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Abstract

Car sharing (CS) services have become popular due to their financial and environmental benefits. The CS operators have offered flexibility by allowing one-way trips which resulted in vehicle imbalance in the service area. They have then introduced rebalancing operations to reduce the imbalance, and thus, to increase the level of service. The methods studied in the literature focus on forecasting the demand to determine the rebalancing strategy. This work proposes a framework which compares different strategies to solve rebalancing operations in one-way station-based car sharing systems in terms of cost and level of service. One of the crucial components of this framework is a demand model that represents the daily flow in the network. Instead of collecting the trip demand data, we feed the trip demand output of Multi-Agent Transport Simulation Toolkit (MATSim) as an input to our framework. This also allows us to explore the different uncertainties that can occur in the system, such as fluctuations in trip demand. The results of the framework help the decision maker to better analyze the system and choose the best rebalancing strategy under different scenarios.

Keywords

Car sharing, MATSim, rebalancing operations

1 Introduction

The global greenhouse gas emissions become more and more concerning. According to the United States Environmental Protection Agency (EPA), the main contributor is found to be the transportation activities with 37.5% of the US CO₂ emissions in 2019. Among several contributors, passenger cars is the largest one with 40.5% (EPA, 2021). Sharing economy is one of the approaches in transportation that aims to reduce emissions. Amatuni *et al.* (2020) show that introducing a car sharing system results in at least 3% and up to 18% reduction in CO₂ emissions.

The history of car sharing starts with the initiative named "Selbstfahrgemeinschaft" in Zurich, Switzerland, in 1948 (Shaheen *et al.*, 1998). As these systems require a user identification, which was not easy at the time, they were small and local. They have become larger and more popular with the advances in technology as it has become much easier to operate these kinds of systems. The raising environmental concerns has also been an important contributor. The usage cost is generally determined as a function of distance traveled and the duration of the rental. Using the car sharing system takes away the burden of maintenance works and insurance costs and spreads it over several users. This makes the car sharing attractive from the user-point of view not only because it is less costly, but also because of its convenience. Some examples from the world include Mobility in Switzerland, SHARE NOW in several cities around Europe, and Zipcar in several countries in the world including the United States.

There are several possible configurations of car sharing systems. The system can be either station-based, i.e., the parking spots are pre-defined and allocated for the car sharing system only, or free-floating, i.e., the parking can be done within a pre-defined area that is in general the whole system operation area. The trip configuration can be round-trip and one-way. In the former, the user is required to return the car to the same parking spot that she picked it up. The latter does not impose this requirement, which results in vehicle imbalance throughout the system operation area. In order to overcome this imbalance, the operators usually deploy rebalancing operations. These operations can take place when the system is closed or low in operation, such as at night, which is called static rebalancing. It is also possible to rebalance vehicles at any time of the day, that is while the system serves the users. The dynamic rebalancing operations further split into two in terms of application: online and offline. In online dynamic rebalancing operations, the rebalancing decisions are made at the beginning of each time horizon and utilize a rolling horizon approach, whilst in offline dynamic rebalancing the decisions are made at the beginning of the horizon and do not change.

The complexity of rebalancing operations in car sharing does not only come from the determination of which vehicle is going to be relocated to which station. As it is impractical to rebalance cars using trucks (as in bike sharing systems), the operator should either hire staff that will relocate the cars or apply incentives to make the users rebalance the system. The latter approach, that is mostly referred as user-based rebalancing in the literature, uses some dynamic pricing techniques. In this application, different prices are offered to the system users. The operator aims to affect users' decisions to make them take the initiative to perform less popular trips. On the other hand, when staff-based rebalancing is used, staff routing adds an additional dimension to the problem. This work focuses on operator-based rebalancing operations.

Although there is considerable amount of research on car sharing, few of them consider disaggregate information. This is due to several reasons. For example, obtaining disaggregate data is not easy. The operator should conduct or obtain a detailed survey. Also, it is computationally difficult to utilize disaggregate data. On the other hand, it is essential to use such data to see the direct effect on the individuals such as mode choice. Activity-based multi-agent transport simulation is one tool to handle this. However, they lack the representation of the supply side such as rebalancing operations. Therefore, we propose a methodological framework that consists of both the demand side (mode choice and disaggregate simulation) and the supply side (rebalancing operations).

