Balancing Shared Mobility Fleet Sizes: A Simulation-Driven Evolutionary Approach

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Abstract. Regulators in cities face the need to enforce limits on the number of free-floating vehicle sharing schemes and vehicles. The tried-and-tested instrument for cities are tenders, for fleet sizes of the individual vehicle types. The composition of fleet sizes is often, however, guesswork or based on anecdotal evidence rather than reliable data. Factors that are of interest include cost of operation, social equity, and environmental sustainability. Balancing them is a complex problem, but solving it could greatly support decision makers in making informed decisions for an optimal configuration of the urban mobility system. We use a large-scale multi-agent simulation, based on empirical data from Berlin, Germany, genetic algorithm and heuristics to generate a partial solution set and discuss its applicability and boundaries.

Keywords: Multi-Agent Simulation · Genetic Algorithm · Shared Mobility · Sustainability · Fleet Sizing

1 Introduction

Urban mobility is undergoing a rapid transformation, driven by technological advancements and the rise of shared mobility services. The emergence of connected, autonomous, shared, and electric (CASE) vehicle technologies has created a digital layer atop the traditional physical mobility system, offering opportunities for a more efficient and sustainable transportation ecosystem [13]. Free-floating vehicle sharing (FFVS) services are a prominent example of this shift, offering on-demand access to transportation without the burdens of ownership [2]. However, the proliferation of these services presents new challenges for city regulators.

A critical challenge is the need to enforce limits on the number of sharing schemes and vehicles operating within a city. Uncontrolled growth can lead to sidewalk clutter, increased competition for limited street space, and potentially negative impacts on public transit and active travel modes. Recent examples show that the absence of well implemented regulation has a detrimental effect on the system [15, 4, 19]. Cities often use tenders as a tried-and-tested instrument to manage this, setting limits on fleet sizes for individual vehicle types. However, determining the optimal composition of these fleets (i.e., the ideal mix of bikes, scooters, cars, et cetera) is often based on guesswork or anecdotal evidence rather than rigorous analysis . This lack of data-driven decision-making hinders the ability of cities to create truly sustainable and equitable mobility systems.

The optimal fleet composition must consider multiple, often conflicting, factors. These include the operational costs for service providers, social equity and accessibility for all residents, and environmental sustainability (e.g., reducing emissions). Balancing these objectives is a complex problem [6], but solving it would provide valuable support for policymakers in making informed decisions about the future of urban mobility. It is clear, that transportation is one of the major sources for energy consumption and emission generation, and to limit the negative impacts, effective policies are needed [20].

Multi-agent simulation (MAS) is a powerful tool for modeling complex socio-technical systems and analyzing the behavioral aspects of their components [22]. It allows researchers to create virtual representations of cities and their transportation networks, including the interactions between individual agents (e.g., travelers, vehicles, service providers). Crucially, MAS can be used to evaluate hypothetical scenarios, testing the impact of different policies and feasibility of interventions without real-world consequences [5, 9].

While some prior work has explored aspects of fleet optimization, it often focuses on single objectives or simplified models. This paper leverages MAS to address the fleet sizing and composition problem for shared mobility services in a more holistic way. Specifically, we use MAS to simulate the operation of various vehicle sharing modes (bikes, scooters, kick scooters, cars) in a realistic urban environment. We evaluate potential fleet configurations based on relevant system metrics, including emissions, service provider profits, and travel demand fulfillment rates. To find good fleet configurations, we further employ evolutionary algorithms, specifically genetic algorithms, known for their ability to handle complex optimization problems.

This work-in-progress paper focuses on optimizing single objective functions individually, while exploring the interplay between objectives by using the fulfillment rate as a penalty for the other objectives. In future work, we will extend this to the full multi-objective optimization problem (MOOP).

2 Related Work

Research on shared mobility systems, encompassing services like car sharing, bike sharing, and e-scooter sharing, increasingly addresses the challenges of fleet sizing and composition. The literature explores this problem space through various optimization and simulation approaches.

One line of research focuses on fleet size minimization. Some algorithms developed for large-scale bike-sharing systems demonstrate potential fleet size reductions, although the magnitude of reduction is sensitive to the inclusion of future demand uncertainties [11]. Other studies have analyzed optimal fleet composition, often highlighting the tension between maximizing service provider profit and maintaining user satisfaction, sometimes suggesting the need for public subsidies [17]. The interaction between shared mobility and other transportation modes is another area of investigation. Research incorporating public transport has explored scenarios where optimized shared vehicle systems partially substitute for public transport and active modes (walking, cycling), rather than primarily replacing private vehicle trips [26]. Studies examining shared electric scooters reveal that larger fleets, while accommodating more trips, can lead to lower overall fleet utilization and a potentially increased environmental burden per kilometer due to vehicle production impacts [25]. This underscores the importance of considering the entire lifecycle impact of shared vehicles. In light of these complex interactions, the role of government regulation and collaboration between stakeholders (local governments, service providers, users) is frequently emphasized [1].

