# A general framework to evaluate different rebalancing operations strategies in one-way car sharing systems

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**Abstract.** Car sharing systems (CSSs) are one of the environmentally beneficial solutions in urban transportation. However, the operators still struggle to make these systems profitable. One of the main contributors in operational cost is rebalancing operations. Therefore, it is important to identify strategies that are tailored according to the needs of the considered system. To overcome this challenge, this work proposes a simulation-optimization framework that compares different rebalancing operations strategies in one-way station-based car sharing systems in terms of cost and level of service. The simulation module utilizes the Multi-Agent Transport Simulation Toolkit (MATSim) whilst the rebalancing operations are determined in the optimization module. The framework allows us to explore the different uncertainties that can occur in the system, such as fluctuations in trip demand thanks to the MATSim. The results of the framework help the operator to better analyze the system and the best rebalancing strategy under different scenarios.

**Keywords:** car sharing systems, optimization, agent-based simulation

## 1 Introduction and literature review

Car sharing systems are considered to be one of the sustainable mobility solutions. The higher parking and vehicle utilization, the more can environment benefit from its usage. From the user perspective, it becomes attractive as they share the fixed costs of owning a car, such as insurance, maintenance, and parking, with other system users. On the other hand, this requires smart decisions at every decision level, i.e., strategic, tactical, and operational. This paper focuses on the tactical and operational level decisions [1]. We kindly ask the reader to refer to [1] for the car sharing system terminology.

Initial systems are formed as round-trip, and later with the technology, they are replaced with station-based one-way and free-floating systems. However, increasing user flexibility leads to more complex challenges for the operator. These include rebalancing operations, trip demand forecasting, and disaggregate mode choice at the operational level.

Rebalancing operations are applied in systems, where one-way trips are allowed, to reduce the vehicle imbalance in the service area. The rebalancing operations can be static or dynamic. In the former, the operations are conducted at night or when the system is low in operation [2], whereas in the latter, they are done during the system operating hours. In general, the network is expanded to a time-space graph to represent the dynamic structure [3,4], which increases the computational complexity of the problem. Therefore, the works propose heuristic algorithms to overcome the burdens of the computational complexity.

Obtaining and utilizing disaggregate data for trip demand forecasting is effortful. It requires a detailed survey, analysis, and computational time, whereas using such data is essential to reflect the heterogeneity of the population and see the direct effects on individuals. Traditional four-step trip-based models (FSMs), that include trip generation, trip distribution, mode choice, and traffic assignment, cannot answer complex questions as they are static and sequential. Therefore, the literature proposes transport simulation toolkits that are activity-based multi-agent platforms to be able to analyze each agent. Some examples to such toolkits are the Multi-agent Transport Simulation Toolkit (MATSim), SimMobility, and mobiTopp [5].

In the literature, most works focus on one specific subject rather than having a holistic approach. Furthermore, although activity-based multi-agent transport simulation toolkits can handle the disaggregate data, they lack the representation of the supply side. To fill this gap, we introduce a framework, that consists of three main components: the agent-based transport simulator, rebalancing operations optimization that follows a rebalancing operations strategy, and choice modeling that affects the plans of the agents. We use this framework to identify the best rebalancing strategy in combination with agent-based modeling for a one-way station-based car sharing system with operator-based rebalancing operations solutions, which is not studied in the literature, to the best of our knowledge. This way both supply and demand sides of car sharing systems are considered. We utilize MATSim as a transport simulator because of the possibility to simulate car sharing transport mode [6]. The disaggregate nature of MATSim allows a detailed analysis regarding the most suitable rebalancing operations strategy.

## 2 Methodology

The proposed framework is presented in Figure 1. In our case, the transport simulation refers to MATSim but any other transport simulation toolkit can be used. We kindly ask the reader to refer to [7] for further details on MATSim.