The rest of the paper is organized as follows. Section 2 reviews the car sharing literature from three aspects: rebalancing operations optimization, discrete choice models, and activity-based multi-agent transport simulation. In Section 3, we introduce the methodological framework and its components. Later in Section 4, we present the first results of this framework. We conclude the paper by giving some future research directions in Section 5.

2 Literature review

This section first investigates both supply and demand side operations of car sharing systems at operational level by reviewing works on rebalancing operations optimization and choice models. Later, we survey the transport simulations that are able to handle disaggregate trip demand information. Finally, we go through works that are similar to our research and specify the research gap.

2.1 Rebalancing operations optimization

The imbalance created in car sharing systems by one-way trips can be overcome by applying vehicle rebalancing. In this subsection, we talk about some works on operator-based rebalancing operations in one-way station-based car sharing systems. For a more thorough review on such systems, the reader is kindly referred to Illgen and Höck (2019).

Rebalancing operations optimization can be decomposed into two sub problems: vehicle rebalancing and staff relocation. The staff can be relocated in several ways, such as by using foldable bikes (Martin *et al.*, 2021), public transportation (Repoux *et al.*, 2019), car pooling with other staff members (Martin and Minner, 2021), and foldable scooters (Martínez *et al.*, 2017). The staff is less restricted when they use foldable bikes or scooters as they do not need to take the public transport schedule into account and do not rely on their colleagues to car pool. On the other hand, it requires physical effort. Although many papers ignore the staff relocation problem in the literature and only deal with vehicle rebalancing, it is important to consider them both because they are crucial to determine whether the proposed solution is feasible and they contribute to the cost function. Some system parameters, such as available number of vehicles and staff, and target level of service impose further constraints to the problem.

The objective of such operations can be operator-focused, i.e., maximizing the profit or minimizing the total cost (Gambella *et al.*, 2018), and/or user-focused, i.e., minimizing the lost demand or maximizing the user satisfaction (Zhao *et al.*, 2018; Repoux *et al.*, 2019). In general, the cost function consists of vehicle rebalancing, staff relocating, and maintenance costs. The user-focused approaches often assume that the trip demand is known a priori and calculate the level of service as the ratio of total satisfied trip demand to total trip demand. The authors usually consider one of these objectives and constrain on the other one.

When electric vehicles are also involved in the system, the charging requirements impose additional constraints (Gambella *et al.*, 2018). On the other hand, deploying autonomous cars in the sharing system eliminates the staff relocation problem. Although this work does not consider neither electric nor autonomous cars, our proposed framework is still applicable with slight changes.

The dynamic rebalancing operations further involves time dimension. Generally, the network is extended to a time-space network, also known as time-expanded and time-extended graph, to keep track of the time (Gambella *et al.*, 2018; Zhao *et al.*, 2018).

This increases the computational complexity of the problem. The literature consists of several approaches such as heuristic algorithms (Gambella *et al.*, 2018), decomposition methods (Zhao *et al.*, 2018), and branch-and-bound (Boyacı *et al.*, 2015) to overcome the computational burden.

2.2 Choice models

Discrete choice models are utilized to describe, explain, and predict among two or more discrete alternatives. In the context of transportation, this can translate to mode choice. Furthermore, the derived utility functions allow analysis on several characteristics of car sharing such as mode share and the effect of socio-economic characteristics on the mode share.

In order to estimate choice models, the first step is to collect the data. These can be obtained through stated-preference (SP) surveys (Dias *et al.*, 2017; Carrone *et al.*, 2020) and combination of both SP and revealed-preference (RP) surveys (Li and Kamargianni, 2019; Cartenì *et al.*, 2016). To the best of our knowledge, there does not exist a work that develops a choice model in car sharing using RP data only. SP surveys can be conducted whether or not the service is available to the users, whilst an RP survey requires a well-established system.

