# Adapting User-Based Vehicle Relocation for E-Carsharing

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**Abstract.** The mobility sector has been established as a prominent example for the sharing economy. E-carsharing offers a way to introduce and utilize electric vehicles as a sustainable mobility service to solve current and future mobility issues. Nonetheless, e-carsharing still faces several challenges that need to be overcome in order to act as a mainstream means of commute.
In this article, we propose user-based relocation to improve the use and availability of electric vehicles within e-carsharing. It enables value co-creation by actively involving the user in value creation, e.g. increasing the position-dependent value of a shared vehicle. By simulating an e-carsharing system, we were able to analyze the capabilities of user-based relocation. The results indicate that user-based relocation has the potential to greatly improve electric vehicle use and demonstrates an example of successful value co-creation in the sharing economy. Furthermore, it strengthens e-carsharing as a part of everyday mobility.

**Keywords:** Carsharing, mobility sharing, vehicle relocation, user-based, information system

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# 1 Introduction

Enabled by internet and mobile technology, the sharing economy unfolds its potential of disrupting industries and markets increasingly [1, 2]. The mobility industry serves as an example of an industry ascending from a product- to service-based business model. Carsharing serves as a prime example since it demonstrates the benefits of collaborative consumption of a resource instead of owning it personally [3, 4]. Within the sharing economy, carsharing is a prime example for the access economy, since it demonstrates the potential of replacing the underutilized resource of a privately owned car with shared vehicles that can be accessed on-demand [5]. While a major challenge for businesses of the platform economy is to accomplish the network effect, systems that provide access to relocatable goods (e.g., car-, e-scooter-, bike-, umbrella-, power-bank-sharing) face the challenge of asynchronous spatial supply and demand [6]. In general, costumers use services of the sharing economy to reach their goal, which in this context means to find the requested good for utilization nearby [7]. Rebalancing the physical goods in the system therefore becomes a success factor of creating value with the service and avoids availability uncertainty.

Against this background, researchers have developed a new concept called user-based relocation. The idea of user-based relocation is to motivate users to return currently rented vehicles at stations with high vehicle-demand [8, 9]. It enables the value co-creation by actively involving the user in value creation, e.g. increasing the position-dependent value of a shared vehicle. Thus, value is co-created [10, 11]: The carsharing provider generates value by offering to rent from a distributed fleet of vehicles, and customers can increase value through relocations.

Despite the cost advantage of user-based relocation, this strategy is yet to be adapted for e-carsharing. The majority of existing research on vehicle relocation takes place predominantly in conventional carsharing and operator-based relocation strategies [12].

Carsharing services with electric vehicle (EV) fleets offer a high potential of reducing CO2 emissions and air pollution [13], but also add a new dimension to the vehicle relocation problem. EVs are dependent on a sufficient charging management and infrastructure to avoid range anxiety and other negative experiences for customers [13, 14]. In this light, current charging status and availability of charging infrastructure must be considered to improve effectiveness of EV relocation.

Thus, we strive to facilitate a decrease in costs through the application of user-based relocation and to subsequently increase the flexibility of e-carsharing by answering the following research question:

RQ: *How can user-based relocation be adapted to the context of e-carsharing?*

# 2 Research Background

In the context of carsharing, the term "relocation" describes the process of altering vehicle distribution to counter the discrepancy of vehicle demand and supply within a carsharing system [15]. Vehicle relocation is an important part of carsharing, as it

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ensures the provision of a satisfactory service quality to its customers through continuous vehicle availability sufficient to meet demand [16]. There are currently two types of relocation approaches [15]: (1) **Operator-based relocation:** In operator-based relocation, staff members rearrange the vehicles by driving, towing or ride-sharing them to the desired location [17]. (2) **User-based relocation:** The idea of user-based relocation is to motivate users to return the vehicle at a different station as opposed to their initial destination during the rental [9].

To evaluate the current status quo of relocation research regarding e-carsharing, we analyzed literature review studies on this topic. Based on the literature reviews [12, 18–20], we analyzed the vehicle type fleet composition (electric vehicles (EV), internal combustion vehicle (ICV) or mixed), relocation method (user-based or operator-based), and carsharing form (free-floating or station-based).

