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Maximizing Carsharing Profits: An Optimization Model to Support the Carsharing Planning

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Abstract

Carsharing services aim to offer short-term car rentals, including round-trip and one-way alternatives. Round-trip clients must deliver the rented car at the same station where the rental has started. One-way clients can return the vehicle in a different station. This work proposes a Mixed-Integer Linear Programming Model to optimize the fleet-sizing of a carsharing service for the one-way and round-trip alternatives, seen as utilization scenarios. The proposed model aims to maximize the company's profit, finding the best number of vehicles to be allocated to each carsharing station. Different scenarios were analyzed for the one-way and round-trip settings, varying service costs, rental prices, number of clients, rental duration and driven distance. Simulations were performed using real spatial data from the city of São Paulo, Brazil. Results showed that round-trip profits can benefit from rentals with higher durations, and that one-way profits can overcome the profits from round-trip if user demand and number of available vehicles are enough.

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1. Introduction

The daily commuting is among the main routines of people living in urban areas. Whether for work, study, shopping or leisure purposes, part of the inhabitants' day is occupied by moving in the city. The spent time while commuting and other issues such as high transportation costs and low comfort, intensified by the population increase[1], mainly urban[2], has motivated studies to improve the transportation means. Among those studies are: improving the accessibility for public transportation [1], analyzing private driving patterns [2], comparing taxi trips from different metropolises [3], suggesting new transportation services [4], optimizing the assigning of buses to travels [5], and reducing transportation time and costs by integrating ride-sharing to public transportation [6].

Despite the bus and subway lines are often the cheapest transportation means, those services can show drawbacks to their passengers, such as:

- Few options (or inexistence of) bus and subway lines in certain regions;
- Low supply of buses at certain times;
- Need to transfer among bus and subway lines;
- Lengthy walks to get to a bus stop or subway station;
- Uncomfortable trips (in certain city regions and/or peak times).

Alternative transportation services can reduce those drawbacks, without substantially increasing the involved costs. Amid those alternative transportation services is the sharing of vehicles (carsharing). On the carsharing, the client rents a vehicle only for the time of use, which can be for only some minutes. As the client is also the driver, is not needed to pay a taxi driver. Therefore, the carsharing fares tend to be lower than the fares from taxi or similar services like Uber. Besides, there are carsharing modes in which the vehicle, after used, can be delivered to a station different from where the rental has started. In that case, the client can also avoid parking costs that could exist if that client was the vehicle's owner or had rented it by the whole day. Thus, carsharing can offer more comfort and flexibility than public transportation, costing less than owning a car [4].

In order to provide comfort and flexibility for a low cost, the vehicle supply in the carsharing stations must be suitable. The best number of vehicles to offer in each station can also varies depending on which carsharing mode is applied [4]. Among the existing carsharing modes, there are the round-trip mode and the one-way mode. On the round-trip mode, clients must deliver the rented car at the same station where the rental has started. On the one-way mode, clients can return the vehicle in a different station.

That difference between the carsharing modes induces two different profiles of rentals. Those different profiles vary mainly at factors that reflect on the rental fare. For example, since rental duration is one of the factors that determines the total rental price, clients who need to park the vehicle for a long duration probably will avoid using the round-trip mode [7]. In that case, the period with the vehicle parked would also be considered on the rental price. In contrast with that, on the one-way mode the vehicle can be delivered at the closest station to the client's destination, not having a parking period to count and probably making the rental cheaper. However, on the one-way mode and after that rental have been finished, whether the client wants to return to the origin station or aims to go to another destination by vehicle, the client would need to start another carsharing rental.

Besides the fare prices, those scenarios also produce different profits. Simulating those scenarios' costs and profits are important to the carsharing planning. With appropriate analysis and suitable software tools, carsharing companies can optimize its vehicle fleet in order to maximize profits by reducing service costs and increasing the number of attended clients. This work proposes an optimization model to simulate the carsharing's supply and demand, in order

[1] https://data.worldbank.org/indicator/SP.URB.TOTL
[2] https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS

to estimate the possible profit. The analyses presented here can be useful for carsharing decision-makers, mainly for those acting (or planning to act) on Brazil due to the utilization scenarios showed. The following section discusses the related work.