The literature consists of several different discrete choice models developed regarding the mode choice in the presence of car sharing system. These include variances of probit model (Dias *et al.*, 2017), logit model (Carrone *et al.*, 2020; Cartenì *et al.*, 2016), nested logit model (Li and Kamargianni, 2019; Catalano *et al.*, 2008), and multinomial logit model (Catalano *et al.*, 2008). Some works also explore the effect of latent variables such as advocacy of car sharing service (Li and Kamargianni, 2019). In general, the considered transport modes are public transportation, private car, bike and walk. Few works also consider bike-sharing, electric bike, taxi (Li and Kamargianni, 2019), ride-sourcing (Dias *et al.*, 2017), car-pooling (Catalano *et al.*, 2008), two-wheeler sharing, and prospective future vehicles (Zhou *et al.*, 2020).

These works present interesting results. Less educated people prefer car sharing less than more educated ones (Li and Kamargianni, 2020; Zhou *et al.*, 2020). Furthermore, they are more sensitive to increase in price of car-sharing service, i.e., an increase in travel cost further pushes away people that are less educated. The findings of Dias *et al.* (2017)

also support that well-educated people tend to use car-sharing more as well as young and rich people. Residing in high density neighborhoods is another common characteristic of car-sharing users. On the other hand, the presence of children plays a negative role in choosing car sharing (Dias *et al.*, 2017), possibly due to more complex activity-travel patterns and budget constraints.

Carrone *et al.* (2020) claim that the value of time spent during park place search with a car sharing vehicle is 20% more than the value of time spent during the actual travel. The survey conducted by Migliore *et al.* (2018) reveals that the car sharing users consider the unavailability of cars as a weakness of the service. These findings imply that the availability of both vehicles and parking is an important factor.

The question of whether car sharing substitutes or complements public transport has different answers in the literature. The results from Migliore *et al.* (2018) show that car sharing is complementary to public transport whilst Migliore *et al.* (2020) claim that a shared car replaces four private cars. Furthermore, Carrone *et al.* (2020) find that station-based services complement public transport while free-floating car sharing substitutes it. In general, it is a substitution for public transport. Last but not least, Li and Kamargianni (2020) note that private car usage does not reduce when car sharing service is more attractive, instead public transport is sacrificed much more. When radical policies are applied, such as considerably increasing private car travel cost and parking cost, the results claim otherwise, meaning that private car usage reduces with a car sharing service.

2.3 Transport simulation

The car sharing research is mostly focused on using aggregate trip demand information. This aggregation can be done at many levels including spatial and temporal. The need for aggregation usually results from the fact that handling disaggregate data is computationally challenging. To utilize disaggregate data, there is a need for a sophisticated toolkit.

Four-step trip-based models (FSM) are one of the most popular approaches in the literature. These models include four main components: (1) trip generation, (2) trip distribution, (3) mode choice, and (4) traffic assignment (Vosooghi *et al.*, 2017). However, these models cannot answer complex questions as they are static and sequential (Balać *et al.*, 2015). There are several transport simulation toolkits in the literature that are activity-based

multi-agent platforms. Some open source examples are Multi-Agent Transport Simulation Toolkit (MATSim), SimMobility, and mobiTopp (Vosooghi *et al.*, 2017). The first is implemented in Java programming language, and is able to simulate millions of agents in a metropolitan area for one day. It is a modular toolkit and follows a queue-based approach (Horni *et al.*, 2016). Another modular platform SimMobility of which the application area is wider than MATSim aims to analyze the impacts on transport networks, vehicle emissions, and intelligent transportation services. It consists of three primary modules, i.e., short-term, mid-term, and long-term. These correspond to operational, tactical, and strategic decision levels, respectively (Adnan *et al.*, 2016). Although mobiTopp was originally designed to simulate one day, it is later extended to run an analysis of one week. It is similar to SimMobility in the sense that it has two parts: short-term and long-term modules (Reiffer *et al.*, 2021).

As car sharing requires modeling both spatial and temporal location of vehicles, the aggregate FSM cannot provide a detailed analysis. Thanks to the disaggregate nature of MATSim and the car sharing API, it is possible to conduct more thorough analyses and answer more complex scientific questions for such systems (Balać *et al.*, 2015). For example, Balać and Ciari (2015) design strategies, i.e., a base scenario and two strategies, that help them to understand potential car sharing demand. Only round-trip car sharing is available in the base scenario. The two strategies are set up as follows: the first starts with the original distribution of the vehicles and tries to find a stable state where the car sharing serves the most number of trips, whilst the second starts with infinite number of cars at each station and the resulting number of cars per station is used as an initial configuration.