The review provides evidence that station-based one-way carsharing and operator-based relocation are more predominant research topics. Free-floating carsharing, user-based relocation, and especially e-carsharing are newer concepts and are currently underrepresented in vehicle relocation research. Despite the potential of user-based relocation in e-carsharing, most of relocation literature focuses on operator-based ICV relocation, and to date, there is only limited research regarding the adaptation of user-based relocation in e-carsharing.

## 3 Research Approach

The development of novel solutions for relevant problems falls under the Design Science Research (DSR) paradigm. Hence, adopting a DSR approach fits the research objective of developing and evaluating a user-based relocation procedure for e-carsharing. Thus, our research adopts a research process from [21, 22] as depicted in Figure 1. We completed all three cycles (relevance, rigor, and design) of DSR in an iterative fashion [22].

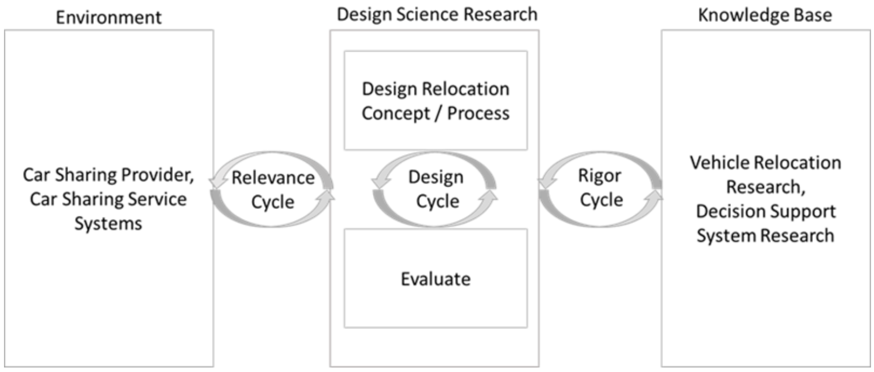


**Figure 1.** Applied Design Science Research Process

The relevance cycle inherits the interconnection of design activities and its application environment and practice, enabling an assimilation of real-world

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requirements. Furthermore, it enables the introduction of newly designed artifacts to the field. The rigor cycle connects design activities with the knowledge base to integrate and extend theories and knowledge. The core of the DSR model is the design cycle, which includes the iterative construction and evaluation of the artifacts [22].

We adapted user-based relocation for e-carsharing in one and a half iterations. The first iteration consisted of a relevance, rigor, and design cycle. The artifact resulting from the design cycle was informed by the environment in the relevance cycle and by the knowledge base during the rigor cycle. The second iteration consisted of a relevance cycle and a rigor cycle. The subsequent artifact was applied within its intended field as a simulation and was evaluated based on its performance in the relevance cycle. Lastly, we reflect on the artifact and related development process, synthesizing the gathered knowledge as a design theory [23] and present our research in this article in the final rigor cycle.

### 3.1 Iteration 1: Problem Definition and Artifact Design

The first iteration started with a relevance cycle, revealing a lack of user-based relocation methods for e-carsharing (see Related Work section). We discussed this result with a local e-carsharing provider who confirmed our findings that e-carsharing is in need of specialized relocation methods. Thus, our relevance cycle resulted in the identification of a practical problem: there are currently no concepts for user-based relocation in e-carsharing.

Subsequently, we began our research process by identifying the aim of relocation method development for implementation within an IS to increase availability of EVs within e-carsharing systems (either with a pure EV fleet or with a mixed vehicle fleet). Based on the literature review (see Related Work section) and an interview with a local e-carsharing provider, we gathered four essential requirements: **R1 – Charge Management:** EVs must be relocated in a way that ensures enough charge for future rentals, **R2 – EV Utilization:** EV relocations should lead to increased use, measured by number of rentals and/or kilometers driven, **R3 – Cost Efficiency:** The number of relocations should be minimized to ensure cost-efficiency, and **R4 – Overall Performance:** The EV relocations must not reduce overall system performance, measured by total number of accepted rentals.