2. Related Work

Recently, complex problems have been solved using Simulation-Based Optimization approaches (SBO). SBO approaches enable the evaluation of parameter changes, being useful to support the decision-making process [8]. Most of the optimization problems for carsharing are deterministic, based on MILP (Mixed-Integer Linear Programming), and are Mono-Objective. However, some works unfollowed this pattern using stochastic methods, regression models or solving Multi-Objective problems. The following works made contributions related to those presented in this paper.

A MILP is proposed in [9] to maximize the profits of a carsharing service. The work aims to optimize the locations for carsharing stations, avoiding fleet disbalancing among the stations on the one-way mode. The authors evaluate three different settings of clients' generation, and showed the feasibility of the proposed MILP for a case study on Lisboa, Portugal.

The authors in [10] used Linear Regression and Beta Regression models to analyze how different factors affect a one-way carsharing station. The analyses were based on Shanghai, China. Among the other results, the authors found that regions with more public parking spaces tends to have more trips made by private vehicles than carsharing ones; and the relationship between subway and carsharing is complementary, but the relationship between bus and carsharing is competitive.

A carsharing network is optimized in [4] in order to enable stations based on round-trip also offer one-way rentals. Although the one-way mode can attend more clients, many carsharing companies does not offer that mode due to disbalancing issues among stations, caused by its different demand along the day. The authors proposed a MILP for the problem, and applied it for a case study on Boston, USA. The results showed that adding the optimized one-way mode to the service would increase the number of attended clients and raise the profits.

Profits and quality of service are optimized in [11]. The authors proposed a stochastic MILP based on Benders decomposition and evaluated the found solutions regarding the number of necessary vehicles, fleet used percentage, relocation costs of vehicles among carsharing stations, and metrics for quality of service. The proposed stochastic MILP performed the optimization faster than the commercial solver Gurobi[3] with default settings for MILP. The analyses were performed on a dataset from the Boston – Cambridge area in Massachusetts, USA.

The authors in [12] proposed a Multi-Objective MILP for the one-way's dynamics. The model has three objectives: minimizing the number of necessary workers to relocate vehicles; maximizing the number of vehicle relocations; and minimizing the lengthiest relocation route. The proposed model was applied in Milan, Italy.

This paper differs from the related works by optimizing the vehicles fleet allocation using data from São Paulo, Brazil. This work proposes a Mixed-Integer Linear Programming Model (MILP) to optimize the fleet-sizing of a carsharing service for the one-way and round-trip modes, seen as utilization scenarios. The proposed model aims to maximize the company's profit, finding the best number of vehicles to be allocated to each carsharing station. Different scenarios were analyzed for the one-way and round-trip settings, varying service costs, rental prices, number of clients, rental duration and driven distance. The following section presents the proposed MILP.

3. Modeling the Simulation-Based Optimization

This section presents the variables, constants, simulation rules and optimization constraints applied to the model. Before starting the optimization, clients are generated in order to simulate the carsharing demand. In this simulation, the clients can be attended or not. Each client is assigned to an origin station, and to a destination station. When the simulated scenario is based on round-trip, the origin and the destination stations must be the same. On the one-way scenarios, the origin and destination stations does not have to be the same. The number of clients starting and ending

[3] http://www.gurobi.com

a rental in each station is proportional to the number of residents in the São Paulo's district where the station is located. That choice was made in order to divide the demand in São Paulo, simulating more clients in regions with more population and vice versa. The stations' location used in the simulation example are the same as real vehicle dealerships located in São Paulo.

In the optimization, the set of all stations is indicated as S. The set of all clients is indicated as X. Each client is represented by a binary variable $x_r^s \in X$, with value 1 whether the client was attended and 0 whether the client was not attended. On the variable x_r^s, $s \in S$ indicates the client's origin station and $r \in S$ is the client's destination station. The constant P_s is a parameter representing the number of parking lots the station s has. The variable n_s indicates the number of vehicles the optimization allocated on the station s.