Simulation has emerged as a key tool for understanding the dynamics of shared mobility systems. Agent-based modeling, implemented in frameworks like MATSim, allows researchers to analyze the integration of multiple shared mobility services and the effects of different fleet sizes on competition and complementarity between vehicle types. These simulations have demonstrated the existence of saturation effects, where increasing fleet size beyond a certain point provides diminishing returns. [10, 2]. Similarly, SUMO has been used to compare the social costs and benefits of Mobility-as-a-Service (MaaS) environments, highlighting the need for a minimum demand level to ensure benefits for all stakeholders [3, 18].

Optimization techniques, often in conjunction with simulation, are used to identify optimal fleet configurations. Genetic Algorithms (GA) have been applied to problems such as determining the optimal location and capacity of shared mobility hubs [26]. GA have also been employed to optimize the placement of electric vehicle charging stations, incorporating demand data, points of interest, and social network information [12]. Other optimization studies often focus on scalability in large urban environments or address specific operational aspects [21, 23]. However, the simultaneous consideration of multiple, conflicting objectives (e.g., cost, emissions, accessibility) within a detailed, realistic simulation environment remains a relatively unexplored area.

3 Method

3.1 Different Perspective Optimization Problems

The decision variable is a vector n of the number of vehicles $n_i \forall i \in \mathcal{M}$, with $\mathcal{M}$ the set of vehicle types in question.

Social Perspective: Fulfillment Rate The first objective takes the society perspective of accessibility and inclusion. Travel demands that cannot be fulfilled by another mean of transport (e.g., public transport), can be fulfilled with

FFVS services. The regulator should aim to maximize the share of fulfilled FFVS demands with the right fleet sizing and composition:

$$\max_{j} \frac{\sum_j f_j}{\sum_j 1} \tag{1}$$

where f_j is an indicator variable that denotes whether trip request j was fulfilled (1) or not (0).

Environmental Perspective: $\boldsymbol{CO_2}$ Emissions The second objective again takes a societal perspective, this one specifically that of minimizing the environmental impact the FFVS services have. The regulator should aim to minimize the emissions that are created from operating fleets of the respective vehicle types:

$$\min_{i,j} \sum_i \sum_j LCA_i f_j m_{ij} d_j \tag{2}$$

where $m_i j$ is an indicator variable that denotes whether a trip was carried out with the vehicle type i and d_j the trip distance. LCA_i is the lifecycle assessment of emissions in gCO_2eq/pkm [1]. Specifically, we use measures derived from a meta-analysis of the literature, as shown in Table 1[3]. By using LCA measures for the emissions, both emissions from fulfilling user demands and operations are captured.

Vehicle Type	Bikes	Kick Scooters	Scooters	Cars
LCA (gCO_2eq/pkm)	46.3	105	51.3	236

Table 1. Emissions from Lifecycle Assessment (LCA) Meta-Analysis

Economic Perspective: Operator Profits The third objective takes the FFVS operator perspective, and can motivate them to participate in the tender. Specifically, the operator aims to maximize their revenue of fulfilled trips:

$$\min_{i,j} \sum_i \sum_j f_j m_{ij} (P_i^u + P_i^t t_j) \tag{3}$$

with the two price components, P_i^u the unlock fee of the vehicle type and P_i^t the price per minute.

Cumulative Fleet Size All three problems must satisfy an equality constraint that limits the total number of vehicles of modes that are on the road, n_i, to some parameter $\mathbf{N}$. This cumulative number of vehicles on the road is expected

[3] Due to space constraints, the meta-analysis is available upon request.

to be set by policymakers. In section 4 we exemplify how a city could inform this step, simplified.

$$\sum_i n_i = \mathbf{N} \tag{4}$$

3.2 Multi-Agent Simulation

The effect of vehicle numbers of the different types on system metrics such as emissions, fulfillment rate, and operator profits is complex and cannot be parametrized in functional form. Rather, we employ agent-based modeling (ABM) to create a function-like, yet opaque, mapping of inputs (decision variables) to outputs (objectives) through MAS.

