategies, proving that point deviation is more efficient in low-density
11 areas and route deviation in low-to-medium density areas.

12 Finally, with respect to simulation-based studies, the first are probably those by Quadrifoglio & Li
13 (2009) and Diana et al. (2009). They both confirmed that on-demand operations have the potential
14 to provide a higher level of service (LoS) when the amount of demand is below a given threshold.
15 Their work was later developed by Ewards and Watkins (2013) to include random passenger arrival
16 rates, non-uniform street layouts, and irregular transit schedules. They reached almost the same
17 results, suggesting that DRT could offer a less expensive alternative for handling trip requests for
18 stations with relatively low demand levels at off-peak hours. Navidi et al. (2018) incorporated a
19 dynamic routing algorithm into an agent-based traffic simulation. They found that replacing CPT
20 with DRT will, under certain circumstances, improve mobility by reducing passengers' perceived
21 travel time without any extra cost. Some recent studies have explored the potential of using
22 autonomous vehicles (AV) to provide a DRT service (Fagnant & Kockelman, 2014; Zhang, et al.,
23 2015; Chen, et al., 2016; Bischoff & Maciejewski, 2016; Fagnant & Kockelman, 2016; Yang, 2017).
24 However, very few have focused on the impacts of replacing a CPT with an AV-based DRT service

1 (Mendes, et al., 2017; Berrada, et al., 2019; Sieber, et al., 2020).

2 All of these simulation studies have focused on the operational effectiveness of DRT in terms of
3 optimizing supply-demand interaction and maximizing vehicle use efficiency. However, these
4 approaches do not consider economic optimization and socio-economic evaluation. For instance,
5 they all assume that passenger costs consist solely of waiting, riding, and walking times, and
6 therefore ignore the fare as a travel cost for passengers. Moreover, operator costs are expressed
7 solely in terms of vehicle-miles traveled, thus ignoring fixed costs, which in reality differ
8 significantly between DRT (mid-sized on-demand vehicles) and CPT (transit vehicles like buses or
9 trams).

10 To summarize the state of the art:

- 11 - Four operative levels of DRT are identified:
- 12 - Scientific research regarding levels 1 and 4 is almost exhaustive.
- 13 - Level 2 needs more scientific research. It should be addressed in future studies.
- 14 - Level 3 is currently attracting substantial research interest, however:
 - 15 ○ Studies on replacing CPT with DRT are very limited.
 - 16 ○ There are no simulation studies that assess the economic impacts of replacing CPT
 - 17 with DRT for operators and public authorities.

18 In this paper, we aim to fill these research gaps by:

- 19 - Undertaking an in-depth economic and socioeconomic exploration of the impacts of
- 20 replacing CPT with DRT;
- 21 - Considering vehicle capacity in addition to fleet size and fares, which are all closely related
- 22 to profit and social welfare optimization;

- 1 - Considering the points of view of the main stakeholders, and accordingly solving the
2 optimization problem that would maximize their benefits;
- 3 - Proposing an application to a real network, with real demand, where the replacement of
4 CPT with DRT during off-peak hours is studied. This study should then provide insight for
5 local operators and public authorities;
- 6 - The economic framework could be replicable in other suburban or rural areas;
- 7 - By coupling the economic framework with an agent-based model, it is possible to assess
8 the economic and socioeconomic impacts of different dispatching strategies (centralized vs
9 non-centralized), relocation strategies (active vs reactive), or charging strategies (full
10 charge vs minimum charge).

11 **3. Model Framework**

12 We consider a reference situation where a scheduled bus service (CPT) is provided. This CPT
13 service is thus characterized by fixed routes and stops, predefined timetables, and set travel times
14 to be maintained by drivers. The service could be provided by private or public operators. The fares
15 are set by public authorities in order to protect passengers from high tariffs. On the other hand, the
16 operator receives subsidies that ensure the viability of the service by covering its operating costs.
17 Unit costs of production are estimated on the basis of typical values for Paris metropolitan area
18 buses. The demand – total volume of bus passengers – is obtained from a four-step model that is
19 calibrated by (DRIEA, 2010).

20
21 We now consider that a DRT service is introduced to replace this CPT service. As presented above,
22 the proposed model is organized into two levels: (1) an agent-based model (Poulhès & Berrada,
23 2017) that simulates movements of DRT services and their interaction with passengers, and (2) an

1 economic optimization, which determines supply conditions that maximize the profitability of the
2 service both for the operators and for society as a whole.

3 This section is therefore structured into two main parts. The first presents the agent-based model
4 and its components, describes the main operational constraints and formulates the assignment
5 equilibrium problem (§3.1). The second part describes the economic optimization problems (§3.2).

6

7 **3.1. Agent-based model**

8 *3.1.1. Supply side*

9 **Road network**

10 Vehicles could share the road with ordinary traffic or use dedicated lanes. Their travel time is
11 exogenous. Road traffic statically influences vehicle assignment and hence service efficiency. The
12 number of vehicles on the road or queues behind another stopped vehicle are not considered in the
13 model.

14 **Stations**

15 The on-demand ridesharing service is station-based. Stations are the sole access points to the
16 service, where passengers can board and alight. Passenger trips are therefore structured into
17 common origin-destination station pairs. Stations are also used by passengers to call vehicles.

18 **Vehicle**

19 To extend the service configuration space, vehicles have free characteristics in the model. In
20 particular, their capacity, running speed and route choice strategies are considered as model inputs.
21 The model assumes that the fleet is homogeneous, with vehicles having the same inputs (capacity,
22 speed, route choice...). Since the vehicles use the dedicated lanes of the replaced CPT, they are

1 assumed to run at a constant speed of 30 km/h. The route choice strategies are based on a utility
2 function, which aims to maximize vehicle loading while reducing passengers waiting time and
3 additional delays induced by ridesharing. The utility function is further calculated in terms of real-
4 time requests for a bounded set of itineraries and stations served.

5 **Call center**

6 A call center receives all passenger requests and classes them on the basis of their origin station,
7 their desired and actual departure time, and their destination station. Passenger requests are updated
8 at each iteration step time in a common database, saved, and communicated to all vehicles. Vehicles
9 make the decisions to board passengers independently on the basis of the utility function. The call
10 center is not a dispatcher; it only alters the status of registered passengers as waiting, reserved, in
11 vehicle, or arrived at the destination station.

12 *3.1.2. Demand side*

13 The demand reflects the number of travelers using the ridesharing service. It depends on the
14 generalized costs of modes that are available to the passenger. Generalized costs, or the utility
15 function, are a combination of monetary costs (i.e. fares) and non-monetary costs (i.e. level of
16 service (LoS) attributes) of a trip as perceived by a passenger. The utility function is extensively
17 used in the economic literature as a vector of attribute values expressed as a scalar.

18 In this paper, we assume that the level of service attributes include the in-vehicle time and the
19 waiting time. The additional time induced by a detour and/or an extra stop is included in the travel
20 time. Similarly, comfort is generally included in travel time and waiting time. These two penalties
21 are therefore not mentioned in the utility function in order to avoid the risk of double counting or
22 at least overlapping.

1 On the other hand, the fare is ignored in the assignment model, since it does not affect the vehicle
2 route and service strategy. However, for the operator and passengers, the price affects both the level
3 of service and the level of demand. Finally, the tariff is assumed to be a flat rate for all passengers,
4 denoted by τ .

5 Consequently, the generalized cost/utility function for a given Origin-Destination (OD) pair ij
6 could be expressed as:

$$C_{DRT}^{ij} = -U_{DRT}^{ij} = \mu_{mp} + \tau^{ij} + (\alpha_w \cdot t_w^{ij} + \alpha_t \cdot t_t^{ij}) \quad (1)$$

7
8 where C_{DRT}^{ij} is the DRT generalized cost for ij , U_{DRT}^{ij} is the utility function, τ^{ij} , t_w^{ij} and t_t^{ij} are
9 respectively the trip fare, the waiting time and in-vehicle time for ij , α_w and α_t are positive
10 weights that correspond to the sensitivity components, obtained from the value of time and
11 passengers' time perception, and μ_{mp} is a positive constant that reflects the mode preference and
12 captures the average effect on utility of all factors that are not included in the model.

13 The utility function measures the attractiveness of the service. In a context where several services
14 are available, passengers will choose the service that maximizes this utility (i.e. minimizes the
15 generalized cost).

16 The agent-based model determines the waiting and travel time for each passenger, characterized
17 by his or her OD trip (Poulhès & Berrada, 2017). At the end of the simulation, average waiting and
18 travel times are calculated by OD pair ij for the whole simulation period.

19 We assume in the simulation that all passengers have the same value of time and the same
20 behavioral considerations.

21
22 The demand function is a function of the utilities of services that are available for the passenger.