Each generated client has a starting time (indicating when the client looks for an available vehicle in the origin station) and an ending time (indicating when the client delivers the vehicle at the ending station). The variable $T_{start}^{x_r^s}$ indicates the client x_r^s starting time, and the variable $T_{end}^{x_r^s}$ indicates the client x_r^s end time. Those times were generated within the range 8:00 AM and 8:00 PM. That range was chosen based on the dealerships operating hours. The variable $D^{x_r^s}$ represents the driven distance by the client x_r^s. The time and distance were generated randomly, and both follows a uniform distribution.

In this simulation, the rental price is calculated according to two different formulas, each of them used by one carsharing company in São Paulo. The company 1 applies the formula presented in the Equation 1, and the company 2 applies the formula presented in the Equation 2. The formula used by the company 1 charges[4] R\$8 per rented hour (represented in the Equation 1 by the subtraction between the end time and the start time), and R\$0.50 per driven km. The formula used by the company 2 charges R\$10 per hour, R\$0.90 per km and has a minimum price per rental of R\$20. As a matter of comparison, on March 10, 2019, 1 US Dollar was about R\$3.87.

$$R_1^{x_r^s} = (T_{end}^{x_r^s} - T_{start}^{x_r^s}) * 8 + D^{x_r^s} * 0.50 \quad (1)$$

$$R_2^{x_r^s} = max\left(20, (T_{end}^{x_r^s} - T_{start}^{x_r^s}) * 10 + D^{x_r^s} * 0.90\right) \quad (2)$$

The optimization's objective function is presented on the Equation 3. The objective function is to maximize the sum of the clients' rental price, minus the sum of the client and vehicle costs. The client cost, represented by $C^{x_r^s}$ is a constant pre-calculated when the client is generated. The vehicle cost, represented by C^s, is a parameter constant determined for each station. The Equations 4-7 presents the MILP constraints.

The Equation 4 assures that a client x_r^s will only be attended if there is at least one vehicle available at the station s. The number of available vehicles at the station s is the number of allocated vehicles for that station (n_s) added to the sum of other clients (u_s^t) who had already rented and delivered a vehicle to that same station, before the client x_r^s. As it is possible that other clients (e_l^s) had already rented a vehicle before the client x_r^s, the vehicles rented by those clients e_l^s are subtracted from the available ones. The Equation 5 limits the number of allocated vehicles in each station to the number of station's parking slots. The Equation 6 defines the client variables as binaries, and the Equation 7 defines the number of allocated vehicles as an integer and positive number, including zero.

$$max \sum_{x_r^s \in X} R^{x_r^s} - \sum_{x_r^s \in X} C^{x_r^s} * x_r^s - \sum_{s \in S} C^s * n_s \quad (3)$$

Subject to:

[4]Brazilian currency: Reais (R\$)

$$x_r^s \leq n_s + \sum_{u_s^t \in X \,:\, T_{end}^{u_s^t} < T_{start}^{x_r^s}} u_s^t - \sum_{e_l^s \in X \,:\, T_{start}^{e_l^s} < T_{start}^{x_r^s}} e_l^s, \qquad \forall x_r^s \in X \tag{4}$$

$$n_s \leq P_s, \qquad \forall s \in S \tag{5}$$

$$X \in \{0,1\} \tag{6}$$

$$n_s \in \mathbb{N}^0 \tag{7}$$

The client cost $C^{x_r^s}$ used at Equation 3 is calculated using the driven distance, rental duration and a fixed cost per vehicle. As well as the two price models presented on Equation 1 and 2, two cost models are applied in the simulations. Those two price models are presented on Equation 8 and 9. On both models, the price cost is set as the same: R$0.50 per km. That value was chosen because it is the lowest charged price per distance between the companies' price models (Equations 1 and 2), and due to the gas price in São Paulo on March 10, 2019 was R$4.144 on average[5]. With that gas price, a vehicle with a consumption of 11 km per liter would spend about R$0.35 per km only for the fuel costs. In this simulation, the other R$0.15 per km is associated to the vehicle maintenance costs.