2.4 This work

Next, we present two papers that adopt a similar idea to the one presented in this paper.

Martínez *et al.* (2017) claim that their work is the first to include both an agent-based simulation and the supply side to analyze a one-way car sharing system. They develop a detailed agent-based model that simulates such a system. This simulation utilizes a stochastic demand model discretized in time and space. The framework is applied to a case study in Lisbon, Portugal. Dynamic rebalancing is adopted and the two types of agents are staff members and users. Staff members stay in a depot, and assigned to a operations such as maintenance, relocation, and refueling, when necessary. In Vasconcelos

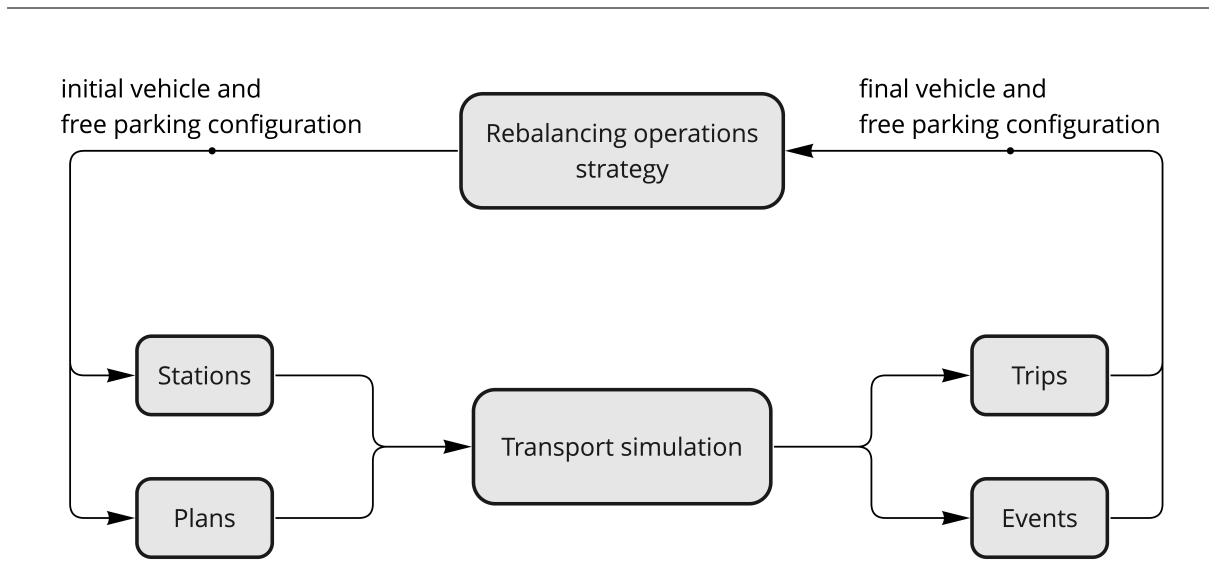
et al. (2017), the authors use the agent-based model developed in Martínez *et al.* (2017). First, they consider two base cases: with and without rebalancing operations. They also investigate three different policies to see the effect of electric vehicle adoption: (1) making parking free for electric vehicles, (2) VAT tax exemption for electric vehicles, and (3) more competitive prices for electric vehicles. The results show that all three policies show positive annual net profit for the operator, where the third policy brings the most annual net profit. However, the first two policies are more dependent on governmental decisions whilst the third depends mostly on the car manufacturer.

We also follow a similar approach to Martínez *et al.* (2017) and Vasconcelos *et al.* (2017) in the sense that we consider both supply and demand side of car sharing to analyze different strategies. Instead of developing a new agent-based simulation, we use MATSim. As discussed earlier, MATSim is a powerful toolkit that always expands and improves. The availability of car sharing API also makes it appealing for our framework. Also, the data for several cities in the world and the source code are openly available for research. This work is a preliminary work where we test two strategies: with and without rebalancing operations similar to Vasconcelos *et al.* (2017). However, our work incorporates a rebalancing operations optimization in the framework unlike these two studies.