1 Distinguishing between the ridesharing service and the bus mode respectively by the indices DRT
 2 and CPT , the demand on the DRT service for an OD pair ij could be written as:

$$Q_{DRT}^{ij} = D(C_{DRT}^{ij}, C_{CPT}^{ij}) \quad (2)$$

3 or by injecting (Eq.1) into (Eq.2):

$$Q_{DRT}^{ij} = D(\tau^{ij}, t_w^{ij}, t_t^{ij}, C_{CPT}^{ij}) \quad (3)$$

4
 5 In particular, if the total demand for the DRT service is denoted by Q_{DRT} , then the relation between
 6 the demand volume Q_{DRT}^{ij} and Q_{DRT} is verified for $Q_{DRT} = \sum_{i,j} Q_{DRT}^{ij}$.

7 **Specific case: Elastic demand**

8 We assume that DRT and CPT are interdependent and subject to the same competition laws
 9 enforced by the public authorities. The demand for DRT and CPT is therefore assumed to be elastic
 10 and dependent solely on their respective generalized costs.

11 In other terms, for an Origin-Destination (OD) pair ij and for a given CPT demand Q_{CPT}^{ij} associated
 12 with a generalized cost C_{CPT}^{ij} , the demand for DRT Q_{DRT}^{ij} is deduced on the basis of its cost C_{DRT}^{ij}
 13 according to a fixed elasticity parameter $\varepsilon > 0$:

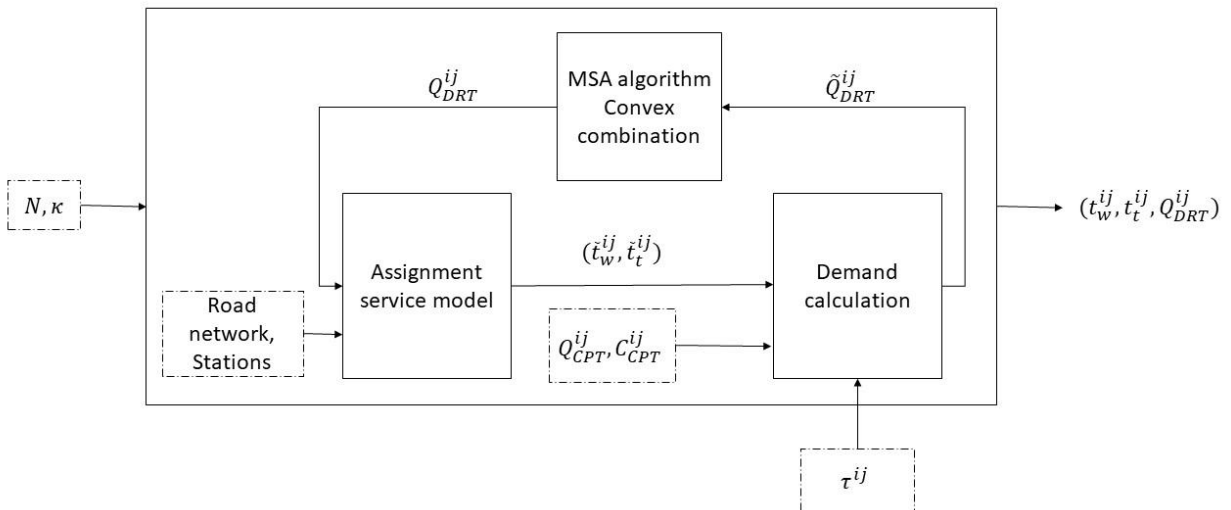
$$Q_{DRT}^{ij} = Q_{CPT}^{ij} \cdot \left(\frac{C_{DRT}^{ij}}{C_{CPT}^{ij}} \right)^\varepsilon \quad (4)$$

14 *3.1.3. Assignment equilibrium problem*

15 The equations above ((Eq.1) and (Eq.2)) describe the impact of the level of service of available
 16 modes on the volume of demand. In reality, the level of service is also affected by the volume of
 17 demand: more users mean longer waiting times and vice versa. The agent-based model developed
 18 (2017; Poulhès & Berrada, 2019) in fact seeks to take account of this reciprocal interaction.

1 Once again considering (Eq.1) and (Eq.2), and observing that $t_w^{ij} = t_w^{ij}(Q_{DRT}^{ij})$, the assignment
 2 equilibrium problem is formulated as a fixed-point problem in Q_{DRT}^{ij} . The solution of the
 3 assignment equilibrium problem is then guaranteed a priori by definition, and indicates that a fixed-
 4 point solution exists.

5 Assume the continuity of the cost function on a compact set. The Method of Successive Average
 6 (Patriksson, 1994) approaches the solution point by updating the cost function in each iteration
 7 using an auxiliary state. The iterative function defined by $C' = C + \xi_i(\tilde{C} - C)$, where $\xi_i, i \geq 0$ is
 8 a decreasing convex suit of numbers converging to zero, \tilde{C} and C are the generalized cost
 9 calculated in the previous and current iteration resp., \tilde{Q}_{DRT}^{ij} and Q_{DRT}^{ij} are the DRT demand volume
 10 calculated in the previous and current iteration resp.. The demand is then also updated using (Eq.2).
 11 The convergence is obtained by the value of the duality gap $Q.(C' - \tilde{C})$. **Figure 1** describes the
 12 assignment equilibrium problem.



13

14 **Figure 1 Diagram of the assignment equilibrium problem**

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3.2. Economic optimization model

3.2.1. Social actors

The main stakeholders in a DRT service are the operators (service providers), passengers (service users) and the public authorities (service regulators). Their principal interests and prerogatives are described in detail in (Berrada, 2019). The economic model developed therefore aims to maximize the benefit for each social actor with respect to their specific interests. The economic model thus distinguishes notably between the operator's profit, the passenger surplus, the environmental benefit, and the total benefit (operator + passenger + environment).

3.2.2. Economic model inputs

Production costs

Production costs consists of fixed costs, or daily costs, and running costs. Typically, the fixed costs are vehicle depreciation, dispatching costs, drivers' wages, maintenance of vehicles and infrastructure, and so on. Energy constitutes the major component of running costs.

Production costs can therefore be written as follows:

$$C_p = \chi N + v c_u (t_L + t_E) \tag{5}$$

where C_p is the total production cost, χ the daily costs relative to the number of vehicles N , c_u the running costs, v the average speed, and t_L and t_E are the total kilometers traveled respectively while loaded and empty.

1 **Passenger costs**

2 Passenger costs are the generalized costs perceived on average by all DRT passengers. Based on
3 (Eq. 1), they can be expressed as:

$$\bar{C}_{DRT} = \mu_{mp} + \tau + (\alpha_w \cdot \bar{t}_w + \alpha_t \cdot \bar{t}_t) \quad (6)$$

4 **Society costs**

5 Society costs cover the costs for operators and passengers alike. They are calculated as the sum of
6 production costs and the generalized cost. They are expressed as:

$$C_S = C_p + \bar{C}_{DRT} = C_p + \mu_{mp} + \tau + (\alpha_w \cdot \bar{t}_w + \alpha_t \cdot \bar{t}_t) \quad (7)$$

7 **Environmental costs**

8 Finally, as with any transport mode, the operation of the DRT service is associated with a wide
9 variety of negative externalities: greenhouse gas (GHG) emissions, air pollution, accidents, noise,
10 congestion. In this paper, we focus on greenhouse gas (GHG) impacts. They are assessed by
11 assuming a fixed emission rate per kilometer traveled given a specific vehicle capacity:

$$C_e = v(t_L + t_E) \cdot e \quad (8)$$

12 where C_e is the environmental cost that corresponds to the total amount of CO₂ emitted, $v(t_L +$
13 $t_E)$ the vehicle-kilometers covered, and e the GHG emissions associated with the vehicle
14 characteristics.

15 **Revenues**

16 Revenues are arrived at by multiplying passenger numbers by tariffs. For a fixed fare per trip,
17 revenues are equal to:

$$R_{\tau} = \tau Q \quad (9)$$

1 here R is the revenues, τ the tariff paid by the passenger, and Q the number of passengers.

2 In reality, there are other sources of revenues for a public mode operator. In the Paris region, for
3 instance, public modes are subsidized through a “mobility tax” paid by companies with more than
4 11 employees to help fund the investment in and operation of the transit system. On the other hand,
5 the public authorities subsidize public mobility services in order to protect operators from loss and
6 thereby maintain their economic sustainability. Consequently, if the amount of subsidy is denoted
7 S_b , the total operator revenues R would be expressed as:

$$R = S_b + R_{\tau} \quad (10)$$

10 3.2.3. *Economic problem optimization*

11 The economic problem is approached from four different perspectives: (1) the operator, (2) the
12 passenger, (3) the environment, and (4) society (operator + passenger + environment). The
13 formulation of the problem will therefore depend on each of these perspectives, in practice entailing
14 four maximization problems. In what follows, we present the four economic problems considered
15 in the model. In addition, the term “surplus” will be used to designate the gain for the operator
16 (profit), for the passengers (user benefit), for the environment, and for society as a whole (social
17 welfare or total benefit).