The rental duration cost and the fixed cost per vehicle are different on the two price models. The cost model 1 defines a cost formula considering that the vehicles are not exclusively used for carsharing. In this scenario, the vehicle cost only applies when the vehicle is rented. When the vehicle is idle, the company can use it for other purposes, not generating costs for the carsharing itself. Therefore, instead of defining a value for the vehicle fixed cost, the cost model 1 (represented by the Equation 8) defines a cost per rented hour.

That cost is calculated from the vehicle depreciation on the first year of use, and adding the applied tax. The vehicle depreciation is about 12% on the vehicle value [13], and the annual tax is 4% also on the vehicle value[6]. Summing both cost rates and 16% per year applied to a vehicle value considered of R$30,000, the vehicle cost per year is about R$4,800. Starting from this value, the cost per day is about R$13 and the cost per hour (considering the 12 working hours per day on the stations) is about R$1.10. The Equation 8 presents the cost model 1, which calculates the vehicle cost per hour, avoiding the daily fixed cost per vehicle. Therefore, in the cost model 1 the fixed cost per vehicle C^s, used in the objective function presented on Equation 3, is equal to 0. The Equation 9 presents the cost model 2, which does not have a vehicle cost per hour. But, when calculating the objective function for the cost model 2, each vehicle has a daily fixed cost C^s = R$13.

$$C_1^{x_r^s} = (T_{end}^{x_r^s} - T_{start}^{x_r^s}) * 1.1 + D^{x_r^s} * 0.50 \tag{8}$$

$$C_2^{x_r^s} = D^{x_r^s} * 0.50 \tag{9}$$

The maximum of vehicles to be simulated is 27, due to limits of the based vehicle dealership. The simulations were also performed varying the number of clients, and the rental duration and distance. The simulated number of clients were 100 and 300. As the users were generated randomly, their rental durations and driven distances varies inside minimum and maximum intervals. For one-way mode, the duration intervals were a minimum of 22 minutes and 30 seconds and a maximum of 2 hours per rental, and its double: going from 45 minutes to 4 hours per rental. The distance

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[5] https://precodoscombustiveis.com.br/pt-br/city/brasil/sao-paulo/sao-paulo/3830
[6] https://portal.fazenda.sp.gov.br/servicos/ipva/Paginas/mi-aliquota.aspx

intervals for one-way started from 2.5 km and ended at 25 km, and the other distance interval is its double: starting from 5 km and going to 50 km. As the round-trip mode consists in the client having to drive back to the origin station, the expected duration and distance on round-trip should be greater than those expected for one-way. By doing so, the intervals set to the round-trip mode are the double of the ones set to the one-way mode. The following section presents the experimental results for the proposed MILP and the chosen parameters.

4. Experimental Results

All the simulation results are presented on the Table 1. The results are sorted on the ascending order by daily profit. Besides the profit, the table also shows the optimal number of vehicles to be allocated and the total cost (summing client and vehicle costs) for each scenario.

The number of clients indicates to be a strong contributor to the profit. All the first 10 scenarios (with less profit) have only 100 clients, while all the last 9 scenarios (with more profit) have 300 clients. The carsharing mode also promotes a big influence to the profits. But the bigger profits with round-trip come together with greater values for the duration and distance interval parameters. Therefore, a naive comparison between the carsharing modes should be avoided. Although, all the scenarios with one-way and 100 clients are in the first half of the Table 1, and all the scenarios with round-trip and 300 clients are in the second half of the Table 1. Besides, the first 8 scenarios and the last 8 scenarios on the Table 1 does not change the carsharing mode and the number of clients. Those scenarios only intercalate the cost model, indicating that it does not influences as much as the mode and the number of clients. Even though there are an overlapping among the modes and parameters, the extreme cases tend to be well separated.

