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The potential of optimization and simulation to better match supply and demand in shared mobility systems

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by

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Literature Review

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Summary

Shared mobility systems allow individuals to rent vehicles on an as-needed basis. The benefit of this is that these individuals does not have to buy the vehicle themselves and only pay for its use. These shared mobility systems are becoming increasingly popular due to the fact that sharing vehicles means fewer are required and fewer resources must be devoted making them. Following that, most of these shared vehicles are electrically powered, which also contributes to a more sustainable future. A crucial factor for the success of these shared mobility systems is its ability to properly match the demand and supply of the vehicles. This is achieved by rebalancing operations, in which vehicles are repositioned from areas with a surplus of vehicles to areas with a deficit of vehicles, based on the expected demand and supply. Determining effective rebalancing operations is a complex challenge that requires the consideration of many different elements. In this review, various methodologies from the literature to rebalance the fleet of vehicles within shared mobility systems are examined. We present an overview of optimization and simulation techniques used in the literature to better match demand and supply.

Keywords: Shared mobility systems · Rebalancing · Optimization · Simulation

1 Introduction

A home sharing economy platform that gives users an alternative to traditional hotel accommodation by allowing them to rent accommodation from people who are willing to share their homes. This is, of course, referring to Airbnb. Airbnb was founded in 2007, and it's platform has since grown to 4 million hosts who have welcomed over 1 billion guest arrivals in nearly every country on the planet [1]. It is one of the most prominent examples of a huge sharing economy, in which people rent assets directly from one another via the internet.

These so-called sharing platforms enable customers to rent pricey assets from others who do not fully utilize them. Renters pay less than they would if they bought the assets themselves. The most common examples are apartments or cars, but also tents, campers, and even tools are being shared throughout these platforms. As proponents of the sharing economy like to put it, access trumps ownership [2].

But it is not just individuals who make use of this sharing economy. Companies also rent out spare offices, parking spaces, and idle machines. In general, as a business-to-business ("b2b") model. Furthermore, in recent years, several companies have emerged that take ownership of assets and rent them out to consumers via a business-to-consumer ("b2c" model. As a result, the individual does not have high investment costs and will just pay for the use when necessary. Another advantage of the sharing economy is the environmental benefit: renting an item or asset when you need it rather than owning one means fewer are required and fewer resources must be devoted making them. As sustainability and climate change become more relevant subjects in everyday life, we are transitioning to a world with a sharing economy [3].

The sharing economy is most commonly employed in transportation, the tourism and hotel industry, the food sector, the financial sector, and within services. Some examples respectively are Uber, CouchSurfing, ShareTheMeal, KickStarter, and TaskRabbit [4].

1.1 Shared mobility

Shared mobility or shared transport is a subgroup of the larger sharing economy. Whereas in principle anything can be shared in the sharing economy, focus is now on transport. Shared mobility is defined as transport services and resources that are shared among users, either simultaneously or one after another. Although the proliferation of tech-enabled shared mobility has occurred mostly within the last decade, shared mobility services are not a new phenomena. Some notable events in the history of shared mobility are highlighted below.

In addition to a few previous initiatives or trials, the first bike-sharing program in the Netherlands was launched in Amsterdam in 1965 as "the white bicycle plan" (Witte Fietsenplan), where a small number of white painted bikes were left unlocked around the city, to be used by anyone in need of transport. The concept drew a lot of attention, but it was short-lived. The free white bikes were quickly removed by the police, but this was just the beginning for bike-share schemes. It was also supposed to be a statement against the increasing number of cars, which was a major issue in Amsterdam [5].

Around 1974, one of the activists (Luud Schimmelpennink) of the white bicycle plan realized one of the world's first technology-based car-sharing projects, known as the "Witkarren", which was a system for sharing small electric cars. To use a Witkar, one had to sign up as a member and pay a nominal fee every kilometer driven. The Witkarren could be driven between stations where they were charged when not in use. Due to financial shortcomings, the network of vehicles and stations was not expanded further, although there were Witkarren on the streets for ten years, proving that such a system could function [6].

Later, several initiatives entered the market worldwide, such as free bike-sharing programs with a deposit or paid options using a chipcard with pick-up and drop-off stations. Eventually, the huge and unexpected success of the "Parisian bike-sharing program" in 2007 encouraged cities all over the world to establish their own systems, all modeled on Schimmelpennink's [7].

With the founding of Ubercap (now known as Uber) in 2009, a new era began in terms of digitization and technology [8]. Uber started as a ride-hailing company that primarily provided on-demand car trips, but has since evolved into a Mobility as a Service (MaaS) platform that facilitates end-to-end journeys. Users are now able to rent cars, bicycles and e-scooters, all as a single charge managed through a single user account. With this, Uber eliminates the friction of having multiple apps and providers, and is therewith dominating the mobility sector. They are even collaborating with public transport operators to include their services in the Uber app [9].

Aside from bike and car sharing, other vehicle sharing systems have entered the market. Scoot Networks, which began operations in 2011, was the first to provide electrically powered mopeds in San Francisco, which consumers could rent through a smartphone app [10]. In the Netherlands, Felyx was the first company to serve the streets with shared electric mopeds, first deploying in 2017 [11]. The company Bird was the first to launch electric scooters, which did no longer needed to be powered by foot like the original scooter [12].

With an increasing demand for shared mobility, more initiatives will undoubtedly emerge in the future. We never know what the future holds, but rumors suggest that research is already underway into Urban Air Mobility (UAM) that will realize shared air transport between suburbs and within cities as early as 2025 [13].

One thing that all vehicle sharing companies have in common is that practically all vehicles have been electrically powered in recent years. Fleet managers ensure the operationality of the fleet by charging the cars at charging stations or replacing the batteries of the mopeds, bicycles, and scooters when they run out. As a result, the shared mobility provider contributes to a sustainable future [14].

1.2 Scope of this literature review

This literature review focuses primarily on gathering knowledge about shared mobility systems up to the present day to understand its many types and characteristics. Following that, research is conducted into various methodologies from the literature to match supply and demand within these shared mobility systems. Descriptions of the methodologies including the benefits and drawbacks from these articles are provided. Finally, potential intriguing areas within the literature are presented where little research has been done yet and hence prospects for improvement. The main question addressed in this literature review is:

How can the expected demand and supply of the vehicles in shared mobility systems be better aligned to optimize the fleet's operational capability?

The remainder of this review is organized as follows. Section 2 provides an overview of the terms and characteristics of shared mobility. Different methods from the literature to match supply and demand within shared mobility systems are discussed in section 3. Finally, section 4 concludes the review.

2 Shared mobility overview

Shared mobility includes multiple terms and characteristics that are used throughout literature. A clarification of most of those terms and characteristics is given in this section.