The MAS takes a mesoscopic perspective, as it does not simulate microscopic travel itineraries of individual inhabitants (like MatSIM [10]) nor simply use stochastic models for system-level metrics [24]. Rather, it utilizes ephemeral user agents characterized by a spatio-temporal travel demand: The modelled city is discretized into cells, and as time progresses, generator processes in each cell draw inter arrival times from a Poisson distribution. After waiting for that arrival time, a user agent is spawned at that origin cell and draws a destination cell for its transport task from a multinomial distribution of weekday, time bucket, and spawning cell [7].

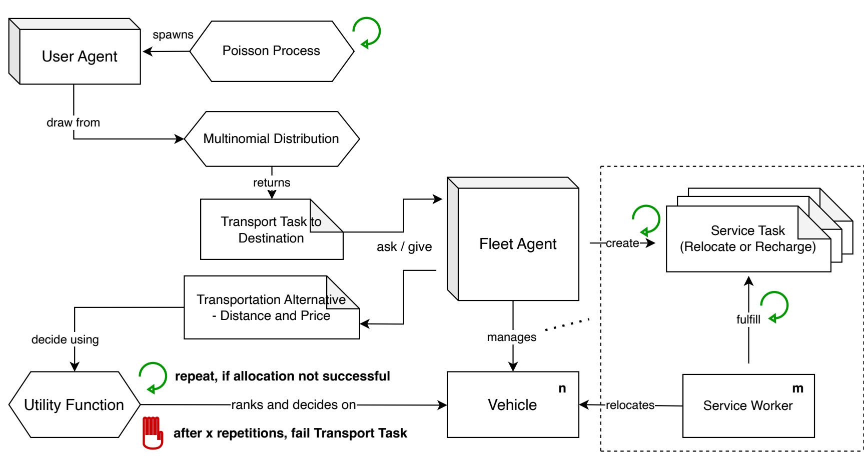

Fig. 1. User, Vehicle, and Fleet Operator Interactions in Simulation

Figure 1 shows core interactions between user agents and vehicles that are operated by a fleet. The fleets present users with valid transportation alternatives for their transport tasks, a selection of vehicle types, each linked to a specific price, distance, and duration. Users choose among the presented alternatives based on utility functions. A lower threshold utility is set to model any outside alternative. The mode choice utilities are derived from Demircan et al. [8]. Fleet operators utilize service workers to recharge and relocate vehicles as needed, creating costs, which are albeit heterogeneous in their structure: Multiple bicycles and kick scooters can be collected in a single service trip to relocate or recharge as needed, as opposed to scooters and cars.

3.3 Genetic Algorithm Solution Approximation

We utilize the MAS to estimate expected values for the metrics through multiple runs, as it has stochastic components and is thus non-deterministic. Using this as the evaluation function of decision variable, we opt for a standard GA approach with direct representation of the decision variable vector as chromosomes and tournament selection. We implement custom crossover and mutation functions to account for the integer nature of the problem. Figure 2 exemplifies how two chromosomes from a parent population breed children chromosomes: A real-valued two point crossover switches out two genes from the parents (2a) and rebalances the genes for the equality constraint (2b). Afterward, a mutation of the children randomly subtracts a value between 1 and 100 from one of the genes and adds it to another to again balance the total number of vehicles.

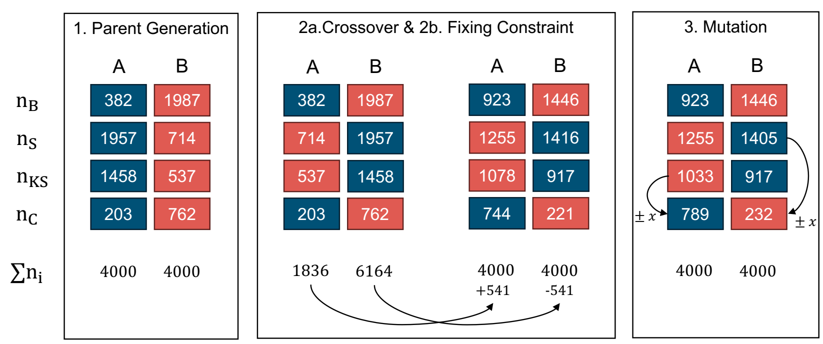

Fig. 2. Example of Custom Crossover and Mutation (B: Bike, S: Scooter, KS: Kick Scooter, C: Car)

Finally, we augment the fitness function, which is just the respective metric at the end of the simulation, with a penalty factor. A penalty is applied when the fulfillment rate drops below a certain threshold, which we set at the benchmark fulfillment rate with equal fleet sizes at **N** vehicles total. In order to favor results that are closer to the threshold than the ones that are far off, an exponential factor using the difference from the threshold and the achieved fulfillment rate is multiplied with the metric x of the respective objective function: For minimization: $e^{0.65\frac{\sum_j f_j}{\sum_j 1}} x$. For maximization: $1/e^{0.65\frac{\sum_j f_j}{\sum_j 1}} x$.