As a second step, we performed a rigor cycle drawing from the existing vehicle relocation literature to select an appropriate starting point for the design process. We identified the user-based relocation information system framework and algorithms/ heuristics of [24] as a promising input source for our design activities.

In the following design cycle, we iteratively adapted the concept of user-based relocation to meet the predefined requirements. Furthermore, we adapted and developed heuristic algorithms for the individual functions of each component. The algorithms developed serve as a valuable tool for optimization [25] and help to gain an initial understanding of a complex problem, thereby guiding development of future solutions.

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### 3.2 Iteration 2: Evaluation and Publication

In DSR, it is important to evaluate artifacts as closely as possible to their real-world environment and intended field of application [21, 26]. Therefore, we developed a discrete-event simulation of an e-carsharing system as part of the relevance cycle. Simulations are commonly used in the general context of vehicle relocation research [27], while discrete event simulations are particularly common for carsharing simulations because they are able to identify system behavior changes when a set of different constraints is implemented. Furthermore, a carsharing system's state changes only through events such as rental requests, supply imbalances, relocations, and returns, which can be described through discrete-event simulation [28]. The developed simulation consists of individual users, vehicles, and stations. Rentals are implemented as an event queue. We built the simulation system based on the carsharing system from which we gathered the rental data as input. The simulation revealed novel design principles for user-based relocation in e-carsharing, which concluded the research design process.

Lastly, we performed a final rigor cycle to add the artifact, its development process, and its design implications to the existing body of knowledge. We contribute to the knowledge base with a summary of our research and reflections on the results in the form of this article.

## 4 Adaptation of User-Based Relocation for E-Carsharing

We base our adaptation of user-based relocation in e-carsharing on the "User-based Relocation Information System Framework" [8], which consists of a prediction, relocation, and customer interaction modules. The prediction module estimates future vehicle demand of each station by analyzing previous rental data. Each station has an individual threshold of vehicles to satisfy future demand. If current vehicle supply at a station is below its threshold, vehicles must be relocated to this station. The relocation module identifies users driving towards under-supplied stations within their vicinity. To motivate user-based relocation, the customer is prompted with an incentive accompanying the relocation request via the customer interaction module.

E-carsharing fleets can consist of a mix of ICVs and EVs, referred to as mixed fleets, or exclusively consist of EVs, referred to as pure EV fleets. In this study, user-based relocation is evaluated for both types of fleets. Furthermore, we argue that the prioritization of EVs (R2) and the allocation of available charging points (R1) is important. Therefore, we developed two adaptation versions of the underlying algorithm to test each approach:

**(1) Prioritizing EVs for relocation:** For mixed fleets, we propose prioritizing EVs before ICVs in the relocation module. This means that users driving an EV will receive relocation requests before users, driving an ICV. Hence, EVs will be prioritized and relocated to stations with a demand for vehicles leading to a higher utilization of EVs within a mixed vehicle fleet.

**(2) Relocating EVs to stations with a free charging point:** In a pure EV fleet, EVs cannot be prioritized for rental. Therefore, we developed a second adaptation

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which not only relocates EVs to stations in demand of vehicles, but also relocates EVs to stations with free charging points in case the charging point at the initial destination is occupied at the time of arrival. This should lead to increased pure EV fleet utilization through charging infrastructure and EV availability optimization. Hence, this approach seems promising for both types of vehicle fleets.

### 4.1 Data Set

A rental data record can include different variables, such as customer ID, start time, end time, origin station, destination station, etc. [9]. For an e-carsharing relocation simulation, rental *r* can be described with the following tuple [29]:

$$r = (\text{origin}, \text{destination}, \tau_s, \tau_t, \text{distance}, \text{power consumption}) \tag{1}$$

where *origin* describes the rental starting point, *destination* defines the station where the rental will end, $\tau_s$ represents the start time, $\tau_t$ is the travel time of the rental, *distance* measures the kilometers driven during the rental, and *power consumption* signifies the electric energy needed.

In this context, real-world data can be insufficient when it is collected from a real-world carsharing system as the data is incomplete and biased by the implemented relocation method. To account for such biases, we generated a data set following an established data generation approach [28]. The approach generates artificial rental data by training machine learning algorithms to learn the patterns within real-world data.