2.1 Terminology

Ride-sharing, vehicle-sharing, and ride-hailing

Ride-sharing, also known as carpooling and vanpooling, occurs when passengers and drivers with similar origin-destination pairs share a vehicle. Actually, it is more accurate to say that the route is shared rather than the vehicle. During these trips, it is possible that additional stops will be made along the route to pick up and drop off passengers. Ride-sharing reduces the need for multiple cars on the road. When multiple drivers share a single vehicle over time, this is referred to as vehicle-sharing. The vehicle might be owned by a person who lends his or her vehicle to someone else (peer-to-peer), but in most shared mobility systems, an organization offers a fleet of vehicles that can be rented. The organization typically provides insurance, gasoline, parking, and maintenance. Two examples are car-sharing and bike-sharing. Passengers who use ride-hailing pay a personal driver to take them to their destinations. Although this might seem similar to ride-sharing, many people who use ride-hailing services are not ride-sharing. The hired drivers don't have the intention to go to the same destination as their passengers, but instead take multiple routes to fulfill their customers' needs. These drivers almost never take on extra passengers along the route, making it a ride-hailing system rather than a ride-sharing system. A more detailed explanation of the definitions of these shared mobility terms is provided in the work by Shaheen and Cohen (**2020**). Examples of these different types of shared mobility are presented in Figure 1.

(a) Ride-sharing [16] (b) Vehicle-sharing [17] (c) Ride-hailing [18]

Figure 1: Different types of shared mobility.

Mobility on Demand and Mobility as a Service

Mobility on Demand (MoD) and Mobility as a Service (MaaS) are sometimes used interchangeably throughout literature, however, they are different. MoD focuses on the commodification of passenger mobility, goods delivery, and transportation systems management, whereas MaaS is primarily concerned with passenger mobility aggregation and subscription services. A distinguishing characteristic of MaaS, according to Shaheen and Cohen (**2020**), is brokering travel with suppliers, repackaging, and reselling it as a bundled package.

Public transport

Public transport is also a form of shared mobility, since the users of busses, trains, trams, and subways share their rides with other passengers. Public transport is known for its fixed routes and schedules.

Micromobility

Micromobility is a subgroup of mobility in general that refers to a range of small, lightweight vehicles that operate at speeds typically below 25 km/h (15 mph) and are driven by users themselves. Bicycles, e-bikes, electric scooters, and electric skateboards are examples of shared mobilitity vehicles. They usually only transport one person at a time. An overview of recent studies on several areas of micromobility is presented by Jiangping et al. (**2022**), including aspects such as type of users, travel characteristics, usage and performance, multimodal integration, competition, and methodologies to operate more efficiently.

All of the above sharing models have one thing in common: they allow customers to obtain transportation services on an as-needed basis. This is fairly common for shared mobility systems nowadays and helps to reduce vehicle ownership. Technological developments and the advance of digitisation are the driving forces behind the emergence and rapid growth of so-called sharing platforms, which allow users to reserve the shared vehicles. However, increased urbanisation and environmental consciousness are also important influences. And lastly, according to Basselier et al. (**2018**), financial motives may likewise be contributing to this development, both among consumers and suppliers of goods and services.

2.2 Characteristics

One-way trips or round-trips

The trips of vehicle sharing systems can be classified as one-way trips or round-trips. One-way trips have their starting and ending points at different locations, whereas round-trips, possibly with a stopover, return to their original starting point of the trip. The pick-up and drop-off locations for one-way trips may either be limited to a rental station or may be anywhere within an operational area in what is called a 'free floating sharing system', as described in the next paragraph. One-way vehicle sharing systems are generally more expensive to operate than traditional round-trip vehicle sharing systems because the locations from which the vehicles can be used change depending to prior users' itineraries. The optimal distribution of where the vehicles are located throughout the operational area will therefore fluctuate over time and may become unbalanced. There are several ways to return the fleet to its ideal distribution, as described in **??**, but most of them are costly. Yoon et al. (**2017**) conducted a survey to investigate the factors that influence the utilization of one-way and round-trip car-sharing in Beijing. Results of the survey indicate that parameters such as gender, age, income, car ownership, and demography have significant effect on the utilization of car-sharing systems.

Station-based or free-floating

Vehicle sharing systems can be characterized as either station-based or free-floating. Station-based, as the name suggests, means that the vehicles need to be picked up at and returned to a station. In most sharing systems it doesn't matter at which station the vehicles are picked up or returned, and there can be multiple stations within a city. As an example, you are able to rent a bike in the city center and then later park it at a station near your hotel. In a free-floating vehicle sharing system, as opposed to a station-based one, the vehicles are independent of a station and can be parked anywhere within the operational area of the provider. Vehicles in free-floating systems are equipped with GPS tracking and GSM module, allowing operators to collect real-time positioning data and riding trajectory data automatically. Examples of these different characteristics of shared mobility are presented in Figure 2.

Demand and supply

To accommodate as many rides as possible, the operator's supply of shared vehicles should be equal to the customer demand for shared vehicles. The spatial and temporal demand, when and where user want vehicles and where they want to drive those vehicles, vary greatly depending on the day of the week, time of the day,

(a) Station-based [21] (b) Free-floating [22]

Figure 2: Different characteristics of shared mobility.

weather, season, and other external factors. As pointed out by many previous studies (Li et al., **2015**; Zhou, **2015**), it is common that without interventions, stations in station-based systems become overcrowded or completely empty, whereas areas in free floating systems have surpluses and deficits, resulting in unsatisfied users and fewer rides than possible. It is therefore the operator's task to ensure that the supply of vehicles matches the demand as closely as possible. Data-driven frameworks are used to determine optimal fleet configurations through rebalancing operations or users incentives to reposition the fleet of vehicles.

Rebalancing the fleet of vehicles does not take place in ride-sharing systems, therefore this term is not used further in this study. Rebalancing does take place also in car-sharing and moped-sharing systems and therefore focus is not solely on micromobility.

3 Methodologies for matching supply and demand

The operational performance of shared mobility systems is impacted by the imbalance between the supply of vehicles and the demand for vehicles. To compensate for this problem, rebalancing the fleet of vehicles is required. Rebalancing in shared mobility systems refers to repositioning the vehicles from areas with a surplus of vehicles to areas with a deficit of vehicles, based on the expected demand and supply.

The literal execution of the rebalancing process is akin to a Traveling Salesman Problem with Pickup and Delivery (TSPPD), which has its origins in literature dating back well before the twenty-first century. Kalantari et al. (**1985**) were the first to extend on the original Traveling Salesman Problem, formulated by Little et al. (**1963**), with pickup and delivery customers, where each pickup customer must be visited before its related delivery customer.

Rebalancing problems also have similarities to the Inventory Routing Problem (IRP), where one needs to determine the routes of the vehicles, as well as the quantities of items to load or unload at each visited node. However, in the IRP, as in most inventory models, demand only depletes the available inventory. Returns, which increase the available inventory at a facility, either do not occur at all, or represent a significant lower volume in the system. Examples, a classification of the characteristics, and different models of an IRP are presented by Bertazzi and Speranza (**2012**).