MATSim receives the daily plans of the agents (i.e., the start and end times of each activity, the transport mode, and purpose of the trip) as well as the system parameters (i.e., location of stations and facilities, car sharing system membership information, initial vehicle and parking configuration, socio-economic

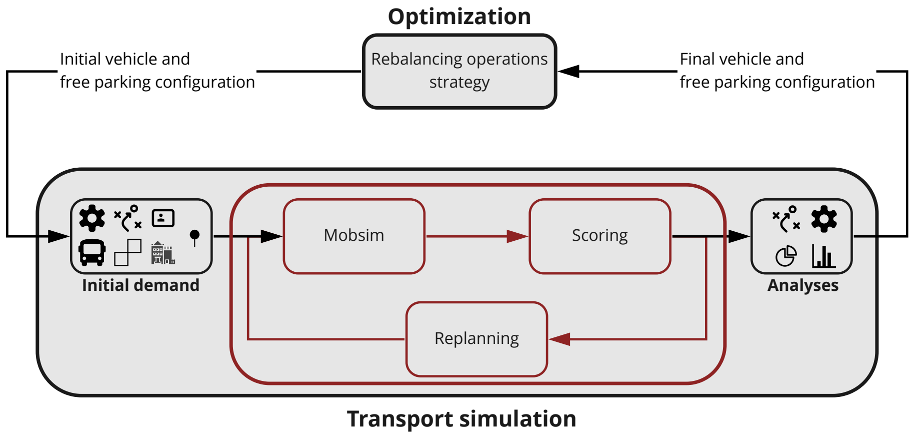


Fig. 1: The framework

characteristics of the agents, and public transport schedule). Then, MATSim simulates the given day, calculates the utilities of each agent, each agent replans their day according to their utilities in the previous iteration and the given day is simulated once again until the pre-specified number of iterations, $I$, is reached. We refer to this loop iterations as *inner-loop iterations* and present it in red arrows in Figure 1.

The output of the simulation gives the realized car sharing trips, which helps us to compute the final state of the vehicles and parking spots. This information is passed to the rebalancing operations optimization module and the initial vehicle configuration of the following day is determined according to the rebalancing strategy. The initial vehicle and parking configuration is modified accordingly and the feedback loop is then closed by triggering the next iteration of the *outer-loop iterations*, which are shown in black arrows in Figure 1. The change in initial configuration modifies the choices of the agents in the next outer-loop iteration. Here, an outer-loop iteration corresponds to a one simulated day and run for pre-specified number of times, $O$, to observe the convergence.

Within MATSim, the generalized cost of car sharing travel from activity $q-1$ to activity $q$ is shown in Equation (1) [7].

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

The first term, $\alpha_{cs}$, refers to the alternative specific constant of the car sharing alternative. The second term relates to the time whilst the third is the distance dependent component of the fee. The access and egress times to and from the stations are considered in the fourth term and the coefficient of the last term represents the marginal utility of an additional unit of time spent on traveling with car sharing, where $t$ is the actual in vehicle travel time.

For the other modes such as walking, private car, public transportation, and bike, the utility of traveling is shown in Equation (2).

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

For the current state of research, we test two different rebalancing strategies. In the first strategy, *do nothing*, the final configuration of the cars from the previous iteration is taken as an initial configuration for the following iteration. In the second strategy, *rebalance*, we follow a heuristic approach. The minimum vehicle inventory reached per station during the day is defined as the minimum number of vehicles required for that station. If the total number of available vehicles is more than the total number of minimum required vehicles per station, we sequentially distribute the excess number of vehicles among stations. Finally, this obtained configuration becomes the initial configuration for the following *outer-loop* iteration.

## 3 Results

We use the Sioux Falls, South Dakota, USA case study to experiment our framework. This network represents a simplified version of the real network and can be seen in Figure 2. 24 car sharing stations are placed at each intersection of the network. The provided plans file consists of 84110 agents and the 100% of the population is used for the experiments. There are three event types, i.e., home, work, and secondary. The four facility types are home, work, secondary, and education. The available transport modes are car, public transport, bike,