18 **Operators** seek to increase the profit from the service. They make decisions concerning fleet size,
19 vehicle capacity, ridesharing strategy, and pricing structure, with just a single goal: to maximize
20 profit. The profit (P_O) is the difference between revenues R and costs C_p :

$$P_O = R(\tau, Q) - C_p(N, Q, t_t, t_w) \quad (11)$$

1 By injecting (Eq.5) and (Eq.10) into (Eq.11), the profit is given by:

$$P_O = \tau Q + S_b - \chi N - \nu c_u(t_L + t_E) \quad (12)$$

2 We assume that the implementation of a DRT service instead of the existing CPT line is allowed
 3 by the public authority if and only if the former requires lower subsidies than the latter. Hence, the
 4 constrained profit maximization problem with respect to fleet size N , vehicle capacity κ and tariff
 5 τ , is written:

$$\max P_O(N, \kappa, \tau) = \max_{N, \tau, \kappa} (\tau Q + S_b - \chi N - \nu c_u(t_L + t_E)) \quad (13)$$

$$\text{u. c.} \quad S_b \leq S_b(\text{bus})$$

6

7 By injecting (Eq.12) into the optimization problem (Eq. 13), we arrive at the new problem:

$$\max P_O(N, \kappa, \tau) = \max_{N, \tau, \kappa} (\tau Q + S_b - \chi N - \nu c_u(t_L + t_E)) \quad (14)$$

$$\text{u. c.} \quad P_O(N, \kappa, \tau) \leq S_b(\text{bus}) + \tau Q - \chi N - \nu c_u(t_L + t_E)$$

8 The gain for **passengers** is reflected through the *passenger surplus*. It is reached by measuring the
 9 difference between the current utility (C_{DRT}) of the service provided and the minimum utility
 10 desired by passengers (C_{CPT}). If the desired utility is higher than the current utility, then passengers
 11 are getting more benefit from using the service. The user's surplus is expressed as the area below
 12 the demand curve and between the horizontal lines at C_{CPT} and C_{DRS} . It is therefore the definite
 13 integral of the demand function with respect to the generalized cost, from the actual generalized
 14 cost to any larger cost value:

$$P_u = \int_{C_{CPT}}^{C_{DRT}} D(g') dg' \quad (15)$$

1

2 The user surplus maximization problem is then:

$$\max_{N, \tau, \kappa} P_u(N, \tau) = \int_{C_{DRT}}^{C_{DRT}} D(g') dg' \quad (16)$$

3

4 The impact on the **environment** is assessed by focusing on GHG emissions. In particular, the
 5 *environmental surplus* is expressed in terms of CO₂ emissions avoided/added as a result of
 6 replacing a CPT service with a DRT service.

$$P_e = \tau_{CO_2} * (CO_2^{(CPT)} - CO_2^{(DRT)} + \beta(Q - Q_{CPT}) \cdot CO_2^{(PC)}) \quad (17)$$

7 where τ_{CO_2} is the carbon price, $CO_2^{(CPT)}$, $CO_2^{(DRT)}$ and $CO_2^{(PC)}$ are respectively the CO₂ emissions
 8 from CPT, the DRT service and private cars, Q_b is the total demand of CPT and β the proportion
 9 of passengers who prefer the private car over the DRT service.

10 Finally, from the perspective of society, the main objectives are to maximize operator and passenger
 11 gain while minimizing environmental impacts. Below, we define a total surplus function which
 12 covers the service provider's surplus (i.e. profit), the passenger surplus and the environmental
 13 surplus. The total surplus, also called the social welfare, is then defined as:

$$P_S = \omega_O P_O + \omega_u P_u + \omega_e P_e \quad (18)$$

14

15 where ω_O , ω_u and ω_e are the respective weights of the operator's profit, the user surplus and the

1 environmental surplus. These weights are fixed in accordance with societal concerns and priorities.
 2 The maximization problem of **social welfare** (or **total benefit**) obeys the same implementation
 3 constraint as the profit maximization problem. In addition, protecting the service provider from
 4 losses imposes an additional constraint on net profit. Therefore, the social welfare maximization
 5 problem with respect to fleet size, vehicle capacity and fares is written as:

$$\max_{N, \kappa, \tau} P_S(N, \kappa, \tau) = \max_{N, \tau} \left(\omega_o \int_{C_{DRT}}^{+\infty} D(g') dg' + \omega_o P_o(N, \kappa, \tau) + \omega_e P_e(N, \kappa, \tau) \right) \quad (19)$$

u. c. $P_o(N, \kappa, \tau) \leq S_b(CPT) + \tau Q - \chi N - v c_u(t_L + t_E)$

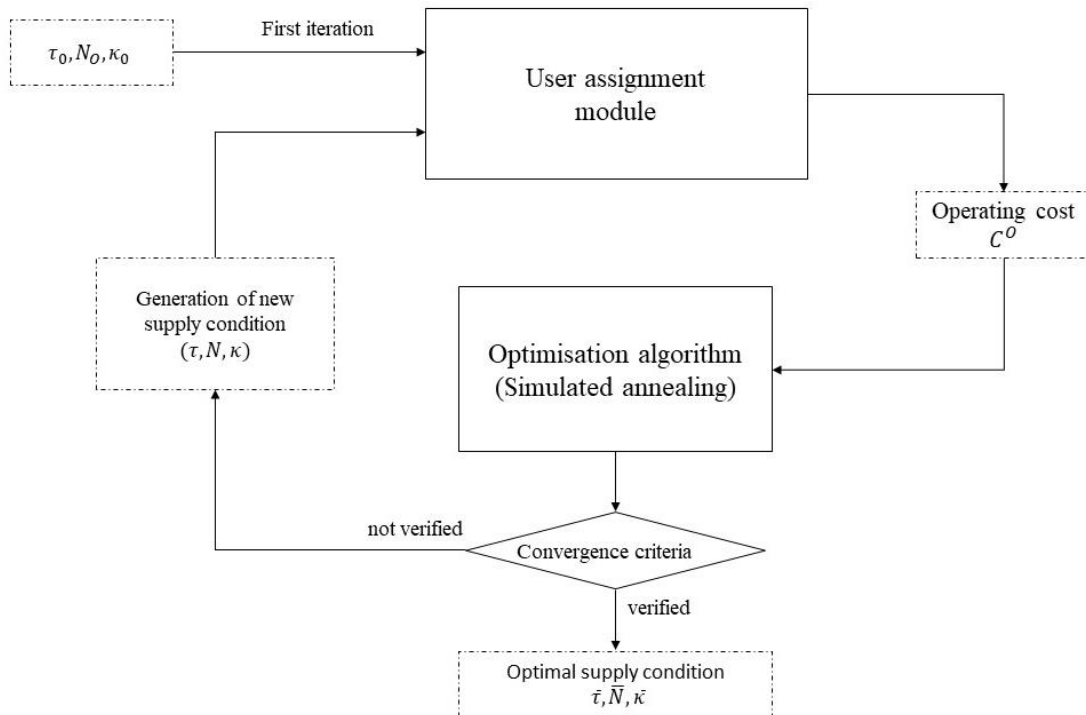
$P_o(N, \kappa, \tau) > 0$

6
 7 *3.2.4. Optimization Algorithm*

8 Maximization problems (Eq.14), (Eq.16) and (Eq.19) could be solved heuristically by using single-
 9 based (e.g. tabu search, iterated local search, simulated annealing, etc.) or population-based (e.g.
 10 ant colony optimization, evolutionary computation, genetic algorithm, etc.) metaheuristics
 11 algorithms. In this paper, we use a simulated annealing method (Metropolis, et al., 1953;
 12 Kirkpatrick, et al., 1983) which is capable of finding an approximately accurate solution for the
 13 global optimum of a complex system. Future work will focus on using other algorithms to improve
 14 the model efficiency.

15 The simulated annealing method starts from an initial state (initial supply conditions: fleet size,
 16 tariff and capacities) and an initial temperature. In each iteration, neighboring solutions are
 17 generated and tested, and the temperature decreases gradually (cooling process) until it reaches a
 18 minimum value. The temperature defines a rule for accepting the best neighboring solution (lower

1 temperature means less acceptance). In this model, the acceptance of damaging moves is controlled
 2 by a Boltzmann's function: $P = e^{-(P_{new}-P_{old})/T}$ where T is the temperature of the current iteration,
 3 P_{old} and P_{new} are respectively the value of the previous iteration and the neighboring calculated
 4 solution. The cooling process is controlled by the Metropolis rule: $T = T_0 e^{-i/M}$ where T_0 is the
 5 initial temperature, i the current iteration number and M the Metropolis coefficient, determined to
 6 ensure temperature convergence. The algorithm stops if the temperature is close to its minimum
 7 value or if a maximum number of iterations is reached. **Figure 2** describes the overall process for
 8 economic optimization using the simulated annealing algorithm. The assignment equilibrium
 9 problem module is detailed in **Figure 1**. It provides the generalized cost C^0 and the demand volume
 10 Q for given supply conditions (N, κ, τ) , which are then used to solve the optimization program.