Rebalancing in shared mobility systems can be performed by the operator or by the users of the system. Furthermore, it can be done in either a static or dynamic system. A brief explanation of these characteristics is given below. This section also examines several methods for matching supply and demand. What always come into play here is predicting the demand, which will be discussed first. Following that, optimization, simulation and eventually a combination of simulation and optimization known as simulation optimization are discussed. The characteristics of these methods are presented, along with references from the literature, on how they are used for rebalancing the fleet of vehicles in shared mobility systems.

Operator-based or user-based

The operator rebalance the fleet of vehicles by physically moving the vehicles. In car-sharing systems, the cars are driven to other locations, whereas in other sharing systems (moped, bike, scooter), multiple vehicles are loaded into a van or on a trailer and are then dropped off at other locations. Rebalancing by the operator can be done a couple times per day at fixed times or when needed.

With user-based rebalancing, users are encouraged to adjust their origins or destinations so that the vehicle distribution of the system better suits future demand. These incentive mechanisms can be classified into pick-up and drop-off incentives. Examples of these incentives include so-called dynamic pricing techniques to make certain vehicles more appealing than others, giving rewards (e.g. free driving minutes) for using specific vehicles, or giving discounts for parking the vehicle in a specific area. With these incentives, the fleet's distribution can be better balanced, allowing the operator to optimize its vehicle utilization time and hence maximizing profits.

Static or dynamic

Rebalancing can be performed by the operator in a static or dynamic system. A static system means that the vehicles are not used, therefore the locations of the vehicles does not vary during the rebalancing operations. This is most common at night, when system usage is at its lowest. Other practical advantages include little or no traffic and no parking issues. In a dynamic system, the vehicles are used during the rebalancing operations, as it is throughout the day. The distribution of the vehicles change continuously which makes it much harder to do the rebalancing, since it includes a scheduling component based on the users' activity.

Rebalancing by the users happens when they're actually using the system, therefore it is always done in a dynamic system where other vehicles are also being used.

Reiss and Bogenberger (**2017**) evaluated operator-based rebalancing strategy and user-based rebalancing strategy and pointed out that at least a share of the rebalancing tasks can be completed by users, almost cost-neutral. However, there is a certain threshold where rebalancing becomes too critical and an operator-based intervention is unavoidable.

3.1 Demand prediction

Demand may be estimated in a variety of ways. Surveys are one method for achieving this. A recent survey has been conducted by Ko et al. (**2021**) to better understand user's intentions to use shared mobility services. The study was undertaken to investigate factors influencing the usage intention of both current and potential users, which aids in forecasting future demand. Another method for evaluating demand is to use historical demand as a proxy for future demand. This might be a bad choice, as demand changes as more people become acquainted with the system. There are also other factors, such as the changing weather conditions that influence the demand. Rudloff and Lackner (**2014**) assessed the demand at station level, based on real data from a bike-sharing system in Vienna, utilizing count data models such as Poisson, Negative Binomial, and hurdle models. These models were used to estimate the demand in the future in order to improve the dynamic redistribution due to a better understanding of the time frame in which a station will fill up or run empty. More recently, machine learning algorithms, such as Neural Networks (NNs) have been used to discover patterns and correlations in shared mobility data sets in order to estimate demand. Most current models are based on recurrent neural networks (RNNs) which uses sequential data or time series data, convolutional neural networks (CNNs) which are mostly used for classification and image recognition, or a combination of the two. Related papers in this field concerning shared mobility patterns are from Ma et al. (**2017**), Yu et al. (**2018**), and Li et al. (**2018**).

Dependencies that must be considered when forecasting shared mobility demand are classified as temporal dependencies (dependency on previous time steps), spatial dependencies (dependency on both distant and nearby surroundings), and external dependencies (dependency on externalities like weather or events). Estimating the demand can assist in decision-making for transportation planners, policymakers and investors, for example.

3.2 Optimization

In general, an optimization model seeks the "best available" values of a given objective function within a predefined domain. These best available values can be determined manually, but algorithms are more commonly used. These algorithms can identify the optimum or near-optimal values of an objective function in a reasonable amount of time. Optimization models can be classified according to some of the following characteristics.

Local and global optima

When solving a convex problem, the local optimum is also the global optimum, which may be obtained using a relatively simple algorithm (local optimization methods). If the problem is non-convex, the simpler algorithms are not always able to search beyond a local optimum, and there is a significant possibility that the global optimum will not be obtained as a solution of the objective function. To overcome this difficulty and eventually solve certain optimization problems, more complex algorithms (global optimization methods) are required.

Deterministic or stochastic

Global optimization can be deterministic or uncertainty may be present. Deterministic optimization models produce the same exact results for a particular set of inputs no matter how many times the model is recalculated. The input data for a given problem is known accurately, no uncertainties are considered.

Optimization models where uncertainties are present, which means that one or more of the input parameters are uncertain, are referred to as stochastic programming or robust optimization. In stochastic programming, the uncertain parameter vector is captured by a number of discrete probabilistic scenarios, whereas with robust optimization, the range of its values is defined by a continuous set. To deal with uncertain parameters, it can be assumed that they follow certain probability distributions, which can even be supported by data. Models dealing with uncertainties are useful in real-world settings because many physical processes entail uncertainty, imprecision, or randomness.

Exact algorithms and heuristics

Exact algorithms and heuristics are used to solve global optimization problems. Exact algorithms can achieve the optimal solution with an exponential computational complexity, while heuristics can achieve the sub-optimal solution with a polynomial computational complexity. In other words, heuristics find sub-optimal solutions but in a much shorter time. They enable us to quickly obtain a suitable solution through exploration, intuition, and sometimes an educated guess. The solution will not necessarily be the best or most precise solution, there will be a trade-off between accuracy and computational speed.

3.2.1 Rebalancing through mathematical optimization

Rebalancing the fleet of vehicles, as read in section 3.1, is inextricably linked to estimating the demand. When information regarding the demand is available, it is possible to establish which areas have low or high demand. Following that, one is able to tell whether there are currently too many or too few vehicles in a certain area to meet its demand. Mathematical optimization models are used to perform optimal rebalancing processes.

The first studies in literature on rebalancing within shared mobility are about static station-based bike-sharing systems, because they were the first to enter the market. Later on, several studies were conducted on also dynamic station-based bike-sharing systems. Following that, both static and dynamic systems were investigated but then in a free-floating system. These numerous studies are listed below, where in this study the focus is only on bike-sharing systems. This is because the majority of study has focused on this type of shared mobility systems, and the process of rebalancing bikes is comparable to the process of rebalancing mopeds, which is where this literature review ultimately leads to. As stated earlier in section 3, rebalancing can be performed by either the operator or the users. In this literature study, focus is only on rebalancing performed by the operator.