3 Methodology

This section presents the proposed framework that aims to determine the added-value of rebalancing operations in one-way station-based car sharing systems. We first explain the framework (Figure 1) in general terms and then go into the details later in this section. This framework has three main components: the agent-based transport simulator (in our case, MATSim), rebalancing operations optimization that follows the rebalancing operations strategy, and choice modeling that affects the plans of the agents. After simulating one day for some pre-specified number of iterations using MATSim, the realized daily trips are obtained. Using this information, the final state of the vehicles and parking spots are computed and given to the rebalancing operations optimization as an input. The rebalancing module applies a rebalancing operations strategy which changes the initial configuration of the following day. This changes the choices of the agents in the next iteration of our framework. The initial vehicle and parking configuration along with the plans, facility, and network files are fed back to MATSim.

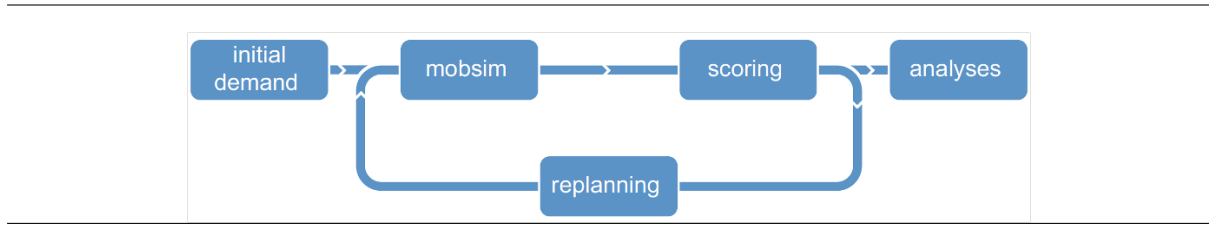
Figure 1: The proposed framework



MATSim is an activity-based, modular, and multi-agent simulation framework (Horni *et al.*, 2016). It implements a queue-based model. This way, it is possible to run large-scale scenarios efficiently. Although it is designed to experiment a single day, it is also possible to implement a multi-day model. The general working principle of MATSim is based on the co-evolutionary principle. It does not only involve route assignment, but also incorporates time, mode, and destination choice.

There are five main modules of MATSim (Figure 2). An *initial demand* that is derived from empirical data through sampling or discrete choice modeling is an input for the first iteration along with the configuration file and the city characteristics such as the city network, transit schedule and facilities. Then, *mobsim* module simulates one single day and the scores are calculated by the module *scoring*. One should note that more recent versions include choice modeling in this part. Then, the *replanning* module allows a certain percentage of agents to modify their plans. This modification can be done randomly or according to some strategy such as best-response. This iterative loop, i.e., transport simulation, is repeated until a pre-specified number of iterations is reached. Then, the output of the last iteration is passed to the *analyses* module for further analysis on both the final state and the progress of the simulation. More detailed information on MATSim, such as how the city network and population are created, is available in Horni *et al.* (2016).

The first efforts to include car sharing in MATSim started in 2009 (Ciari *et al.*, 2010).

Figure 2: The MATSim loop (Horni *et al.*, 2016)

All three configurations of car sharing, i.e., round-trip, one-way and free-floating, are currently available in car sharing API of MATSim. Ciari and Balać (2016) present the general functionality of this API.

For the sake of completeness, we next present the working principle of one-way car sharing: (1) after the agent finishes her activity, she finds the closest car sharing station with an available car and reserves one, (2) walks to the station, (3) finds the closest station to her destination and reserves a free parking spot, (4) drives the car to the reserved spot, (5) parks it and ends the rental, (6) walks to the next activity, and (7) follows the rest of the daily plan Ciari and Balać (2016).

After a specific number of iterations is reached, the realized trips information provides the final state of the vehicles and parking, that can be used by the rebalancing operations. The literature consists of several different strategies to conduct rebalancing operations, such as proactive and reactive. For the current state of the research, we build up the framework and get preliminary insights by following two simple rebalancing operations strategies.

The first strategy is a "do nothing" strategy. As the name implies, the final configuration of vehicles of the previous iteration is taken as an initial vehicle configuration for the next iteration. The second strategy is called "rebalance". We first calculate the minimum vehicle inventory reached per station during the day, and define this as minimum number of vehicles required for that station. Then, if the total number of minimum required vehicles per station is less than the initial number of vehicles, we sequentially distribute the excess number of vehicles among stations. This becomes the initial vehicle configuration for the following iteration. The initial free parking configuration is computed by taking the difference between available spots and the number of vehicles at each station.