To generate our data set, we used two different car-sharing data sets: one from a conventional carsharing system and one from a smaller e-carsharing system. For *origin, destination,*$\tau_s$, $\tau_t$, we used a data set consisting of 2,062 rentals gathered over the course of 3 months from the conventional carsharing system, on which we modeled our simulation. The system offers vehicles from a fleet of 50, excluding transporters and other special vehicles, and contains 10 stations that are strategically distributed within a German city of around 100,000 inhabitants. For measuring *distance* and *power consumption,* we used an additional data set containing 2,849 rentals gathered over the course of 437 days supplied by a German provider with a station-based one-way e-carsharing system. The e-carsharing fleet consisted of eight VW e-ups with three stations and two charging points per station.

We generated simulated data following the approach of [29] based on the following equation:

$$P(\tau_s \cap \tau_t \cap \text{origin} \cap \text{destination}) =$$

$$P(\tau_s \cap \tau_t) \cdot P(\text{origin} \mid \tau_s \cap \tau_t) \cdot P(\text{destination} \mid \tau_s \cap \tau_t \cap \text{origin}) \tag{2}$$

$$* \; P(\text{distance, power consumption} \mid \tau_s \cap \tau_t \cap \text{origin} \cap \text{destination})$$

A Gaussian Mixture Model was used to generate the time tuple $(\tau_s, \tau_t)$, a decision tree for $origin$, and one for the $destination$. We also used a Gaussian Mixture Model to add *distance* (based on the km per min.) and *power consumption* (based on

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the Difference of “State of Charge” (SoC) per km) to each rental [29]. We used the scikit-learn Python library for the implementation and grid search to obtain the configurations of each algorithm [30].

Consequently, we generated two data sets for the simulation: One representing a normal demand situation and the other representing a higher demand situation. To define a normal demand situation, we analyzed our first data set (normal carsharing) containing 2,062 rentals carried out over the course of three months. Thus, the resulting generated data sets consisted of 2,000 rentals (normal demand situation) and 4,000 rentals (high demand situation) within a three-month timeframe, allowing analysis of adapted user-based relocation approaches under the two different circumstances.

## 4.2 Simulation

The functions, parameters, and assumptions of the simulation are described in the following section. It is important to note that EVs are prioritized before ICVs to be rented out to customers. If multiple EVs are available and not currently charging, the EV with the highest SoC is selected for rental.

**Relocation Method**

Following the common threshold approach, each station requires a threshold representing the minimum number of vehicles needed, which is defined as follows [24]:

$$\mathrm{T}_\tau^\mathrm{S} = \frac{\mathrm{B}^\mathrm{S} * \mathrm{nv}_{\tau_1,\tau_2}}{\mathrm{K} * \mathrm{B}} \qquad (3)$$

$T_\tau^S$ = Minimum threshold for station S at time point τ
$B^S$= Number of rentals at station $S$.
$B$ = Total number of rentals
$nv_{\tau_1,\tau_2}$ = Number of vehicles available in the time frame $\tau_1$, $\tau_2$
$\tau_1$ = Start of time frame; $\tau_2$ = End of time frame
$K$ = Risk of rejection

When the threshold is breached, relocations are needed. Threshold breaches are defined by the following equation:

$$\mathrm{T}_\tau^\mathrm{S} > \mathrm{ci}^\mathrm{S} + \mathrm{ct}^\mathrm{S} \qquad (4)$$

$T_\tau^S$ = Threshold of a station $S$ at the time point $\tau$.
$ci^S$ = Number of vehicles at station $S$
$ct^S$ = Number of vehicles driving to station $S$

The number of relocations needed to balance station supply and demand is calculated as follows:

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$$R^S = T_\tau^S - (ci^S + ct^S) \qquad (5)$$

$R^S$ = Number of relocations needed at station $S$

Customers will be asked to return their vehicles to a station with a breached threshold (referred to as a critical station) instead of the intended destination. Customers are selected for relocation as follows: (1) Select rentals with a destination near the critical station, (2) filter out any rentals with a critical destination or those already requested for relocation, and (3) sort filtered rentals by arrival time, prioritizing soon ending rentals.