Static station-based bike-sharing

Raviv et al. (**2013**) were probably the first to study the static case. These authors present two Mixed Integer Linear Program (MILP) models where multiple vehicles are used. In both cases, the objective is to minimize the weighted sum of the station's penalty costs and the total travel time. The penalty function for each station may represent any objective of the operator, such as the expected number of shortages. The solution is defined as the routes for each vehicle and the number of bicycles to load or unload at each station along its route. The demand in this case is based on past demand on similar days, acquired from a historical data set. The two MILP formulations are capable of solving problem instances of a moderate size of up to 60 stations with acceptable optimality gaps. Forma et al. (**2015**) later present a three-step matheuristic (combination of mathematical programming model and a metaheuristic) for the same problem. First, the stations are clustered by using a specialized saving heuristic. Following that, the repositioning vehicles are routed through the cluster while tentative inventory decisions are made for each individual station. Finally, the original repositioning problem is solved. The second and final step are formulated as MILP models that are solved by a commercial solver. Here, similar to Raviv et al. (**2013**), the sum of the penalties incurred at all stations and the total travel time is minimized. This method outperformed earlier methods in the literature when evaluated on instances of up to 200 stations and three repositioning vehicles.

Schuijbroek et al. (**2017**) worked on a simplified version of the models of Raviv et al. (**2013**). These authors propose a cluster-first route-second heuristic to rebalance the inventory, in which a polynomial-size clustering problem simultaneously considers the service level feasibility and approximate routing costs. The objective function contains only the cost calculated as the sum of the travel times. Benchimol et al. (**2011**) propose a simple method where a single truck repositions bicycles in order to bring the inventory of each station to a predetermined value. Their objective is to minimize the routing cost. Chemla et al. (**2013**) revisited the model of Benchimol et al. (**2011**) and propose a relaxation of the problem yielding lower bounds. They present a branch-and-cut algorithm for solving the rebalancing problem with a single-vehicle, with results on instanced of up to 100 stations. Rainer-Harbach et al. (**2014**) propose an efficient local search algorithm and some variations of it for a generalization of the problem, considering the case of multiple trucks and with a target inventory value that is not a hard constraint, but imposed as a penalty in the objective function. Erdoğan et al. (**2014**) propose the first exact algorithm in the context where the inventory of each station must lie in a predetermined interval. They develop and implement a Benders decomposition scheme and an branch-and-cut algorithm for this problem. Instances involving up to 50 stations are solved to optimality. The problem considered by Erdoğan et al. (**2014**) assumes that the truck visits each station at most once, whereas Chemla et al. (**2013**) allow multiple visits to the same station.

Dell'Amico et al. (**2014**) study the repositioning problem for the case where each station has a specific positive or a negative demand. The authors consider a fleet of capacitated trucks used to redistribute the bicycles throughout the network with the objective to minimize the total routing cost. They view the problem as a one-commodity pickup-and-delivery capacitated truck routing problem. The authors propose four mixed integer linear programming formulations for the problem, which they solve by branch-and-cut. Two years later Dell'Amico et al. (**2016**) improve themselves by using a metaheuristic based on Destroy and Repair to solve the problem, which lead to an increase in solving instances with 116 stations up to 500 stations. Szeto et al. (**2016**) consider a single-truck repositioning problem in which the objective is a weighted sum of penalties for unmet customer demand and operational time on the vehicle route. The problem is solved by an enhanced version of a local search metaheuristic called Chemical Reaction Optimization (CRO). Ho and Szeto (**2014**) solve similar problems by iterated tabu search and obtained high quality solutions efficiently. Later, Ho and Szeto (**2017**) consider a single truck variant of the model of Raviv et al. (**2013**) and develop a hybrid large neighbourhood search to solve it. This algorithm is able to solve instances involving up to 518 stations and five trucks and therewith outperform the previous matheuristic of Forma et al. (**2015**). Wang and Szeto (**2021**) propose a enhanced artificial bee colony (EABC) algorithm to solve the problem with a single vehicle only. The problem aims to design the route and loading instructions for the repositioning vehicle such that the weighted sum of the absolute deviation from the target inventory level, the penalty caused by broken bikes at stations, and the CO_2 emissions or the repositioning vehicle are minimized.

Dynamic station-based bike-sharing

Pfrommer et al. (**2014**) consider the routes for the rebalancing process in the case when the trucks have to react in an on-line manner to the current state of the system, based on the demand for the next 30 minutes. Research in dynamic rebalancing has not yet been fully explored because of the modeling difficulties it involves. Earlier papers deal with the case when the time-dependent demand is known in advance and the truck operations are planned off-line. Contardo et al. (**2012**) present a mathematical formulation which cannot handle medium or large instances. They therefore present an alternative modeling approach that takes advantage of two decomposition schemes, Dantzig-Wolfe decomposition and Benders decomposition, to derive lower bounds and feasible solutions in short computing times. Kloimüllner et al. (**2014**) extend their previous work on the static variant of the problem by introducing an efficient way to model the dynamic case with greedy heuristics, GRASP, and variable neighbourhood search (VNS). Computational experiments are performed on instances based on real-world data, where the model for user demands is derived from historical data. Ghosh et al. (**2017**) develop a large-scale routing model that jointly considers routing costs and future expected demand. They develop two solution methodologies, one based on a natural decomposability of the model into bicycle repositioning and truck routing, the other based on the aggregation of stations. Zhang et al. (**2017**) propose a methodology including inventory level forecasts, user arrival forecasts, bicycle repositioning and truck routing. The authors model the problem with a multi-commodity time-space network flow model. The model is linearized and solved heuristically in a rolling-horizon mode. Chiariotti et al. (**2018**) use a discretization of time and historical data to compute an approximation of the 'survival time' of each station in the network. Rebalancing is only performed if the gain obtained by reallocating bikes exceeds the cost of moving the rebalancing truck. Some results show that some of the issues of rebalancing systems are due to an inaccurate estimation of the demand patterns. In order to be more effective, the system should not just take into account historical data, but also current trends and weather data. Shui and Szeto (**2018**) propose a repositioning problem that simultaneously minimizes the total unmet demand and the fuel and CO_2 emission of the repositioning vehicle. This study adopts a rolling horizon approach to break down the proposed problem into a set of stages, in which a static bike repositioning sub-problem is solved in each stage. An EABC algorithm to optimize the route design in each stage and a route truncation heuristic to tackle the loading and unloading sub-problem are jointly used for optimization. Datner et al. (**2019**) formulate a mathematical formulation of the inventory problem with considering the interactions among stations. They use a local search algorithm that extracts information from the dynamics observed in a simulation.

Table 1 summarizes the literature on static and dynamic station-based bike-repositioning problems according to number of repositioning vehicles used, number of stations that can be considered, type of algorithm, methodology, and problem objectives.