The generalized cost of car sharing travel from activity $q - 1$ to activity q used in MATSim

is shown in Equation (2) (Ciari and Balać, 2016).

$$U_{trav,q,cs} = \alpha_{cs} + \beta_{c,cs} \cdot c_t \cdot t_r + \beta_{c,cs} \cdot c_d \cdot d + \beta_{t,walk} \cdot (t_a + t_e) + \beta_{t,cs} \cdot t \quad (1)$$

Here, the first term α_{cs} refers to the alternative specific constant. This value differs for different types of car sharing configurations. The next two terms relate to the time and distance dependent components of the fee, respectively. Specifically, t_r is the total reservation time and c_t is the cost of one hour of reservation time, d is the distance travelled by car sharing vehicle and c_d is the cost of one kilometer travel. The fourth term takes the access and egress times into account and the last component considers the in-vehicle travel time. Therefore, the coefficients related to car sharing can be interpreted as follows:

- $\beta_{c,cs}$ is the marginal utility of an additional unit of money spent on traveling with car sharing and
- $\beta_{t,cs}$ is the marginal utility of an additional unit of time spent on traveling with car sharing.

For the other modes available in MATSim, such as walking, private car, public transportation, bike, the utility of traveling is as follows:

$$U_{trav,q,mode} = \alpha_{mode} + \beta_{c,mode} \cdot c_d \cdot d + \beta_{t,mode} \cdot t \quad (2)$$

One should note that this work presents a very early stage of the research. For the time being, neither rebalancing operations optimization nor choice modeling is integrated into the framework. Instead, we use some easy-to-apply strategies for rebalancing operations and the utility function definitions for the transport modes are used as they are suggested in the instance provided by the MATSim developers for the studied case study. In fact, following the literature review on rebalancing operations optimization in one-way station-based car sharing systems, we have selected two different strategies from the literature as candidates to be integrated to our framework (Gambella *et al.*, 2018; Zhao *et al.*, 2018). However, we do not discuss them in details here as they are still under development.

4 Preliminary results

This work utilizes the Sioux Falls, South Dakota, USA scenario, that is publicly available in (MATSim, 2022). The simplified network, that contains the major roads of the city, can be seen in Figure 3. The population file includes 84110 agents, and we run 100% of the population. The three main activities that the agents have in their plans are home, work (67%), and secondary (32.3%). As all the plans start and finish at home, this is always included in agents' plans. The facilities consist of home (83.3%), work (11.1%), secondary (5.3%), and edu (0.3%) places. The available transport modes are car, public transport, bike, walk, and one-way car sharing. The two other types of car sharing available in MATSim, i.e., return-trip and free-floating, as well as competition between different car sharing service providers are not considered in this study.

Figure 3: Sioux Falls scenario



We further create car sharing stations and membership information as this scenario does not provide car sharing infrastructure. The created car sharing stations can be seen at each main intersection of the network in Figure 3. This makes to 24 stations in total.

For preliminary experiments, we start with an initial configuration where 5 vehicles and 5 free parking spots are available at each station. Then, for the "do-nothing" scenario, we determine the final configuration of the vehicles for one iteration, and feed it back to MATSim as an initial configuration for the next iteration and run it. This reflects not doing any rebalancing. For the "rebalance" scenario, the minimum required vehicles per station is computed and the free parking is determined where each station has 10 total parking spots.

The literature argues that the search distance, that is willingness to walk to a car sharing station, changes between 400 meters and 800 meters (Shaheen *et al.*, 2016). As these distances translate to a very wide area in a small network like Sioux Falls, we set the search distance to 200 meters. For the time being, we assume that every agent has access to the car sharing system. In other words, every agent has a car sharing membership.

For the preliminary experiments, we run the transport simulation for 100 iterations and the outer loop of the framework for 10 iterations. We observe that 100 iterations within MATSim takes around 20-25 minutes. In Figure 4, we see that the simulation converges after 65-70 iterations. So, for future work, we can lower the number of iterations within MATSim to 70 and save from computation time. We assume that the rebalancing operations take place instantly and they do not incur any cost. In future work, this will be included in the framework to be able to evaluate the added-value of rebalancing operations.