In general, the round-trip mode gets more profits than one-way because the price models valorize more the rental duration than the driven distance. Thus, even whether a one-way scenario attends more clients than the round-trip, if the one-way vehicles be more time idle than the round-trip ones, probably the one-way profits will be the less than the round-trip. But that situation can reverse as the one-way get more clients, making the vehicles less idle.

The extreme profits are strongly different. The scenario with the smallest profits makes R$223 a day, and the scenario with the highest profits makes R$4,373 a day, about 19.61 times greater than the smallest profit. The cost and price models also made a big difference among the results. The first 8 scenarios used the price model 1, and the last 24 scenarios used the price model 2. Although the cost models 1 and 2 appeared through all the table, all the scenarios with less than 27 vehicles appeared only with the cost model 2. That happened because at the cost model 2, the vehicles are considered to be exclusively used for carsharing. Therefore, if some of the 27 vehicles will not be used at least the enough to cover its fixed cost, it is more profitable to remove those idle vehicles from the carsharing than keep them, paying more costs than receiving profits. All the scenarios that did not use all the 27 vehicles appear among the first 20 scenarios in the Table 1.

Table 1. Simulation of carsharing profits on São Paulo, sorted by daily profit.

#	Mode	Clients	Duration	Distance (km)	Cost Model	Price Model	Vehicles	Cost (R$)	Profit (R$)
1	one-way	100	22m:30s - 2h	5 - 50	2	1	15	601	223
2	one-way	100	22m:30s - 2h	2.5 - 25	2	1	14	510	256
3	one-way	100	45m - 4h	2.5 - 25	2	1	16	552	309
4	one-way	100	45m - 4h	5 - 50	2	1	21	818	490
5	one-way	100	22m:30s - 2h	5 - 50	1	1	27	642	563
6	one-way	100	22m:30s - 2h	2.5 - 25	1	1	27	537	580
7	one-way	100	45m - 4h	2.5 - 25	1	1	27	566	647
8	one-way	100	45m - 4h	5 - 50	1	1	27	853	815
9	one-way	100	22m:30s - 2h	2.5 - 25	2	2	20	597	849
10	one-way	100	22m:30s - 2h	5 - 50	2	2	23	686	863
11	one-way	300	22m:30s - 2h	2.5 - 25	2	1	27	1416	878
12	one-way	300	22m:30s - 2h	5 - 50	2	1	27	1671	888

Table 1 (cont)