Following this order, customers will be requested until a certain number of relocation requests $R^S$ are accepted or until no suitable customers are left, at which point the process is to be repeated later. We limited relocation requests to only prompt users with a rental ending in the next 15 minutes to avoid long-term distance relocations.

To adapt user-based relocation in e-carsharing, we propose the prioritization of EVs over ICVs for relocation. This might also have a positive influence on user acceptance since costumers prefer to experience an EV over an ICV [31]. The customer selection process described above is altered in step 3. Before filtering rentals by arrival time, rentals are divided into two groups: EV rentals and ICV rentals. Each group is then sorted by arrival time, and customers of EVs receive a relocation request first. Only when the option of requesting EV customers for relocation is exhausted, ICV customers are requested to relocate.

As a further step to adapting user-based relocation in e-carsharing, in cases where the charging point at the initial destination is occupied at the time of arrival, we also propose the relocation of EVs to stations with a free charging point. For each arriving EV, the availability of a charging point is checked 15 minutes before arrival. If no charging point is available, the stations within the vicinity of the destination will be checked for free charging points, and the EV customer receives a relocation request if a nearby charging point is available.

To model user behavior with regard to acceptance or rejection of relocation requests, relocation acceptance rates (RAR) serve as appropriate measures for carsharing simulation studies [24]. The RAR has a big impact on system performance and a RAR of fewer than 100 can lead to inconsistent results in the same setting [8]. Hence, we will use a fixed RAR of 100 for the entire course of the simulation to ensure consistent results and simulate an optimized user-based relocation system capable of successfully motivating user relocation behavior.

**Vehicles and Fleet Size**

The composition of a carsharing fleet has a significant influence on system performance and efficiency [32]. Therefore, fleet size must be determined prior to the estimation of other parameters like relocation thresholds.

The reference carsharing system had a fleet of 50 vehicles. However, pre-tests have shown that 50 vehicles are too many and a vehicle fleet with 40 vehicles can provide a similar service level for 2,000 rentals (normal demand situation). Furthermore, a

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smaller fleet leads to a system which is more sensitive to relocations, which is necessary to observe reactions to relocation process changes according to pre-test results. Larger fleets are less dependent on relocation, hiding the impact of relocation strategy variations. Based on these findings, we tested different fleet sizes with un-adapted user-based relocation and determined a vehicle fleet size of 24 for our simulation test case. A 24-vehicle fleet still has an 85% success rate (4.5% less than a fleet of 50 vehicles), despite being less than half the size of the referenced vehicle fleet. Therefore, a fleet of 24 vehicles is capable of providing a sufficient and relocation-sensitive carsharing system for our test-case and is used for the simulation. To evaluate the capability of the relocation approaches, we used two kinds of fleets: a mixed vehicle fleet and a pure EV fleet. The mixed vehicle fleet includes 14 ICVs and 10 EVs with one EV for each charging point (see next section). We describe the fleet as relatively homogeneous, as each vehicle has no further distinguishable characteristics such as speed or vehicle size, besides motor type.

**Stations and Charging Infrastructure**

The simulation included 10 stations with the same geographical distribution as in the referenced German carsharing system. Each station has one single charging point (charging 33.3 SoC per hour) allowing EV returns at any station and avoiding "stranding" of under-charged vehicles at stations without charging points.

**Charging Strategy**

Charging EVs is an essential part of e-carsharing and therefore requires simulation within its logistic limitations. E-carsharing providers can either always charge their vehicles or use some kind of charging management service [28]. Continuous charging is the strategy used by the referenced e-carsharing system and is therefore implemented in the simulation. Furthermore, EVs meant to be charged at an occupied charging point will start charging as soon as the slot is free. It is assumed that an operator will plug the EVs in.

**Risk Factor and Thresholds**

Risk factor ($K$) for rental rejection represents the risk of insufficient vehicle supply of a carsharing provider and is an important component of station threshold computation. A high risk factor leads to lower thresholds and therefore to a higher risk of insufficient supply and rental request rejection. A low risk factor leads to a higher threshold and better vehicle distribution but also to more relocations, leading to higher costs. Therefore, the risk factor must be determined in order to consider the number of accepted rentals and the number of relocations [24].