11

12 **Figure 2 Economic optimization scheme**

4. Demonstration

The model developed is applied to a real case in order to assess its performances. In the following paragraphs, the case study is presented (§4.1), the simulation setups are defined (§4.2) and the results are described (§4.3).

4.1. Study case presentation

4.1.1. Territory issues

The model is applied to Palaiseau, a municipality located in the Paris metropolitan area, 17km south-west of the center of Paris. Palaiseau is home to some 32000 inhabitants and 22000 jobs. The urban development plan reflects an expectation of rapid urbanization of the area over the next ten years. Since it is also at the center of the French scientific cluster, Palaiseau is becoming a focus of interest for research studies in France. Today, Palaiseau is mainly connected to the rest of the Paris metropolitan area by the RER B train line. However, by 2030 the Greater Paris Express will maintain the public transport supply in the area through transit line 18.

By 2020, several experimental studies will provide transport services using autonomous vehicles to serve universities, graduate schools and research labs and institutes.

4.1.2. Network design

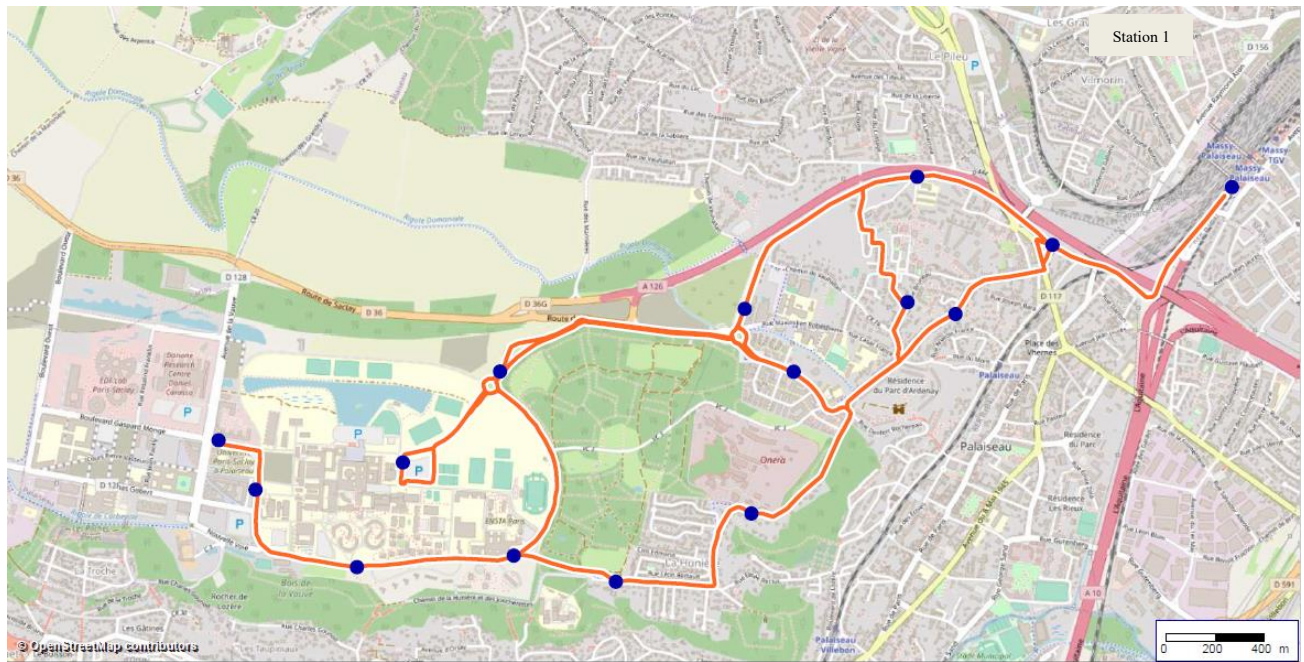
The ridesharing service is implemented to replace an existing bus line service, the characteristics of which are provided by data of DRIEA (Regional and Interdepartmental Direction of Equipment and Planning) and presented in **Table 1**. The network has a total length of 13 km and serves 21 stations including a RER B station. A portion of the network has dedicated busways while the rest

1 is shared with private cars. Vehicles travel at a constant speed of 30 km/h. They all depart from
 2 station 1, which is the Massy-Palaiseau station. The network is presented in **Figure 3**.

3 **Table 1 BRT technical characteristics**

Technical characteristics	Value
Travel time	20min
Length	10km
Commercial speed	30km/h
Headway	10min (during Peak Hours) 15min (during Off-Peak Hours)
Number of vehicles	5 (during Peak Hours)
Number of stations	13

4
5



6
7 **Figure 3 Map of the study area including the service network framework**

1 4.1.3. Demand generation

2 The simulation is carried out for one morning peak hour and for home-to-work trips. Trips are
3 estimated using a calibrated four-step model for the Paris area (DRIEA, 2010) and then
4 disaggregated into taxi stations by analyzing the distribution of homes and jobs (Berrada, et al.,
5 2019). The total number of CPT trips is found to equate to 572 passengers, 31% of which are
6 students going to the university cluster (Berrada, et al., 2020). The average waiting time and travel
7 time are found to be 5 and 10 minutes respectively. The DRT demand matrix is then deduced for a
8 given generalized cost using (Eq.1). Finally, trips are generated in time using a Poisson distribution
9 per one-minute time step for one hour of simulation.

11 **4.2. Simulation design**

12 The agent-based model for simulating the behavior of the DRT service is written in Matlab, makes
13 it possible to solve complex mathematical programs and to visualize simulation results. The model
14 imports the network infrastructure, including links and stations, as well as the costs of each OD
15 trip. The initial demand corresponds to that of the bus service (CPT). The model allows one to set
16 parameters of supply (e.g. speed, fleet size, vehicle capacity...) and demand (e.g. value of time,
17 elasticity).

18 In this section, we present the main ingredients of the simulation design: simulation period (§3.2.1),
19 simulation scenarios (§3.2.2), optimization setups (§3.2.3) and simulation parameters (§3.2.4).

20 4.2.1. Simulation period

21 Indicators are calculated and saved over a reference period of one hour. The simulation starts with
22 prior runs in order to have a realistic situation where vehicles are serving passengers and are

1 distributed over the study area. The total period of runs corresponds in practice to the longest OD
2 travel time.

3 Symmetrically, a second period closes the simulation when the last passengers boarded in the
4 reference period alight. During this period, passengers continue to flow into stations and to board
5 vehicles.

6 *4.2.2. Simulation scenarios*

7 The profit, the passenger surplus and the social welfare depend on fleet size, fares, and vehicle
8 capacity. The operator has the possibility of varying the fleet size between 1 and 100 vehicles. The
9 fare is limited by the authorities to €4 per trip. Finally, the capacity ranges from 1 seat (individual
10 vehicle) to 10 seats (shuttle). These three constraints constitute the service's feasibility domain for
11 the operator. They are optimized in order to maximize the profit for all stakeholders according to
12 production costs and elasticity values.

13 *4.2.3. Optimization setups*

14 The assignment equilibrium problem is obtained after 15 iterations or when the value of the duality
15 gap is below 50 (§2.2.4). There are four main criteria for the stopping of the economic equilibrium:
16 (1) the number of consecutive success iterations exceeds 10, (2) the number of consecutive rejected
17 iterations exceeds 100, (3) the maximized surplus (profit, social welfare, etc.) does not vary for 15
18 consecutive iterations, and (4) the temperature reaches its minimum value. The initial and final
19 temperatures are respectively 1 and 10^{-8} . The temperature decreases in accordance with the
20 Boltzmann function. The surplus maximization is calculated for five initial states in order to ensure
21 convergence to the global maximum. In each iteration, neighbor states are generated on the basis

1 of random initial values that are limited by the feasibility domain (i.e. the feasibility domain of
2 fleet sizes is [1,100], of vehicle capacity is [1,10] and of fares is [0,4].

3

4 *4.2.4. Simulation parameters*

5 **Production costs**

6 Let us consider an investment cost of €30000 and €60000 respectively to purchase one medium-
7 sized vehicle and one minibus (Renault, 2018). For a lifespan of 5 years, the depreciation costs are
8 respectively €16 a day and €32 a day. A driver's wage in Ile-de-France is €2300 per month (Rabreau,
9 2016). Since the maximum workweek is 35 hours, at least three drivers are required for each vehicle.
10 Including taxes, the wage cost would be some €320 a day. Fixed costs would therefore amount to
11 €336 per day ($16 + 320 = €336$) and €352 per day ($32 + 320 = 352$) for medium-sized vehicles and
12 minibuses respectively.