4 Case Study

We use Berlin, Germany as a case study scenario. We use data from six incumbent vehicle sharing services of four vehicle modes $\mathcal{M}$: Bicycles, (electric) kick scooters, (electric) scooters, and cars. Figure 3 shows the distribution of trip distances carried out with the four modes in the data set. The data set consists of origin-destination encoded trips and features like estimated price, distance and duration. We use this to estimate a) the Poisson distributions for demand spawn times in the discretized city grid, and b) the multinomial distribution of travel destinations. The space is discretized to equidistant cells of about 1 kilometer across. We simulate for one full week (with warm start).

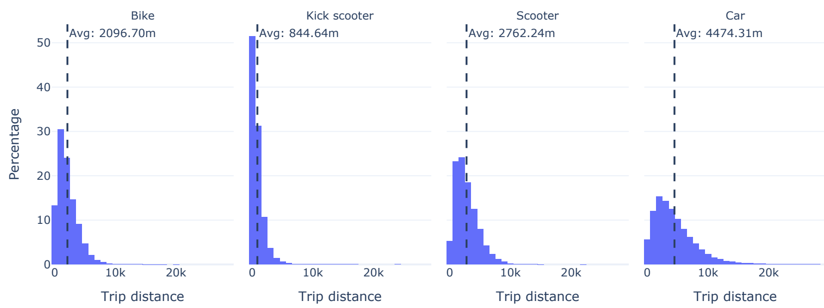

Fig. 3. Histogram Plots of the Distances Travelled by Vehicle Type

As a preliminary step, we simulate with a focus on fulfillment and fleet utilization rate over an increasing total number of vehicles. Figure 4 shows the metrics for fleet sizes from 400 to 8000 total vehicles. For this step only, we assume an equal share of each mode. We define the point of diminishing returns as the configuration which does not improve over the previous configuration by more than 1%. We use the resulting cumulative fleet size of $\mathbf{N} = 4000$ vehicles as the equality constraint in all other steps.

5 Preliminary Results

In this work, we present preliminary results from individual optimization of the three objectives and a discussion of how one objective (fulfillment rate), impacts the other two as a constraint. We do not have Pareto front results at this stage due to the extended runtime of the full multi-objective optimization problem. Figure 5 presents the solutions of the single-objective problems solved individually. Bicycles and cars clearly drive the min emission and max fulfillment objectives solution, respectively. The max revenue solution interestingly

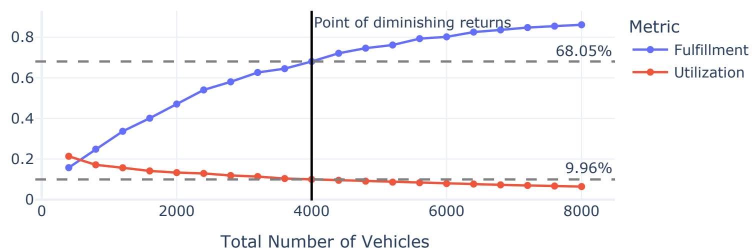

Fig. 4. Finding Fleet Size Equality Constraint

trades off both kick scooters and cars for more bicycles compared to the max fulfillment solution. This is likely due to the cost structure of operations, as the non-electric bicycles rarely need to be relocated and charged. This, moreover, provides a clear indication that the problem indeed has competing objectives, and the relationship is not trivial.

Fig. 5. Comparison of Individual Objective Solutions

Figure 6 illustrates the evolution of fleet composition across three distinct optimization perspectives, each targeting a different objective: minimizing CO2 emissions (a), maximizing revenue (b), and maximizing fulfillment rate (c). Each plot tracks the changes in the number of vehicles of each type over several generations of the optimization process.

In the emission minimization perspective (a), the number of cars decreases substantially, while the population of bikes remains relatively constant. Scooters and kick-scooters show a slight downward trend, suggesting a selection pressure towards lower-emission modes within the evolving population. In the revenue maximization perspective (b), the number of cars initially decreases but then stabilizes at a relatively high value, indicating their importance for revenue.