To set sufficient thresholds, different values for the risk factor ($K$) must be tested. We compared risk factor values for both demand level datasets including 2,000 and 4,000 rentals, a mixed vehicle fleet (24 vehicles), and continuous charging. To evaluate the best K value, we use the success rate (percentage of accepted rentals) and the effectiveness of relocation ($E$) [24]. The results showed K=1.5 as the most

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effective and efficient risk factor value in both demand cases and was therefore selected.

### 4.3 Results and Findings

To evaluate the capabilities of the adapted user-based relocation approaches, four scenarios were defined: (1) No relocation, (2) un-adapted user-based relocation, (3) user-based relocation prioritizing EVs, and (4) user-based relocation prioritizing EVs and free charging points.

**Table 1.** Scenario #1 (No relocations) and Scenario #2 (Un-adapted user-based relocation)

| **Scenario** | **#1** | | | | **#2** | | | |
|---|---|---|---|---|---|---|---|---|
| **Fleet** | **Mixed** | | **EV** | | **Mixed** | | **EV** | |
| Number of rentals | 2,000 | 4,000 | 2,000 | 4,000 | 2,000 | 4,000 | 2,000 | 4,000 |
| Case number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| **Success rate** | **66.97** | **64.75** | **65.32** | **60.55** | **85.03** | **80.46** | **81.84** | **78.97** |
| Relocations (all) | - | | - | | 678 | 1234 | 620 | 1,221 |
| Successful rentals (total) | 1,342 | 2,595 | 1,309 | 2,427 | 1,704 | 3,225 | 1,640 | 3,165 |
| Successful rentals (EV) | 864 | 1,589 | | | 1,002 | 1,913 | | |
| Rental errors | 90 | 139 | 128 | 216 | 98 | 166 | 155 | 279 |
| Rentals per charging cycle | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 125 |
| Avg number of charging cycles | 86.4 | 158.9 | 54.54 | 101.13 | 100.2 | 191.3 | 164 | 316.5 |
| Avg total charging time | 56.98 | 105.1 | 37.33 | 68.07 | 64.91 | 121.3 | 42.84 | 73.35 |
| Avg total rental time (EV) | 120.9 | 225.5 | 105.8 | 199.41 | 136.5 | 267.5 | 131 | 269.3 |
| Avg total rental time (ICV) | 107.8 | 223.1 | - | | 157.5 | 278.3 | - | |
| Avg idle time (EV) | 34.7 | 18.08 | 44.68 | 18.97 | 21.89 | 13.97 | 30.05 | 19.06 |
| Avg idle time (ICV) | 32.73 | 22.45 | - | | 26.25 | 21.14 | - | |
| Operator plug-ins | 1 | 2 | 3 | 12 | 1 | 2 | 3 | 15 |

Each scenario contains four cases. This is due to the two by two factor design of our research approach (composition: mixed or pure EV, demand: normal or high). Scenario 3 contains only two cases because EVs cannot be prioritized within a pure EV fleet. The scenarios and cases were chosen to simulate different stages of user-based relocation adaptation within e-carsharing for comparison.

To evaluate requirement fulfilment in each case, the following measurements were defined: (1) **Success rate:** Percentage of accepted rental requests, (2) **Relocations:** All completed relocations, (3) **Successful rentals (total):** Number of successful rentals of any vehicle type, (4) **Successful rentals (EV):** Number of successful EV rentals, (5) **Rental errors:** Number of reassigned ICV rentals due to insufficient EV charge, (6) **Average number of charging cycles:** Mean of total rental amount per

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charging cycle, (7) **Average total charging time**[1]**:** Total charging time of all EVs (in hours), (8) **Average total rental time:** Mean hours of all rental per vehicle, (9) **Average idle time:** Mean hours of idle time between rentals per vehicle, and (10) **Operator plugins:** Number of EV charges per operator.

The results of the simulations are shown in Table 1 and Table 2.