Table 1: Summary of station-based bike-repositioning problem literature.

Reference	Problem Type	No. of Vehicles	No. of Stations	Solution Methodology		Objective: Minimize
Raviv et al. (**2013**)	S	> 1	60	E	MIP	weighted sum of total travel time and penalty cost
Forma et al. (**2015**)	S	> 1	200	E, H	3-Step Matheuristic	weighted sum of total travel time and penalty cost
Schuijbroek et al. (**2017**)	S	> 1	135	E, H	Constraint Programming and MIP	tour length
Benchimol et al. (**2011**)	S	1	-	E	9.5-Approximation Algorithm	total travel cost
Chemla et al. (**2013**)	S	1	100	E, H	Branch-and-cut with Tabu Search	total travel distance
Rainer-Harbach et al. (**2014**)	S	≥ 1	700	H	Greedy Heuristic, GRASP, and VNS	weighted sum of the total absolute deviation from the target number of bikes, total number of loading/unloading activities, and overall travel time
Erdoğan et al. (**2014**)	S	1	50	E	Branch-and-cut with Benders decomposition	travel and handling costs
Dell'Amico et al. (**2014**)	S	1	116	E	Branch-and-cut	total routing cost
Dell'Amico et al. (**2016**)	S	1	564	H	Metaheuristic based on Destroy and Repair	total routing cost
Szeto et al. (**2016**)	S	1	300	H	Chemical Reaction Optimization	weighted sum of unmet customer demand and operational time on the vehicle route
Ho and Szeto (**2014**)	S	1	400	E, H	Iterated Tabu Search	total penalty cost
Ho and Szeto (**2017**)	S	> 1	518	H	Hybrid Large Neighbourhood Search	weighted sum of total travel time and penalty cost
Wang and Szeto (**2021**)	S	1	300	H	Enhanced Artificial Bee Colony algorithm	weighted sum of the absolute deviation from the target inventory level, penalty induced by broken bikes, and generated CO_2 emissions
Pfrommer et al. (**2014**)	D	≥ 1	-	H	Predictive model and Greedy Heuristics	operating costs for a given service level
Contardo et al. (**2012**)	D	> 1	-	H	Hybrid MIP approach using Dantzig-Wolfe and Benders decomposition	unmet demand
Kloimüllner et al. (**2014**)	D	≥ 1	-	H	Greedy Heuristic, GRASP, and VNS	weighted sum of unfulfilled demand, absolute deviation from the target fill level, total number of loading instructions, and total drive time
Ghosh et al. (**2017**)	D	≥ 1	300	H	MIP with Lagrangian dual decomposition	unmet demand and routing cost
Zhang et al. (**2017**)	D	≥ 1	200	H	Time-space network flow approach	total vehicle travel costs and user dissatisfaction
Chiariotti et al. (**2018**)	D	> 1	280	H	Nearest Neighbour Heuristic	unmet demand
Shui and Szeto (**2018**)	D	1	180	H	Enhanced Artificial Bee Colony algorithm	unmet demand and fuel and CO_2 emissions of repositioning vehicle
Datner et al. (**2019**)	D	-	300	H	Simulation-based guided Local Search algorithm	a journey dissatisfaction function

Explanation of terms:

S = Static, D = Dynamic, E = Exact, H = Heuristic, MIP = Mixed Integer Programming, GRASP = Greedy Randomized Adaptive Search Procedure, VNS = Variable Neighbourhood Search

Static free-floating bike-sharing

Pal and Zhang (2017) present a Novel Mixed Integer Linear Program for solving the problem. The proposed formulation can handle single and multiple vehicles and also allows for multiple visits to a node by the same vehicle. They present a hybrid large neighbourhood search with variable neighbourhood descent algorithm, which is both effective and efficient in solving large-scale rebalancing problems. Liu et al. (2018) propose an enhanced version of Chemical Reaction Optimization (CRO) to solve the problem. The computational results demonstrate that the enhanced CRO gets better solutions than the original CRO and has potential to tackle the repositioning problem for larger, longer repositioning duration, and more vehicle instances. The effectiveness of this heuristic compared with traditional meta-heuristics, such as variable neighbourhood search, tabu search, and genetic algorithm, is not known. Du et al. (2020) considers rebalancing of normal bikes and malfunctioning bikes simultaneously, in order to realize the ideal distribution. The authors present an integer linear programming model to formulate the problem, and an effective greedy-genetic heuristic is designed to solve it for large instances. Ma et al. (2021) found that the rebalancing demand in different areas has stochastic characteristics with multiple demand scenarios. They design eight stochastic simulation-based genetic algorithms to address this problem. Zhang et al. (2022) uses real data collected by a bike-sharing company in an adaptive hybrid nested large neighbourhood search and variable neighbourhood descent with several well-designed operators to solve the problem.

Dynamic free-floating bike-sharing

Caggiani et al. (2018) first propose a spatio-temporal clusterization of the system. Following that, the authors present a Nonlinear Autoregressive Neural Network model to forecast the trend of available bikes in each spatio-temporal cluster. Finally, they present a Decision Support System aimed at the maximization of user satisfaction. Warrington and Ruchti (2019) adapt the Sparse Phase and Amplitude Reconstruction (SPAR) algorithm to this problem. They cast the rebalacing problem as a two-stage stochastic program, where the operator makes rebalancing decisions in the first stage without knowledge of the realization of customer demand, which happens in the second stage. By doing this, the difficulties of the first and second stage are separated and therefore easier to solve. Luo et al. (2021) study the reposition of bikes among gathering points, with explicit consideration of the collection of scattered bikes under stochastic demand within a specific area. First, they formulate a Markov Decision Process (MDP) model. Following that, they design a policy function approximation (PFA) algorithm and apply the optimal computing budget allocation (OCBA) method to search for the optimal policy parameters.

Table 2 summarizes the literature on static and dynamic free-floating bike-repositioning problems according to number of repositioning vehicles used, number of bikes that can be considered, type of algorithm, methodology, and problem objectives.

Table 2: Summary of free-floating bike-repositioning problem literature.