13 Running costs are calculated using the cost per kilometer coefficient (PRK), which comprises the
14 costs of fuel, insurance and maintenance. For medium-size vehicles, the PRK is €0.6 per kilometer.
15 For the CPT service (reference scenario), the purchase cost of a bus is approximately €220000
16 (JDN, 2009) for a lifespan of some 7 years (Transbus, 2018). Vehicle depreciation costs are then
17 about €100 per day. Station depreciation costs are not included in this estimation. On the other
18 hand, we assume that drivers receive the same wage for both the CPT and DRT service (€320 a
19 day). We thus ignore additional wage costs, such as those associated with working at weekends or
20 at night, or with factors such as length of service.

21 To sum up, the total fixed costs for a bus service thus amount to around €420 a day.

22 Based on the PRK for large vehicles, we estimate the running costs at €3/km (Pelletier, 2018).

23 Since the service covers some 1610 veh.km (DRIEA, 2010) per day, the total production cost per

1 vehicle is $(1600/15) \times 3 + 420 = \text{€}742$ per day.

2 **Environmental costs**

3 With regard to energy costs, the French environmental and energy management agency (ADEME,
4 2017) estimates emissions of medium-size vehicles at around 90 gCO₂/km (CAROOM, 2019),
5 while for buses they are some 130 gCO₂/km (ConsoGlobe, 2017; Consoglobe, 2017). On the other
6 hand, we assume that all former CPT passengers who are not convinced by the DRT service will
7 opt to use private cars.

8 Finally, the carbon price in France was set by the French government in 2018 at some €50/tCO₂
9 (Ministère de l'Environnement, de l'Energie et de la Mer, 2018).

10

11 **Revenues**

12 A monthly travel pass in the Paris region costs around €70 for some fifty home-work trips, with an
13 average distance of 14 km per trip (Caenen, et al., 2011). If we assume that CPT trips correspond
14 to the first/last kilometer, the price of a CPT trip would be $(70/50) \cdot (2/14) = \text{€}0.2$ per trip. In addition
15 to revenues generated by business activity, transport modes are subsidized through the “mobility
16 tax” and departmental, regional and state allocations. **Table 2** shows the structure of revenues for
17 transit modes in the Paris region area (Rapoport, et al., 2019).

18 **Table 2 Revenue structure for public modes in Ile-de-France**

	Million Euros	Percentage
Mobility Tax	4238	42%
Commercial revenues	3664	36%
Public subsidies	1839	18%
Departmental	782	8%
Regional	646	6%
State	292	3%
Other	343	3%

1 As a result, total revenues for transit modes are around €0.72 per trip.

2 **Demand properties**

3 Demand in reference Q_0 corresponds to trips completed by users of the existing CPT line. It is
4 assumed to be uniform and set to 572 trips per peak hour, as calculated previously in §3.1.3. The
5 ratio between real and perceived travel and wait times on CPT is assumed to be 1:1.5 (Wardman,
6 2004). Given the French mean value of time of €12 per hour (Quinet, 2013), the weights of the
7 utility function for CPT are set to €0.4/min.

8 Consequently, the generalized cost of reference g_0 is : $g_0 = 0.2 + 0.4 * (15 + 5) = 8.2 \text{ €}$

9
10 Moving to the DRT service, the travel and waiting times are assumed to be perceived similarly to
11 taxis, with respective ratios of 1:1.2 and 1:1.5 compared with actual elapsed time (Wong, et al.,
12 2015; Borja, et al., 2018).

13 The elasticity to generalized cost for a DRT service in the Paris region is estimated at about -2.3
14 (Berrada, 2019). This suggests that increasing the generalized cost by 1% will reduce the demand
15 by 2.3%. The values of generalized cost, waiting time, travel time, fare, and demand are then
16 estimated by the agent-based model.

17 **Summary of simulation parameters**

18 **Table 3** summarizes the main simulation parameters considered on the demand and supply side.

19 **Table 3 Simulation parameters**

	<i>DRT</i>	<i>CPT (bus)</i>
<i>Production costs</i>		
Fixed costs	€16/veh.h (medium size) €18/veh.h (shuttles)	€24/veh.h
Running costs	€0.5/km	€3/km
<i>Revenues</i>		
Ticket price per trip	(To optimize)	€0.2/trip

Subsidies per trip	$\leq \text{€}0.52/\text{trip}$	$\text{€}0.52/\text{trip}$
Revenues per trip	<i>(To optimize)</i>	$\text{€}0.72/\text{trip}$
<i>Environmental costs</i>		
GHG Emissions	90 g/km (medium size) 100 g/km (shuttle)	130 g/km
<i>Demand inputs</i>		
Total number of passengers	<i>(To optimize)</i>	570
Travel time penalty (€/min)	€0.3	€0.4
Waiting time penalty (€/min)	€0.4	€0.4
Elasticity to generalized cost		-2.3

1

2 **4.3. Simulation results**

3 Three types of results are presented in this section. First, the optimization results are shown in
4 accordance with the objective function chosen. The resulting services and the performance are
5 compared by reference to the current bus service for optimization of the operator’s profit alone, the
6 user surplus, the environmental benefit, and finally the sum of these three components: the social
7 welfare. This total benefit will then be analyzed in a second part, with a more precise exploration
8 of how the total benefit varies for each of the benefits broken down per type of service. The last
9 part of the results presents sensitivity analyses on the key variables of the model: elasticity, fixed
10 cost of service, and initial demand for the bus service.

11 *4.3.1. Optimal solution from the stakeholders’ perspectives*

12 Using the unit cost assumptions for the DRT service and the demand assumptions for the existing
13 CPT service, the economic optimization is performed for all benefits (Eq.14, Eq.16, Eq.17 &
14 Eq.19). The results are presented in **Table 4**, which shows for each optimization problem the impact
15 on all stakeholders’ benefits as well as the corresponding optimal operating conditions (fleet size,
16 vehicle capacity, and fare).

17

1 **Table 4 Results of economic problem optimization**

	Optimization Objective	Operator profit	Environmental benefit	User surplus	Social welfare
Benefits	Social welfare	-1531	-1249,3	-2998	-336
	User surplus	-1979	-1615	2493	-308
	Operator profit	477	372	-5185	12
	Environmental benefit	-29	-6.3	-306	-40
Demand outputs	Total demand	163	168	1243	502
	Average user cost (in euros)	19	19	6,9	11
Optimal operating conditions	Number of vehicles	1	1	94	17
	Tariff per trip (in euros)	1.6	1	0.05	0.95
	Vehicle capacity	4	2	5	9

2
3 The results above show that if we focus on the operator's profit, a service with only one vehicle
4 and a fare of 1.6 Euros (for a maximum under a 2 Euro constraint) and a low capacity of 4 seats
5 logically leads to an optimization of the operator's profit at a higher level than the bus. Conversely,
6 the social benefit is reduced fourfold relative to the operator's profit. The environmental cost is of
7 course quite low because of the small number of cars in service. The modal shift of three-quarters
8 from initial demand to other modes (notably 50% to private cars) therefore explains this increase
9 in GHG emissions.

10 Optimization of the environmental benefit shows zero benefit for the environment. The service
11 corresponds to a single vehicle with the lowest possible capacity. The modal shift by users to the
12 private car (50% according to our assumptions) offsets the gain from the elimination of buses. On
13 the other hand, services that offer a large number of vehicles have an even higher environmental
14 cost. It can therefore be concluded that no service is environmentally beneficial compared with the
15 bus service in our case study.

16 By contrast, the third optimization problem focuses solely on optimizing user well-being, whatever
17 the cost to the operator and therefore to society, which will have to pay for the losses if the operator

1 offers an unprofitable service. The service implemented considerably increases the user surplus
2 compared with the current service. On the other hand, the cost to the operator is double the benefit
3 to users. Similarly, the environmental cost is significant. This service is of course attractive, with a
4 doubling of demand compared with the CPT service. With a maximum number of vehicles limited
5 to 100 in the optimization, the service has 94 vehicles with a fare of almost zero and a capacity per
6 vehicle of only 5 seats.

7 Finally, the social welfare optimization shows that, under the current assumptions, the DRT service
8 is not an effective replacement for the CPT service. The service that would do most to limit the
9 differences from the current service is a DRT service that favors the operator by providing a benefit
10 compared with the current service, but degrades travel conditions for users and increases GHG
11 emissions. There is a 15% loss of users and the corresponding service is consists of seventeen 9-
12 seater vehicles with a fare of almost one euro per trip.

13 4.3.2. 2D-space solutions

14 This section presents value maps of social, operator, environmental, and combined (i.e. the sum of
15 the three) benefits with different service features. To aid comprehension, the focus is on fleet size
16 and price, with vehicle capacity accordingly set at a maximum fixed value of 10 persons per vehicle.
17 **Figure 4** shows the differences in profit between DRT and CPT services that are obtained for each
18 pairing (number of vehicles, fare). From bottom to top, the four cost maps are the environmental
19 benefit, the difference in operator profit, the user surplus, and finally the social welfare. Zero profit
20 lines share the service type maps. They are approximated with a straight pink dotted line. The
21 uncertainty of the results makes it impossible to be as precise in the breakdown as the close-grained
22 results of the maps suggest. **Figure 5** shows the difference in average generalized cost and in
23 demand volume between the two services, CPT and DRT. Zero difference lines share the service

1 and bus efficiency areas.