13	one-way	100	45m - 4h	2.5 - 25	2	2	22	611	974
14	one-way	300	45m - 4h	2.5 - 25	2	1	27	1359	1026
15	round-trip	100	45m - 4h	5 - 50	2	1	27	1257	1090
16	round-trip	100	45m - 4h	10 - 100	2	1	26	1608	1204
17	one-way	300	45m - 4h	5 - 50	2	1	27	1821	1217
18	one-way	100	22m:30s - 2h	2.5 - 25	1	2	27	539	1226
19	one-way	100	22m:30s - 2h	5 - 50	1	2	27	634	1278
20	one-way	100	45m - 4h	5 - 50	2	2	25	874	1331
21	round-trip	100	45m - 4h	5 - 50	1	1	27	1350	1337
22	one-way	300	22m:30s - 2h	2.5 - 25	1	1	27	1300	1350
23	one-way	100	45m - 4h	2.5 - 25	1	2	27	555	1354
24	one-way	300	22m:30s - 2h	5 - 50	1	1	27	1549	1367
25	round-trip	100	1h:30m - 8h	10 - 100	2	1	27	1363	1382
26	round-trip	100	1h:30m - 8h	5 - 50	2	1	27	1257	1404
27	round-trip	100	45m - 4h	10 - 100	1	1	27	1739	1439
28	one-way	300	45m - 4h	2.5 - 25	1	1	27	1282	1459
29	round-trip	100	1h:30m - 8h	10 - 100	1	1	27	1527	1568
30	round-trip	100	1h:30m - 8h	5 - 50	1	1	27	1408	1604
31	one-way	300	45m - 4h	5 - 50	1	1	27	1756	1640
32	one-way	100	45m - 4h	5 - 50	1	2	27	851	1677
33	round-trip	300	45m - 4h	10 - 100	2	1	27	2292	1809
34	round-trip	300	45m - 4h	5 - 50	2	1	27	1908	1840
35	round-trip	300	1h:30m - 8h	5 - 50	2	1	27	1629	1992
36	round-trip	300	45m - 4h	10 - 100	1	1	27	2469	1998
37	round-trip	300	45m - 4h	5 - 50	1	1	27	2045	2035
38	round-trip	300	1h:30m - 8h	10 - 100	2	1	27	1891	2067
39	round-trip	300	1h:30m - 8h	5 - 50	1	1	27	1835	2138
40	round-trip	300	1h:30m - 8h	10 - 100	1	1	27	2123	2179
41	one-way	300	22m:30s - 2h	2.5 - 25	2	2	27	1442	2337
42	round-trip	100	45m - 4h	5 - 50	2	2	27	1286	2355
43	one-way	300	45m - 4h	2.5 - 25	2	2	27	1372	2447
44	one-way	300	22m:30s - 2h	5 - 50	2	2	27	1739	2546
45	round-trip	100	45m - 4h	5 - 50	1	2	27	1392	2605
46	round-trip	100	1h:30m - 8h	5 - 50	2	2	27	1286	2734
47	round-trip	100	1h:30m - 8h	10 - 100	2	2	27	1388	2801
48	round-trip	100	45m - 4h	10 - 100	2	2	27	1743	2831
49	one-way	300	22m:30s - 2h	2.5 - 25	1	2	27	1282	2838
50	one-way	300	45m - 4h	2.5 - 25	1	2	27	1256	2916
51	round-trip	100	1h:30m - 8h	5 - 50	1	2	27	1446	2938
52	round-trip	100	1h:30m - 8h	10 - 100	1	2	27	1551	2989
53	one-way	300	45m - 4h	5 - 50	2	2	27	1824	2997
54	one-way	300	22m:30s - 2h	5 - 50	1	2	27	1588	3040

Table 1 (cont)

55	round-trip	100	45m - 4h	10 - 100	1	2	27	1851	3075
56	one-way	300	45m - 4h	5 - 50	1	2	27	1727	3437
57	round-trip	300	1h:30m - 8h	5 - 50	2	2	27	1708	3743
58	round-trip	300	45m - 4h	5 - 50	2	2	27	2016	3776
59	round-trip	300	1h:30m - 8h	5 - 50	1	2	27	1919	3896
60	round-trip	300	45m - 4h	5 - 50	1	2	27	2173	3977
61	round-trip	300	1h:30m - 8h	10 - 100	2	2	27	2030	4104
62	round-trip	300	45m - 4h	10 - 100	2	2	27	2570	4174
63	round-trip	300	1h:30m - 8h	10 - 100	1	2	27	2290	4224
64	round-trip	300	45m - 4h	10 - 100	1	2	27	2725	4373

5. Conclusion

In this paper was proposed a Mixed-Integer Programming Method to simulate the carsharing dynamics in order to maximize the company profits. The model optimizes the carsharing fleet-sizing for diverse scenarios, evaluating the one-way and round-trip modes, their expected rental durations and driven distances, comparing two proposed cost models, and relating them to two rental prices formulas used by carsharing companies in São Paulo. The results showed that the round-trip mode tends to make more profits due to the longer rental durations. But the more flexible characteristics of one-way can bring more clients to the service, reducing the vehicle idle times, and raising profits.

Even with many small differences of profits through scenarios, it is possible to find clearer patterns on the Table 1 extremes. The relation between carsharing mode and number of clients become evident on both start and end of the table, as well as the relation between the cost model and number of vehicles used. As future works, is recommended simulating on different and more extensive scenarios; changing the vehicle depreciation cost to better accommodate the years of use further than the first one (applying different depreciation rates); and analyzing which parameters have more impact on the simulation-based optimization.

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