Reference	Problem Type	No. of Vehicles	No. of Bikes	Solution Methodology		Objective: Minimize
Pal and Zhang (2017)	S	≥ 1	400	H	Hybrid Large Neighbourhood Search and VND	makespan of the fleet of rebalancing vehicles
Liu et al. (2018)	S	> 1	400	H	Chemical Reaction Optimization	weighted sum of inconvenience level, unmet demand, and total operational time
Du et al. (2020)	S	≥ 1	4760	E, H	ILP and a Greedy-Genetic Heuristic	makespan of the fleet of rebalancing vehicles
Ma et al. (2021)	S	> 1	-	H	Stochastic Simulation-based Genetic Algorithm	total cost for the rebalancing vehicles
Zhang et al. (2022)	S	1	500	H	Adaptive Hybrid Nested LNS and VND	total cost of rebalancing process
Caggiani et al. (2018)	D	1	200	H	Decision Support System, Genetic Algorithm	unmet demand and lost users
Warrington and Ruchti (2019)	D	> 1	1103	H	SPAR algorithm	total cost of rebalancing process
Luo et al. (2021)	D	1	8	-	Policy Function Approximation	unmet demand

Explanation of terms:

S = Static, D = Dynamic, E = Exact, H = Heuristic, VND = Variable Neighbourhood Descent, ILP = Integer Linear Programming, LNS = Large Neighbourhood Search, SPAR = Sparse Phase and Amplitude Reconstruction

3.2.2 Summary

Most of the papers from the literature regarding rebalancing optimization of bike-sharing are devoted to static repositioning which assumes that the demand variation can be neglected. Less are associated with dynamic repositioning. There are also fewer papers on vehicle repositioning in free-floating systems than in station-based systems, because free-floating bike-sharing systems entered the market later and are more complex to model. In most papers they transform free-floating systems into station-based systems by defining virtual stations (nodes) and repositioning vehicles among these virtual stations. Some other papers divide the operating area into smaller zones (segments, clusters, partitions, regions, etc.), aggregate each zone as a virtual station, and only reposition among the virtual stations. Furthermore, the repositioning scenarios include single-truck and multi-truck repositioning where the stations can be visited only once or multiple times. The target function is also variable, such as minimizing the total cost, minimizing the total travel time, or it is a combination with user dissatisfaction and penalty costs. In addition, the solution methods mainly include branch and bound methods, relaxation methods, meta-heuristics and complex heuristics. Finally, some articles employ deterministic demand, whereas others employ stochastic demand. As mentioned by Neumann-Saavedra et al. (**2021**), employing stochastic demand requires significantly more run-time and memory capacity, which is not always possible but is preferred to obtain more accurate solutions.

In certain literature, the effectiveness of the algorithms is tested using data from real-world bike-sharing systems. The sizes of the instances they can handle varies per study. The methodologies from these studies that can handle the largest instance size are listed below.

For the static station-based problems: Rainer-Harbach et al. (**2014**) apply their methodology to real data from CityBike Wien, the major public bike-sharing system in Vienna, Austria. They experiment with small, medium, and large-size instances with up to 700 stations, where rebalancing is performed by a maximum of 5 vehicles. Dell'Amico et al. (**2016**) evaluate their strategy with data of 10 different bike-sharing systems from across the world. These real-life data sets contain data from 150 to 564 stations, rebalanced by one single vehicle. Ho and Szeto (**2017**) test their large neighborhood search on 518 stations and 5 vehicles. In the dynamic station-based case: Both Ghosh et al. (**2017**) and Datner et al. (**2019**) validate their methodologies on two real world data sets from Capital Bikeshare (Washington, DC) and Hubway (Boston). The data sets include 300 stations as well as 5 vehicles that perform the rebalancing.

For the static free-floating problems: Du et al. (**2020**) evaluate their methodology on two real world data sets with up to 4760 bikes from Share-A-Bull in South Florida and Divvy in Chicago. To tackle this problem, they cluster the distribution of bikes across 476 nodes and only rebalance the bikes between these virtual stations. In the dynamic free-floating case: Warrington and Ruchti (**2019**) validate their methodology using real world data from Philadelphia's public bike-sharing scheme, which includes 1103 bikes and 102 rebalancing node. They even increased the data set to 400 nodes to experiment with. According to this paper, if more research on free-floating systems is required, a way to map the infinite-dimensional input to a finite decision problem at acceptable computational cost must first be discovered.

3.3 Simulation

A simulation model mimics the operation of an existing or proposed system over time, providing evidence for decision-making by being able to test different scenarios or process changes. Simulation models can be classified according to some of the following characteristics.

Deterministic or stochastic

A simulation model is deterministic if its behavior is entirely predictable. Given a set of inputs, the model will result in a unique set of outputs. A simulation model is stochastic if it has random variables as inputs, and consequently also its outputs are random. These random variables are not always random; they may also be a distribution around the true or expected value.

Static or dynamic

Simulation models can be static or dynamic. A static simulation model represents the system at a particular point in time. Dynamic simulation models represent systems as they evolve over time. A static stochastic simulation model is often called as a Monte Carlo simulation.

Discrete or continuous

Dynamic simulations can be further categorized into discrete or continuous simulations. The variables of interest of discrete simulation models change only at a discrete set of points in time. Between these points in time, the system does not change state, it is therefore useless to inspect the system in more detail than only at these points in time. The discrete set of points in time are also called events. In continuous simulations, the variables of interest change continuously over time.

An overview of the classification of simulation is given in Figure 3.

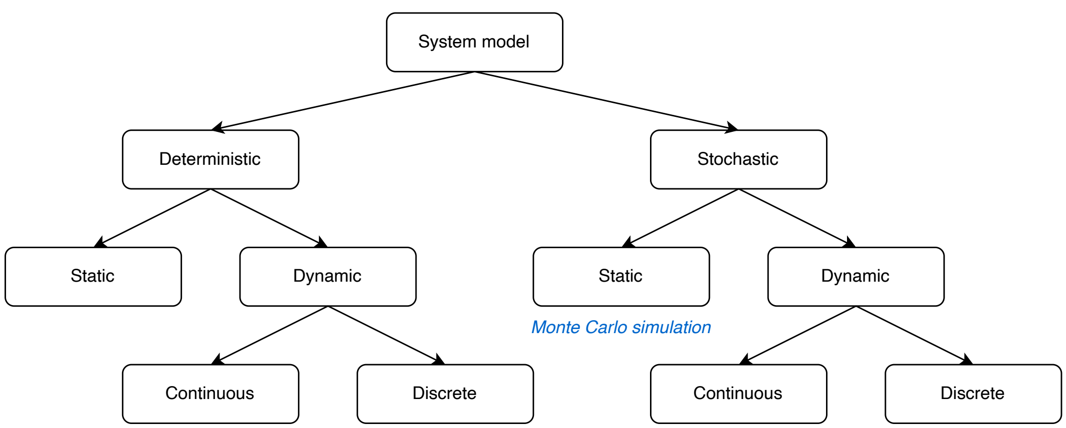

Figure 3: Simulation overview.

Techniques

The main simulation techniques used in operational research are: Discrete-Event Simulation (DES), System Dynamics (SD) and Agent Based Simulation (ABS). Each of these techniques has its own pros and cons, it is therefore necessary to carefully consider which technique best reflects the system.