2 Some logical results emerge from the benefit maps. User surplus increases when fares are lowest.

3 The large number of vehicles keeps waiting time at stations to a minimum. In addition, it can be

4 noted that CPT is more profitable for users when the number of DRT vehicles is less than 30

5 vehicles, even if the DRT service is free. Conversely, operator profit increases when fare revenues

6 rise, but only slightly due to the shift in demand to other modal alternatives. Similarly, increasing

7 the size of the vehicle fleet, though the increased demand generates more revenues, is not efficient

8 enough offset increased costs. The orders of magnitude of the differences in surplus and profit are

9 roughly comparable, so that they balance each other fairly well, and when the two are added

10 together in the social welfare, the differences between the benefits of CPT and DRT decrease. We

11 then obtain types of service that are almost as efficient as the bus service on almost the entire 2D

12 map. This will become apparent in sensitivity analyses where the results achieved between two

13 parameter values may be completely different. The social welfare map shows notably that services

14 with few vehicles are so efficient from an operator point of view that the loss of user surplus is

15 almost offset. Conversely, services with numerous vehicles are not as efficient in terms of the socio-

16 economic balance. This means that in this analysis operator profit is more important than user

17 surplus, which may raise questions.

18 The shape of the contours of the user surplus map shows that price has a large impact when the

19 number of vehicles is high, and a low impact otherwise, since in this case the contour lines are

20 almost vertical. This feature makes it easy for an operator who wishes to make a profit to increase

21 the fare when the number of vehicles is low. The second graph in **Figure 5** confirms that demand

22 will not be as sensitive to a fare increase and people will not so easily quit the service. It is therefore

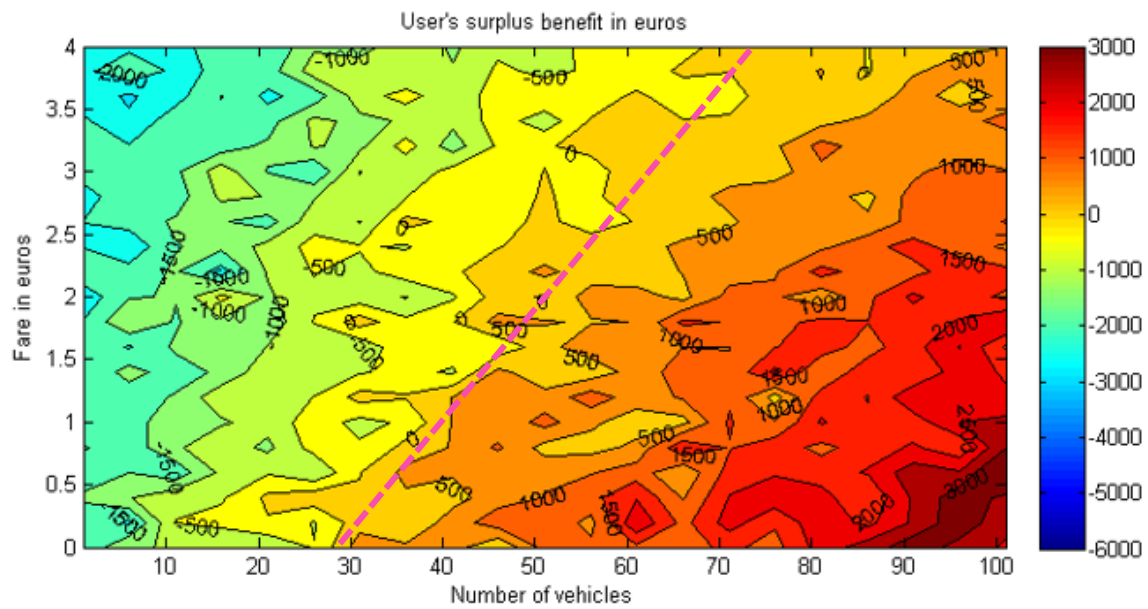
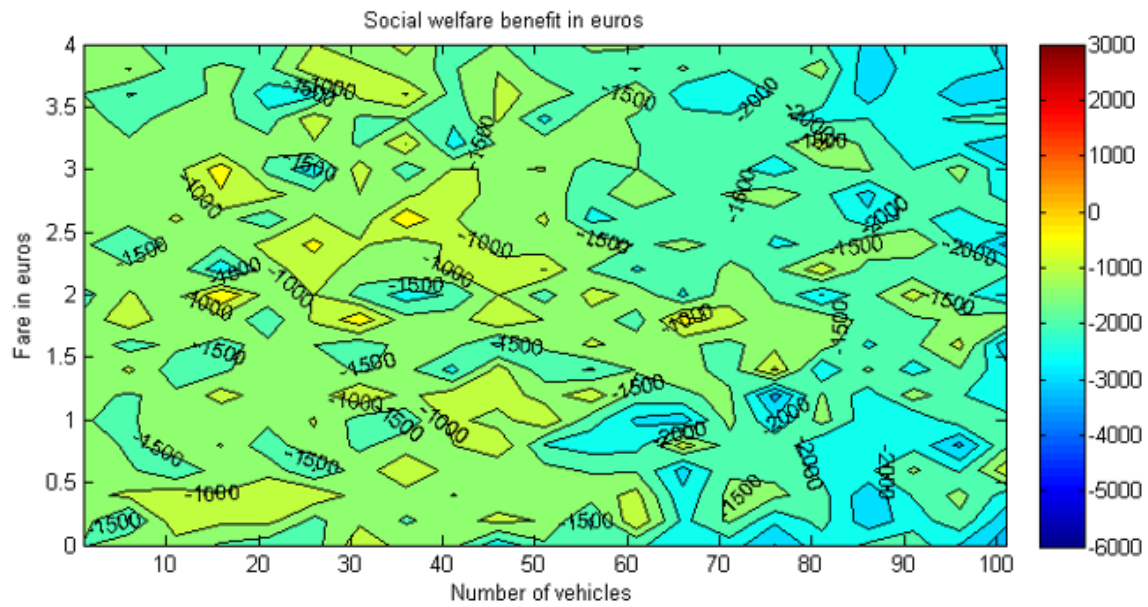
23 possible to have services where demand is fairly high despite a very high fare with conventional

24 cost elasticity assumptions in socio-economic balance sheets. The graphs in **Figure 5** show that the

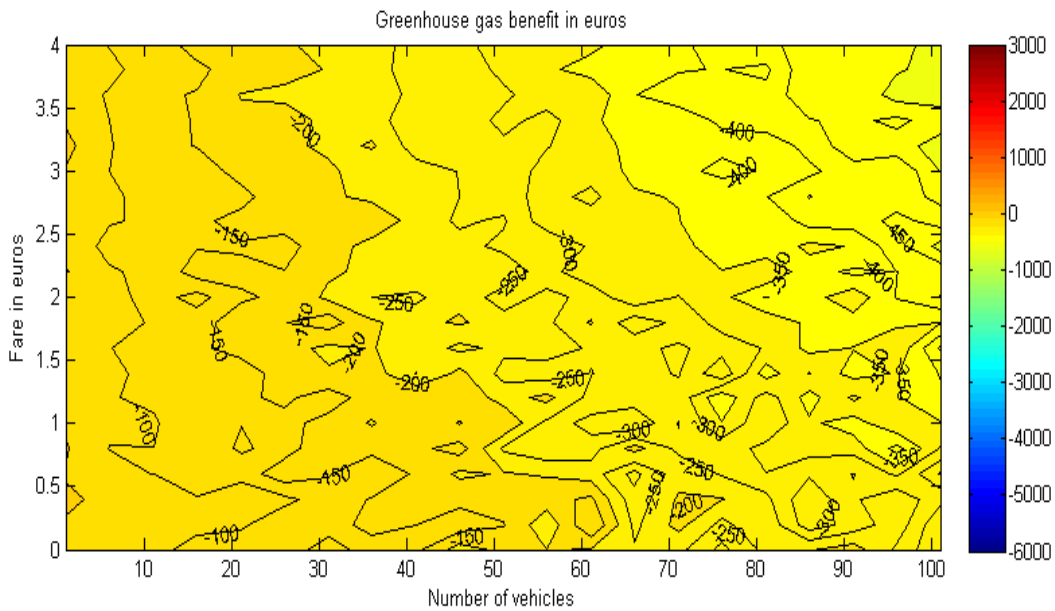
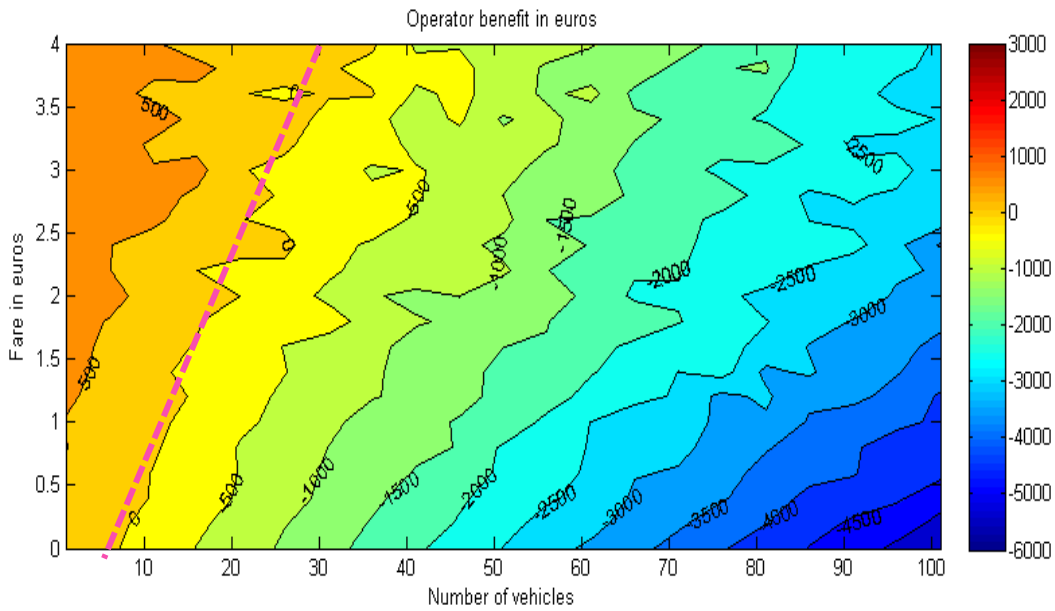
1 level of demand of the initial CPT service corresponds to a DRT service of 30 vehicles for a zero
2 fare and 60 vehicles for a fare of 4 euros.