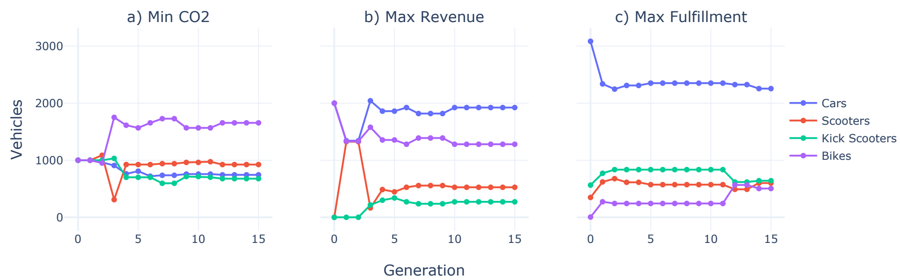

Fig. 6. Number of Vehicle Types over GA Generations

Scooters decline sharply, while bikes increase significantly before stabilizing, potentially reflecting a balance between cost and demand. Kick scooters see a modest increase.

The fulfillment maximization perspective (c), sees the number of cars drop dramatically as soon as the second generation. Scooter and kick scooter numbers rise and stabilize, while bike numbers also decrease and then stabilize. The slight fluctuations observed towards the later generations in (c) can be attributed to the stochastic nature of the simulation and the algorithm exploring the solution space using *estimates* of the fitness function. Near-optimal fleet compositions might exhibit very similar performance, leading to minor variations in the vehicle counts as the GA fine-tunes the solution.

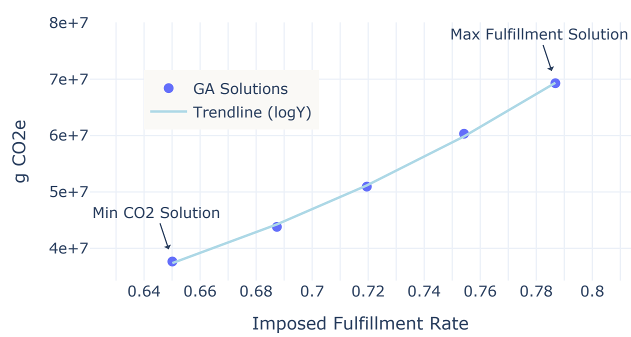

Fig. 7. Varying the Imposed Fulfillment Rate Impacts the Emission Objective

Finally, we briefly look at the interplay of two of the objectives (perspectives): Fulfillment rate (social) and emissions (environmental). Figure 7 shows the effect of varying the fulfillment threshold in the penalty term of the fitness function. The leftmost solution is the fulfillment rate achieved with the emission minimization objective, the rightmost solution represents the one achieved in the maximization of fulfillment rate. The solutions in between use uniformly distributed fulfillment rate thresholds and a log-transformed trend line is fitted to interpolate them. This highlights the inherent conflict between environmental sustainability and demand fulfilling. By effectively visualizing a rough estimate of a portion of the Pareto front, this analysis provides valuable insights for decision-makers, allowing them to understand the environmental consequences of different service level targets.

6 Discussion and Conclusion

This work is still a work-in-progress, and as such we list some next steps necessary, but also limitations and open questions.

Most obviously, we will implement the full MOOP to search the Pareto front of the solution space. We will discuss how regulators can interpret the results and select solutions on this front based on preference weighting.

Additionally, we will reformulate the equality constraint of fleet size to account for the fact that different vehicle types take up a different amount of parking space on the road. This will introduce a more realistic space constraint on the fleet size. Because this will be computationally much more taxing, we will limit the integer mutation and crossover steps to multiple of, e.g., 10. This does not only shrink the number of solutions on the Pareto front and thus take some mental load away from policymakers, it is also still much more fine-grained than the rule-of-thumbs that are currently in place and round vehicle numbers to hundreds.

Next, the operator perspective objective (max revenue) lacks an explicit model of costs. In the MAS, we track both revenue and costs during all phases of the fleet lifecycle, but as of now, costs are only implicitly modelled in the rental prices that operators post. Because these costs are intricately linked to the fleet size and potential under-/overutilization of resources, we will model *profit* as a function of revenue and costs to alleviate this limitation.

Lastly, runtime is a serious limitation of our work. Even if we reduce the number of solutions drastically, a drawback of the simulation as a function simulator is its runtime, which is a couple of minutes for two full weeks simulated. As the simulation is in parts stochastic, several runs are necessary for each configuration to be able to work with expected values in the EA. Because of this, at some point, we might be forced to try out some form of surrogate modelling combined with clever initialization, sampling, and update (e.g., Latin hypercube sampling) [16, 14]. This, however, could defeat the purpose of using intricately modelled MAS as opaque function models. We are highly interested in inputs on this point.

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