DES is the most widely used simulation technique in operational research. As the name suggests, it models a process as a series of discrete events in time. It is a stochastic model and therefore uses probability distributions as input values. The model consists of entities (objects that move through the system), events (processes which the entities pass through), and resources (object which are needed to trigger events). SD takes a different approach to DES, focusing on flows around the networks rather than queuing systems. It is usually a deterministic model and continuous. The model consists of stocks (basic stores of objects), flows (movement of objects between different stocks in the system), and delays (time between the measuring and then acting on that measurement). ABS is a relatively new technique and is used to study the interactions between independent agents. A feature of ABS is its flexibility and can therefore easily be integrated into DES or SD simulation environments. The attributes of the agents can be static, not changeable during the simulation, or dynamic, changeable as the simulation progresses. The model consists of a set of agents (self-directed objects which move around the system), rules or methods of interaction (which the agents follow to achieve their objectives), and an environment (where the agents interact with other agents).

Once a simulation model has been constructed, it is validated against historical data that describes the behaviour of the system over time. A major advantage of simulation is that the model can be used to make modifications and predict effects on the system's performance. Such computer experiments can be performed without disrupting the practical setting.

3.3.1 Rebalancing through simulation

Simulations are more effective at capturing system interdepencies. Simulators also take into account uncertainties and randomness. By running multiple simulations, the sample mean averages of the solutions can be obtained. However, simulations are not employed solely to decide how to rebalance the fleet of vehicles in shared mobility systems. Simulations can be used to generate demand, for example. This could be because the actual data, which consists of the rides that occurred, only represents the fulfilled demand and not the unfulfilled demand, in which customers would like to take a ride but there is no availability. In such a case, one can opt to simulate the data by taking samples from a Poisson distribution, for example, as can be seen in Ghosh et al. (**2017**). Another approach is to evaluate the results of optimization models by using simulation and determine the number of rides that could occur, the expected profit and/or lost demand, which is done in the paper of Datner et al. (**2019**). As previously stated, a simulator takes the uncertainties into consideration more thoroughly, allowing for more realistic answers.

3.4 Simulation optimization

It is often difficult to obtain nice form analytical models of certain systems that can be used to accurately capture the behavior. Simulation techniques are commonly used in these systems to evaluate and compare design alternatives to identify the best design among them. However, when the systems are complex and the number of design alternatives is very large or infinite, simulation can be both expensive and time consuming. Therefore, it is important to improve the simulation output to evaluate and compare the systems while the resources used are minimal. This area of research, known as simulation optimization (SO), simulation-based optimization, or optimization via simulation (OvS) is a technique used to optimize stochastic simulations. It involves the search for those specific settings of the input parameters such that an objective, which is a function of the simulation output, is maximized or minimized. Some examples of classical simulation-optimization applications include supply chain inventory, queuing systems, and financial systems.

Local and global optima

Similar to optimization problems, simulation optimization methods can produce local or global optima. Suppose the decision variables take on continuous values and that the true function looks like a rolling landscape with many valleys and basins. Unfortunately, no simulation optimization algorithm can observe the entire landscape and therefore cannot distinguish between local and global optima. If you're lucky, there may be derivative information available to take you a little farther in locating the optima, but discovering global optima remains quite difficult.

There are many different methods used in simulation optimisation problems, each having its specific application. A global classification scheme of simulation optimization methods is given in Figure 4 based on the article of Ammeri et al. (**2010**).

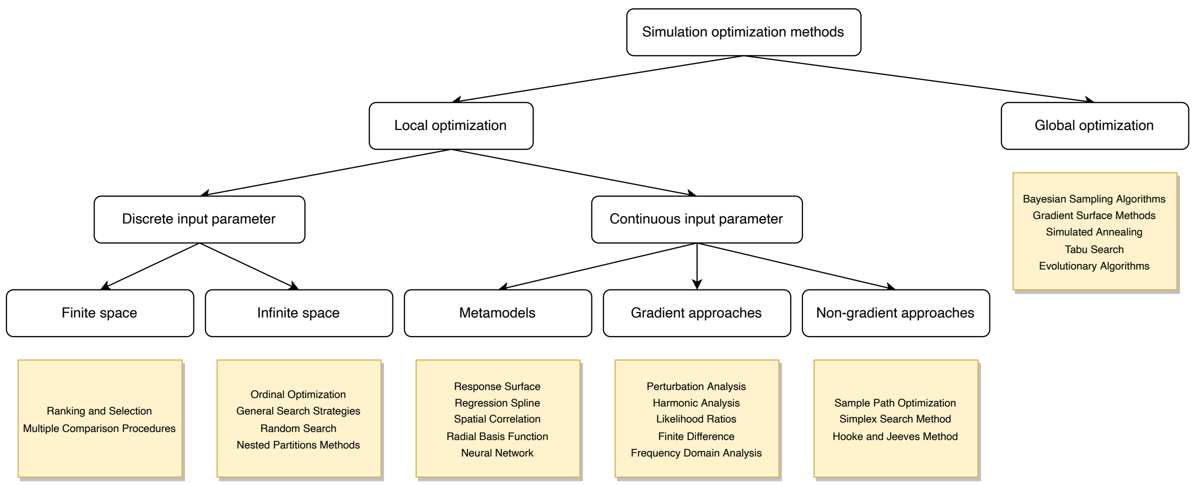

Figure 4: Simulation optimization overview.

3.4.1 Rebalancing through simulation optimization

Simulation optimization can also be applied to shared mobility systems to determine the optimal decisions to rebalance the fleet of vehicles. Related literature is provided below. These papers focus on various sharing systems such as car-sharing, mobility on demand (MoD), and bike-sharing systems.

Cepolina and Farina (**2012**) propose a methodology, based on the Simulated Annealing (SA) algorithm to optimize the fleet distribution of a station-based car-sharing system. The reason for this is that there is no analytical expression for the cost function, so the chances are high that a local optimum is reached instead of a global optimum, and the search space is extremely large. The methodology includes a simulation model of the proposed transport system which allows one to track the second-by-second activity of each user, as well as the second-by-second activity of each vehicle. The cost function consisting of the transport management cost (i.e. the cost of vehicles) and the cost to the customer (i.e. the total customer waiting time) is minimized by explicitly simulating the arrival of the users, the departure of the vehicles from the stations and the arrival of the vehicles at the stations. Deng (**2015**) develop a decision support tool to assist with determining the optimal fleet configuration of a MoD system accounting for stochastic demand and the effect of conducting vehicle distribution as part of daily operations. An optimization problem is defined to find the optimal fleet configuration is terms of minimizing cost and satisfying a certain level of service. A discrete-event simulator

(DES) that includes a sub-optimization model to calculate hourly rebalancing schemes is built to estimate the performance of a given configuration. Finally, an algorithm is devised that combines Particle Swarm Optimization (PSO) and Optimal Computation Budget Allocation (OCBA) techniques to efficiently search the design and decision space. Jian et al. (**2016**) use DES to model a station-based bike-sharing system. They tackle the rebalancing problem over bikes and docks as a simulation-optimization problem. Ideally, they would apply standard simulation-optimization methods, such as stochastic gradient-search and random search, to solve the problem, but this seems computationally infeasible. Instead, they develop heuristic search procedures that use statistics from a single simulation run in order to update the allocation of bikes and docks between stations. In each iteration they generate a trial solution and evaluate it with the DES model. If the trial solution improves the objective, then they move to that solution, otherwise they stay at the last solution. They do not claim that they find local or global optima, but instead see the value of these algorithms in the improvements they make in performance relative to that of starting solutions.