3 Another important finding to discuss is the low significance of environmental costs or benefits in
4 the final balance. The final values of the differences in environmental costs are negligible compared
5 to the other terms of the balance, implying that whatever the environmental efficiency of the
6 services offered, the gains will be valued very little in the socio-economic balances and will
7 therefore have very little influence on the final choice of decision-makers, who would only look at
8 the overall results.

9

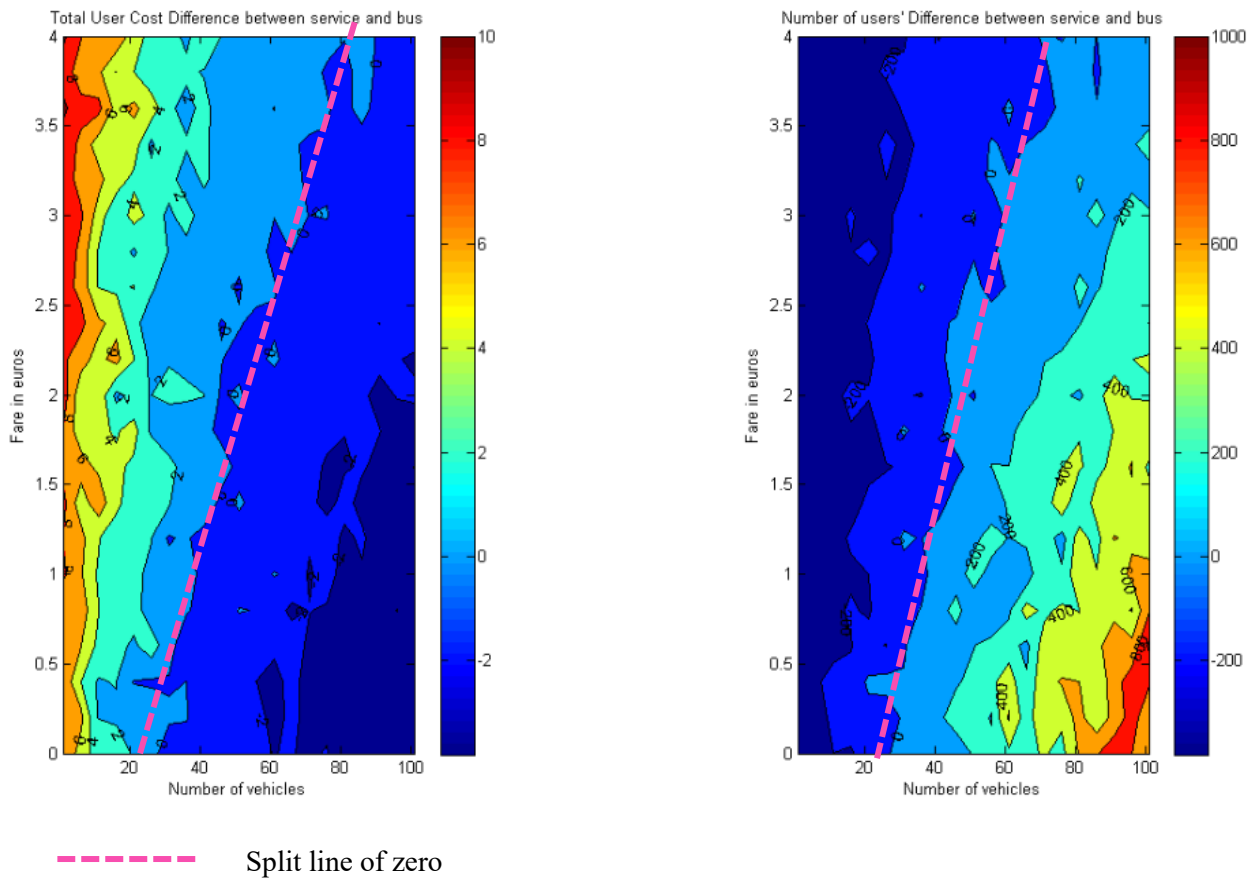


----- Split line of zero



----- Split line of zero

- 1
- 2 **Figure 4 Results of the socioeconomic maximization problem for GHG emissions, user**
- 3 **surplus, operator profit, and social welfare, with respect to fleet size and fare**



1

2 **Figure 5** Respectively cost and user difference between service and bus network

3 4.3.3. *Sensitivity analysis*

4 The final section of the results presents the sensitivity analysis. The tables and graphs in Figures 6,
 5 7 and 8 show the evolution of the benefit to society (i.e. social welfare) as a function of different
 6 values of variables in the model:

- 7 (i) Different values of the elasticity of demand (-0.3; -1.3; **-2.3**; -3.3; -4.3)
- 8 (ii) A multiplicative ratio of the fixed cost of the DRT service (0.8; 0.9; **1**; 1.1; 1.2)
- 9 (iii) A multiplicative demand ratio (0.8; 0.9; **1**; 1.1; 1.2)

10 **Important note:** Sensitivities to the carbon price and the rate of modal shift to the private car were

1 also tested. However, it was observed that the influence of the emissions term in the calculation of
2 the final benefit is almost insignificant; it therefore does not permit more than approximate
3 variations in the approach to the supply-demand balance and in the resolution of the total benefit
4 optimization.

5 For each sensitivity analysis, results are presented by means of one table and one graph.

6 The table presents the characteristics of the optimal service obtained from the economic
7 optimization of the total benefit. The average generalized cost of users and the associated demand
8 are also included in results (by way of reminder, demand for the bus service is 570 during the hour
9 of simulation).

10 The graph shows the evolution of the benefits with respect to the values of the parameters analyzed.

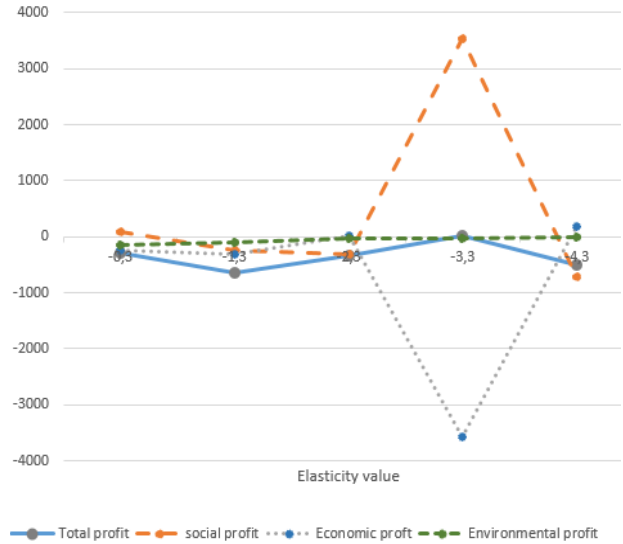
11 The broken blue line represents the total benefit, the orange dotted line the user surplus, the grey
12 dotted line the operator profit, and the green dotted line the environmental benefit.