When we look at the mode share results from the "rebalance" strategy in Figure 5, we see that the mode shares for car, public transport, bike, walk, and one-way car sharing are 70.9%, 9.6%, 9.6%, 9.7%, and 0.2%, respectively. Martínez *et al.* (2017) observe that the modal share of car sharing service is 2.4% in Lisbon, Portugal. Among these users, 40% of them shifts from walking, 26% from private car, and 32% from public transportation, compared to the baseline scenario where no car sharing service is available. Li and Kamargianni (2020) show that the modal split for car sharing changes between 18.8% and 21.6% for short distance and between 19% and 23.3% for long distance, depending on the adopted scenario in Taiyuan, China. In Palermo, Italy, Catalano *et al.* (2008) claim that the modal split of car sharing can be increased up to 10% depending on some future pricing strategies. Our results show that the mode share for the car sharing service much lower than the ones indicated in the literature. Therefore, future work includes analyzing this.

Figure 4: The score statistics for "rebalance" strategy

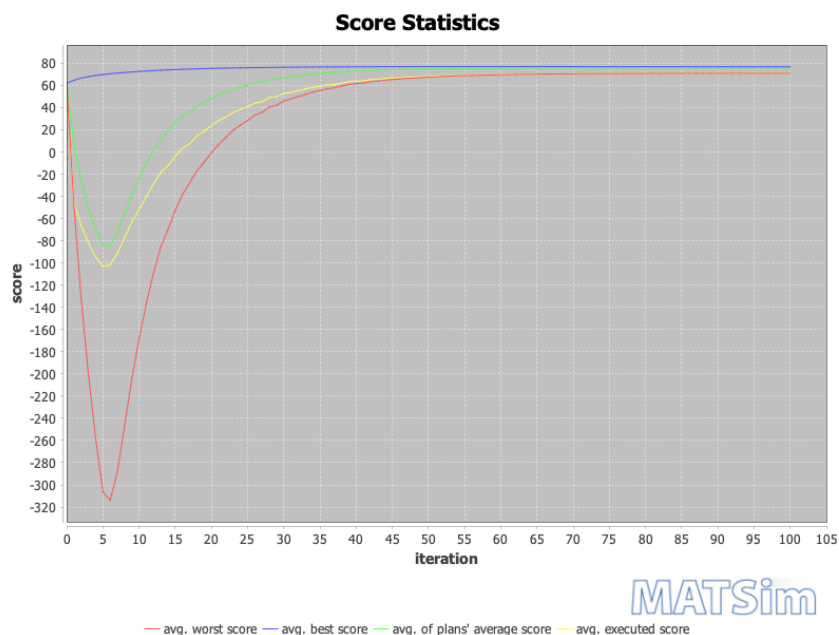
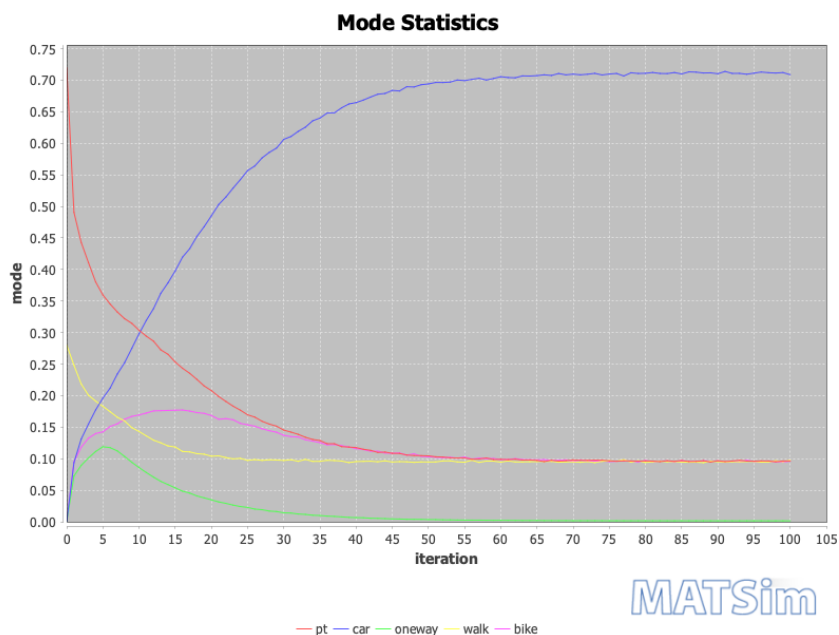