Marczuk et al. (**2016**) develop several optimization models for three rebalancing policies within car-sharing systems: i) no rebalancing (baseline), ii) offline rebalancing, and iii) online rebalancing. The performance of the three policies are then evaluated using the simulation program SimMobility. Zhou et al. (**2017**) propose a car-sharing optimization problem also as a simulation-optimization (SO) problem. Here, no analytical expression of the objective function is available, hence traditional (analytical) discrete optimization algorithms cannot be used. A novel metamodel is formulated, which is based on a MIP formulation. The metamodel is embedded within a general-purpose discrete SO algorithm. The combination of the problem-specific analytical MIP with a general-purpose SO algorithm enables to address high-dimensional problems and become computationally efficient. More generally, the information provided by the MIP to the SO algorithm enables it to exploit problem-specific structural information. Hence, the simulator is no longer treated as a black box. Gómez Márquez et al. (**2021**) develop a simulation-optimization framework to determine the bike inventory for stations in a large-scale bike-sharing system. The framework helps to optimize both the bike inventory at the beginning of the day, which is the focus of static rebalancing, and the bike inventory throughout the day, which is the focus of dynamic rebalancing. They implement several simulation-optimization methods including nested partitions (NP), interactive particle algorithm (IPA), cross entropy, and discrete simultaneous perturbation stochastic approximation (DSPSA) and find that IPA provides good solutions within reasonable computing time. Jin et al. (**2022**) propose a simulation framework for evaluating different rebalancing and maintenance strategies to model the daily operations of large-scale bike-sharing systems with docking stations. The framework can be integrated with any multi-vehicle static or dynamic rebalancing optimization model. An optimization model solved by an enhanced k-means clustering method (EKM) and an Ant Colony Optimization (ACO) algorithm is provided as an example for demonstrating such integration. Although the proposed simulation framework is developed for bike-sharing systems, it can be easily modified for modeling other transportation systems with non-floating stations (e.g. electrical bikes and scooters).

3.4.2 Summary

The field of simulation optimization has progresses significantly in the last decade with several new algorithms, implementations, and applications. Different approaches and algorithms are used to imitate reality as precisely as possible with the simulations, and then integrated with optimization techniques to ultimately make good decisions regarding rebalancing the fleet of vehicles. There is still plenty to discover in this field of research. It is notable that all of the aforementioned references from the literature focus on station-based sharing systems. Currently, no simulation optimization techniques are applied to free-floating sharing systems.

Some of the algorithms used in the literature are tested using data from real-world bike-sharing systems. The sizes of the instances they can handle varies per study. The methodologies from these studies that can handle the largest instance size are listed below.

Jian et al. (2016) apply their methodology to real data of Citi Bike in New York City. They exclude the lower demands seen on weekends and hence only use data from 14 weekdays. The data set includes 466 stations and 6074 bikes. Zhou et al. (2017) evaluate their strategy using data from Zipcar in Boston, one of the world's leading car-sharing service providers. This real-world data set contains data from 315 stations and 894 cars. Gómez Márquez et al. (2021) initially test their methodology on real data from Ecobici, a bike-sharing company in Mexico City. Later, they also test their methodology using the data of Citi Bike in New York City, similarly to Zhou et al. (2017), and achieve relatively similar results. Due to the rapid growth of Citi Bike, the data at this time includes 620 stations and 12,500 bikes. One year later, Jin et al. (2022) validate their methodology as well on real data from Citi Bike New York City. At the time, the data consists of 858 stations and 19,506 bikes.

4 Conclusion

In this review, the origins of the sharing economy are first examined, along with certain key historical events up to the present day. Subsequently, the many aspects and characteristics of shared mobility systems are addressed in order to provide a thorough understanding. Following that, the various methodologies used in the literature to match vehicle supply and demand within shared mobility systems are explored. The conclusions about these methodologies are explained below.

To begin with, predicting the demand in shared mobility systems is crucial. Demand remains an ambiguous factor since it depends on users' decisions. Furthermore, demand varies drastically depending on the day of the week, the time of the day, the weather and whether or not an event is taking place somewhere. It is critical to identify patterns in this unpredictable demand in order to adjust vehicle supply accordingly. Don't merely look at historical data to see what happened in the past. The potential mainly lie in better forecasting demand. This can be accomplished using a variety of machine learning methods, such as Neural Networks.

One method to better match supply and demand is by using optimization models. These optimization models determine the optimal or near optimal distribution of the vehicles throughout the service area, under certain constraints. A lot of research has been conducted into methodologies for optimizing the distribution of the vehicles within station-based bike-sharing systems. However, research on free-floating bike-sharing systems has been limited. This is due to the fact that these systems were introduced to the market later and are significantly more complex to model. In free-floating studies, the service area is often divided into a grid in order to define these problems as station-based systems. As a result, the solution space is reduced, making it easier to solve these problems quickly and efficiently. The studies for both station-based and free-floating systems vary in the number of repositioning vehicles used, number of stations or bikes that can be considered, type of algorithm, methodology, and problem objective.

One shortcoming of these optimization models is that in most cases they cannot properly account for uncertainty and randomness in the input parameters. Simulation models, on the other hand, are able to represent reality much better and are therefore highly suitable for real-life cases where these uncertainties often apply. Simulation models are doing well in imitating reality but not in optimization. Simulation optimization, in which a simulation model is integrated with an optimization model, is a rising topic in today's literature. In this way, the benefits of both models are combined.

Research within simulation optimization in shared mobility systems is only from recent years, and there is still plenty to discover. There are some studies in the literature that apply simulation optimization to station-based systems, but to the best of our knowledge, no one has yet succeeded in extending simulation optimization to free-floating systems. Furthermore, most models require a large amount of computational time and power to provide meaningful results.

To answer the main question addressed in this literature review (see section 1.2): Rebalancing the fleet is required to better align the expected demand and supply of vehicles in shared mobility systems in order to optimize the fleet's operational capability. The optimal distribution of the fleet can be established using optimization models and simulations combined with optimization models, also known as simulation optimization, to get as close to reality as possible.

Another possibility to combine simulation with optimization is to use them sequentially rather than integrated. Based on the expected supply and demand, an optimization model determines the optimal decision or the near optimal decisions for rebalancing the vehicles. The distribution of the vehicles after the rebalancing actions have been performed, can then be evaluated with a simulation model to ensure a more accurate representation of reality and to revise the possibly differing near optimal outcomes of the optimization model to ultimate performance.

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