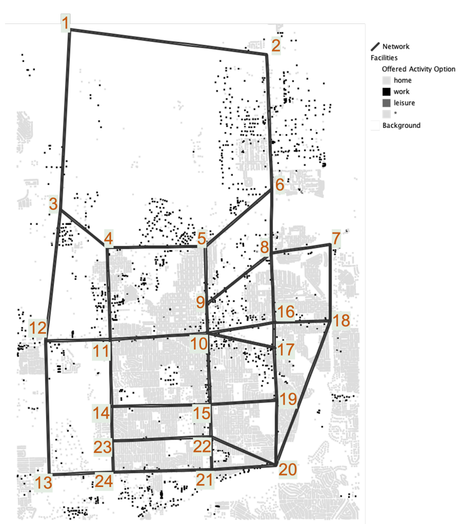


Fig. 2: Sioux Falls network

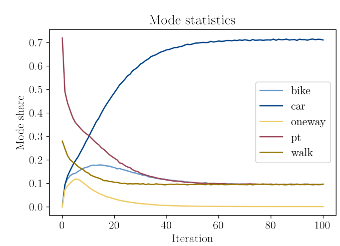


Fig. 3: Mode statistics

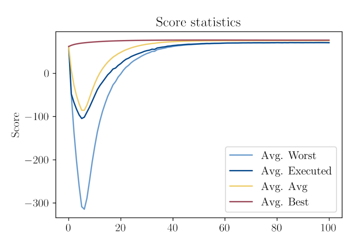


Fig. 4: Score statistics

walk, and one-way car share. Although the literature states that the willingness to walk to a car sharing station changes between 400 and 800 meters [8], we set the search distance of a car sharing vehicle to 200 meters as Sioux Falls is a very small network. We assume that static rebalancing is deployed and the operations happen instantaneously. As we are using a heuristic approach, the rebalancing optimization takes less than a second showing that it is suitable for operational level decisions.

For preliminary experiments, we run 100 inner-loop, and 10 outer-loop iterations. When we look at Figures 3 and 4, we see that the transport simulation converges at around 70 iterations. This observation is important as determining the cut-off iteration number saves considerable amount of computation time. Furthermore, Figure 3 gives us some insights on the mode share. The respective mode shares for the modes car, public transport, bike, walk, and one-way car share are 70.9%, 9.6%, 9.6%, 9.7%, and 0.2%. Regarding the trip purpose, we observe that 56% percent of the activities are work related whereas 44% are secondary activities such as from home to secondary or vice versa.

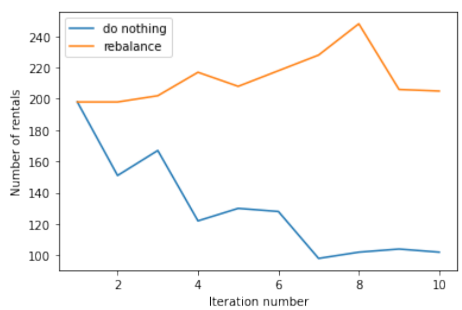


Fig. 5: Number of rentals both strategies

Figure 5 shows the results for both strategies. The outer-loop iterations are depicted in the x-axis and the y-axis shows the number of rentals at each outer-loop iteration for both strategies. We see that *rebalance* strategy is more stable than the *do nothing* strategy. Also, in line with the intuition, the *rebalance* strategy leads to higher number of rentals than the *do nothing* strategy. The fluctuations for each strategy can be explained by the fact that unnecessary rebalancing operations are conducted which leads to few number of parking spots in some specific stations where the drop-off demand is high. For the *do nothing* strategy, the trend of number of rentals is negative, i.e., the number of rentals is less and less with increasing number of iterations. This is expected due to the fact that the pick-up stations have less and less vehicles and drop-off stations do not have enough parking spots to serve the drop-off demand.

After analyzing the fluctuations, we observe that the number of rentals tend to decrease for some number of iterations after reaching a relatively high number of iterations for *do nothing* strategy whereas for *rebalance* strategy, the behavior is opposite, i.e., the number of rentals tend to increase after reaching a relatively low value. This also results in the positive and negative trends of the strategies.

## 4 Conclusion and future work

In this work, we introduce a holistic framework that aims to compare different rebalancing strategies involving agent-based transport simulation, rebalancing operations optimization, and choice modeling. Later, we present a case study based on Sioux Falls, USA, and preliminary results for two rebalancing strategies. Future work includes investigating the results with higher number of outer-loop iterations to see the convergence and generalize results. We also plan to include more sophisticated rebalancing strategies as well as simplistic approaches such as equal distribution of vehicles. Furthermore, incorporating user-based rebalancing strategies, where operator offers incentives to the users for specific trips, would be interesting as the choices of the users would depend on the pricing. Finally, as transportation involves discrete choice by its nature, we aim at including a choice model that takes pricing into consideration in the framework.

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