Figure 5: The mode statistics for "rebalance" strategy

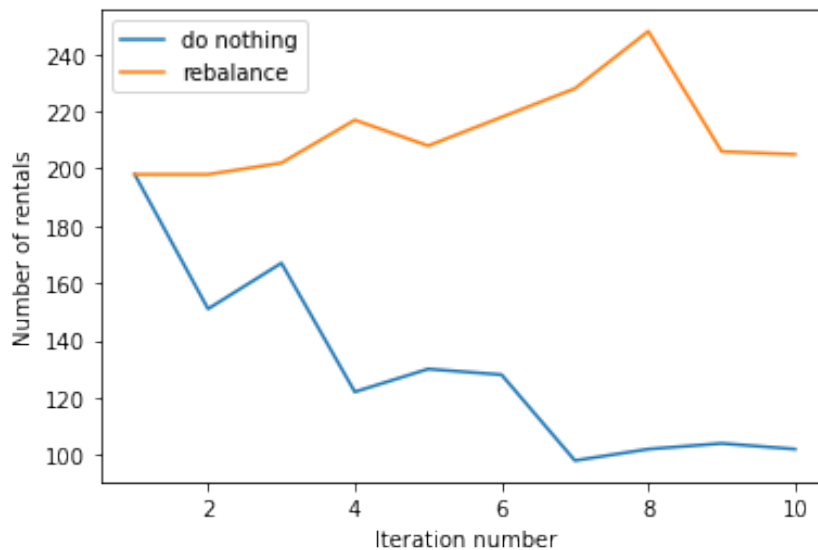


Regarding the trip purpose of car sharing trips, we observe that 56% is related to work activities (47.9% from home to work, 8.1% from work to home) and 44% is related to secondary activities (22.2% from home to secondary, 21.8% from secondary to home).

We also analyze the number of rentals for each iteration (Figure 6). The x-axis refers to the iterations conducted in the outer loop of the framework rather than within MATSim.

With the "rebalance" strategy, we see that the number of rentals stay around the same values (minimum value is 198 and the maximum value is 248). Interestingly, we see fluctuations instead of a trend. One reason can be due to unnecessary rebalancing that hardly leaves parking spots in the necessary positions. On the other hand, we need to run the tests several times to confirm whether this fluctuation occurs in the long-run, and if so investigate the possible reasons. When we look at the values obtained with "do nothing" strategy, we see consistent results as there is lower number of rentals with this strategy compared to "rebalance" strategy. In fact, the number of rentals gets lower and lower as the iterations proceed. This is expected as the stations who have more pick-ups than drop-offs start emptying and the stations who have more drop-offs than pick-ups start being filled with vehicles that are not used.

Figure 6: The number of rentals for both strategies



Another interesting observation from Figure 6 is that with "do-nothing" strategy the number of rentals tend to decrease for some number of iterations after reaching a high number of rentals. On the other hand, with the "rebalance" strategy, we see that the number of rentals tend to increase after reaching a low number of rentals. This makes sense as the overall trend of number of rentals decreases with the "do nothing" strategy whereas it increases with the "rebalance" strategy. This promising result will be further examined in future work.

5 Conclusion and future work

In this paper, we present an early attempt to create a framework that integrates transport simulation, rebalancing operations optimization, and choice modeling. The main purpose of this framework is to exploit the disaggregate nature of the multi-agent transport simulation (MATSim) toolkit and evaluate different strategies to solve rebalancing operations in one-way station-based car sharing systems. We go through the literature regarding these three main topics in one-way station-based car sharing systems to better position ourselves in building this framework. Later, we present some preliminary analyses on a case study from Sioux Falls, US.

As this is a preliminary work, future work includes many aspects. First of all, investigating the two simple rebalancing strategies studied in this paper with more number of iterations is important to achieve stable results. Then, we plan to integrate the rebalancing operations optimization in our framework. To do that, we consider using the two strategies by Gambella *et al.* (2018) and Zhao *et al.* (2018). Finally, we aim at including a choice model in the framework. Regarding the case studies, to be able to compare our results with the literature, we plan to use Switzerland scenario.

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