13 (i) Demand elasticity analysis

14 The sensitivity analysis on elasticity to generalized costs confirms the high volatility of the results
15 in the space of possible service types. The elasticity value has little influence on the socio-economic
16 balance sheets. The total balance varies between 30 and -650, where the lowest value is for an
17 elasticity of -1.3 and the highest for -3.3, for which the balance value is positive. For this elasticity
18 value, the very high benefits for users are compensated by an equally high loss for the operator; it
19 should be recalled that the optimization is performed for total benefit only. Such a low elasticity (-
20 3.3) reflects high user volatility. On the other hand, when elasticity values are higher (-0.3), demand
21 is less elastic, and the operator can afford to charge a high fare and keep demand strong. However,
22 the large number of vehicles in the service, which allows users to increase their surplus slightly
23 compared to the bus service, is not enough to make the service profitable for the operator.

1

Elasticity value	-0.3	-1.3	-2.3	-3.3	-4.3
Number of vehicles	35	26	17	97	1
Fare (in Euros)	2	1.5	0.95	0.1	0.14
Capacity	9	8	9	9	8
Average User Cost	9.7	10.7	10.7	6.5	19
Total Demand	575	525	502	1902	181

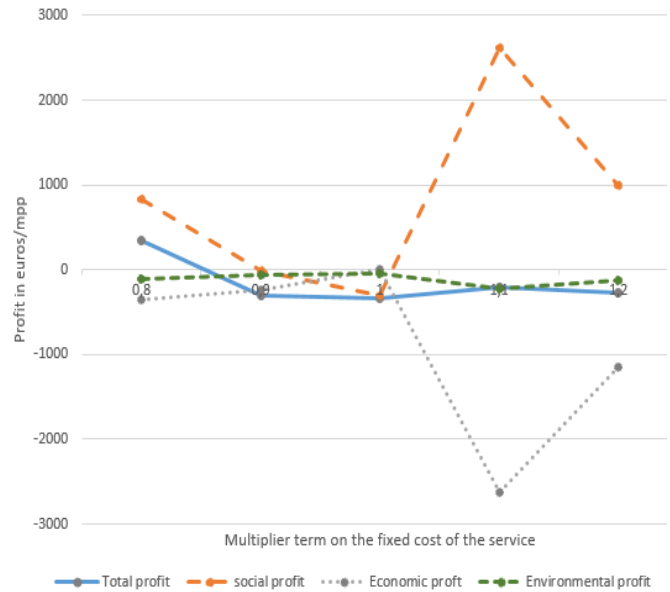


2 **Figure 6 Simulation results for elasticity sensitivity**

3 **(ii) Fixed cost sensitivity**

4 Higher fixed costs do not necessarily mean a decline in the overall balance sheet. Even if operator
 5 costs appear increasingly high, each time, as with elasticity, the optimal solution compensates for
 6 the high costs to the operator by equally high gains for users with fairly high fares but a substantial
 7 number of vehicles despite the increase in costs. The balances obtained found that there is a
 8 threshold value (€15/veh.h) above which the DRT is not profitable from the perspective of society.
 9 Again, it seems to be socio-economically more rewarding to favor the users than the operator. In
 10 spite of a high fare (1.46€/trip), a fleet of 40 vehicles with 10 seats leads to a 15% increase in
 11 demand compared with the initial bus service.

Fixed cost ratio	0.8	0.9	1	1.1	1.2
Number of vehicles	40	26	17	81	47
Fare (in Euros)	1.46	1.4	0.95	0.76	1.46
Capacity	10	7	9	7	8
Average User Cost	9	9.5	10.7	7.1	8.4
Total Demand	724	607	502	1215	815



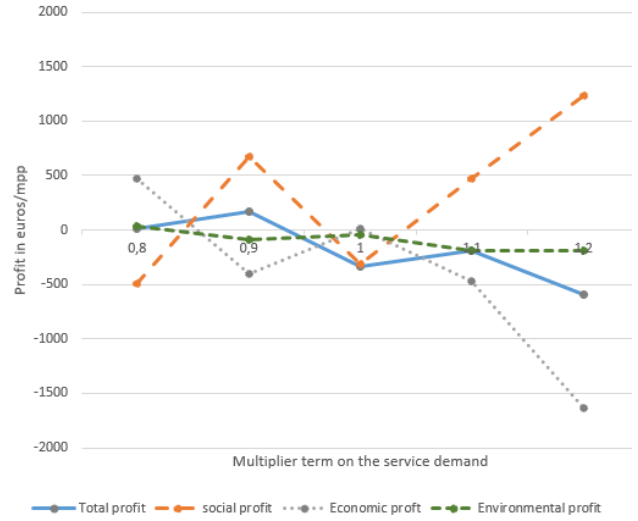
12 **Figure 7 Simulation results for fixed cost sensitivity**

13 **(iii) Sensitivity to the total volume of demand**

14 In increasing the total volume of demand, we assume that the density of demand increases. The
 15 sensitivity analysis confirms that the CPT service is not pertinent for low-density areas. On the
 16 other hand, the lower the density of demand, the more appropriate DRT services become. Again,
 17 we observe a threshold demand volume (95% of the reference scenario demand) above which the
 18 CPT is more suitable than the DRT service. This also confirms the assumption behind this research
 19 study, which aims to investigate the complementarity between DRT and CPT services. For very
 20 low-density areas, it seems that the DRT service would be closer to a premium taxi service with
 21 low vehicle capacity and high fares. For higher demand volumes, the service would tend to operate
 22 as a form of shuttle service, with higher capacities and lower fares.

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Parameter value	0.6	0.8	1	1.2	1.4
Number of vehicles	6	37	17	44	58
Fare (in Euros)	2	0.75	0.95	1.9	2
Capacity	6	9	9	9	7
Average User Cost	13.2	8.8	10.7	9.7	8.7
Total Demand	198	602	502	767	1100



1 **Figure 8 Simulation results for total demand sensitivity**

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5. CONCLUSION

The paper proposes a theoretical economic model for the analysis of the economic and social benefits of replacing a scheduled transit system (CPT) with an on-demand responsive ridesharing service (DRT). The economic model is embedded with an assignment model and a numerical application is performed on a real locality in the Paris region.

The optimization is carried out from the perspectives of the operator, passengers, the environment and society with respect to the supply conditions: fleet size, tariff, and capacity. The results of the socioeconomic optimization using a simulated annealing algorithm showed that from the societal perspective, it is not beneficial to replace the CPT by the DRT service. Another pertinent result of simulations is that using mid-sized vehicles (shuttles) is more profitable for society, while the operator would opt for small vehicles (taxi service), where the depreciation costs are lower. The 2D- heat maps revealed that in order to attract existing bus demand, the operator would need to provide a DRT service with about 30 vehicles, with a price per trip of €0.5. On the other hand, it demonstrated that while the user surplus and operator profits have well-defined areas of relevance, the social benefit could be optimal for different combinations of fleet size and fares within the feasibility domain. In particular, it showed that higher social welfare could be achieved when the level of service is high enough to satisfy very few passengers, while bringing high profits for the operator. Further development work should include and explore weightings for user, operator, and environmental profits in the total social benefit formula.

Demand in this study is considered elastic to the generalized cost. The elasticity for the DRT service is assumed to be equal to that of the CPT and the mode split is calculated accordingly. The

1 impact of the elasticity factor is therefore critical in our model. However, the sensitivity analysis
2 showed that its influence on the total benefit is not highly significant.

3 The sensitivity analysis with respect to fixed costs and demand volume proves that thresholds exist
4 beyond which the CPT service is more appropriate. Operators and public authorities should thus
5 determine their strategy accordingly. For instance, the deployment of electric and automated
6 vehicles in low-to-medium density areas, which also promises to reduce production costs, would
7 be beneficial to users, operators and society alike.

8 There are however some limitations in this study. The production costs of CPT are estimated
9 globally. They do not include investment costs. Data is therefore required for a precise cost
10 analysis. This cost analysis could also include more sophisticated pricing strategies for CPT and
11 DRT. Data would also be needed to confirm OD trips, which are based on the distribution of jobs
12 and population within the territory, without calibration of actual trips. The demand choice
13 determinants for DRT could be developed further by considering heterogeneous users profiles and
14 by enriching the model with the results of stated-preference surveys.

15 Another limitation of this study relates to the assignment model. The assignment strategies assume
16 that each vehicle makes its route and passengers choices independently. However, centralized
17 coordination of vehicles could lead to different and interesting results. In addition, transfers to
18 other transport modes are not considered at all.

19 Further work will address these issues by exploring complex coordination strategies between
20 vehicles that maximize the efficiency of the whole system. In addition, the interaction between
21 CPT and DRT could be developed further by considering a competitive/cooperative context where
22 both modes are available. As recommended by Sørensen et al. (2021), integration in the form of
23 intermodal transport will make DRT systems more feasible and applicable in the future. Finally,
24 using autonomous vehicles to provide the DRT service would be economically more profitable

1 and – according to (Sieber, et al., 2020; Berrada, 2019) – could outperform regular CPT services.
2 The consolidation of their results using our economic model is left to future research.
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