**Table 2.** Scenario #3 (User-based relocation – prioritizing EVs for relocation) and Scenario #4 (User-based relocation – prioritizing EVs and relocation to free charging points)

| Scenario | #3 | | #4 | | | |
|---|---|---|---|---|---|---|
| Fleet | Mixed | | Mixed | | EV | |
| Number of rentals | 2,000 | 4,000 | 2,000 | 4,000 | 2,000 | 4,000 |
| Case number | 9 | 10 | 11 | 12 | 13 | 14 |
| Success rate | 85.03 | 80.16 | 86.16 | 83.88 | 80.99 | 80.99 |
| Relocations (all) | 677 | 1,235 | 854 | 1,690 | 789 | 1,793 |
| Relocations for charging points | - | | 558 | 1,063 | 657 | 1,423 |
| Successful rentals (total) | 1,704 | 3,213 | 1,727 | 3,362 | 1,623 | 3,246 |
| Successful rentals (EV) | 1,029 | 1,916 | 1,127 | 2,057 | | |
| Rental errors | 102 | 165 | 117 | 176 | 154 | 280 |
| Rentals per charging cycle | 1 | 1 | 1 | 1 | 1 | 1 |
| Avg number of charging cycles | 102.9 | 191.6 | 112.7 | 205.7 | 67.63 | 135.25 |
| Avg total charging time | 66.77 | 125.83 | 73.93 | 138 | 45.1 | 85.59 |
| Avg total rental time (EV) | 141.1 | 267.37 | 157.27 | 290.01 | 137.54 | 263.08 |
| Avg total rental time (ICV) | 153.77 | 275.95 | 141.67 | 286.66 | - | |
| Avg idle time (EV) | 24.67 | 15.72 | 11.08 | 12.47 | 50.11 | 14.86 |
| Avg idle time (ICV) | 19.42 | 21.04 | 27.57 | 22.55 | - | |
| Operator plug-ins | 1 | 2 | 2 | 2 | 2 | 4 |

A comparison of scenario 1 and scenario 2 reveals that user-based relocation increases success rate by 15.7% up to 18.4%, requiring between 620 and 1,234 relocations. The other parameters increase according to the number of accepted rentals. For scenario 2, the duplication of rentals leads to a 5% decrease in success rate for mixed fleets. Nearly all other parameters (relocations, successful rentals, average number of charging cycles, average total charging time, deep discharges and average total rental time) are doubled, while the idle time is halved. For pure EV fleets, the success rate is lower than that of a mixed vehicle fleet's due to rental distance limitation of SoC, leading to a much higher number of rental errors in cases 7 and 8 in comparison to cases 5 and 6.

Relocating EVs to free charging points results in an increased success rate in comparison to all previous cases. The success rate drops when the number of rentals is doubled by ~2%, in comparison to cases 11 and 12, while the success rate stays the same for cases 13 and 14 with a pure EV fleet. Additionally, EV rental time and

[1] All time values are in hours. Total values are aggregated for the simulated timeframe of 3 months.

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successful EV rentals are increased significantly by around 10%. The other parameters react similarly when the number of rentals is doubled as in the other cases.

Thus, for mixed vehicle fleets, adapting user-based relocation has little to no effect on EV use for adaption approach 1 (scenario 3), while adaption approach 2 not only increases EV rentals by around 10% (R1 and R2) but also increases the overall success rate by 1% to 3% for a mixed vehicle fleet (R4). Furthermore, the number of relocations is only increased by around 25% (R3). Thus, in contrast to intuitive approaches concentrating EVs at stations with a high vehicle demand, results show that the most effective strategy for optimizing EV utilization is to spread EVs over multiple stations. This implies that strategies strictly prioritizing EVs for relocation should be avoided in favor of also prioritizing relocations for open charging points.

For a pure EV fleet using un-adapted user-based relocation, the number of accepted rentals increases significantly to a rate of 18.4% (R1, R2 and R4). Fully adapted user-based relocation strategies (scenario 4) increase the success rate for 4,000 rentals by around 2% while reducing the success rate for 2,000 rentals by over 1% (R4). Additionally, when evaluating rental increases in the context of the number of additional relocations, the conclusion is that un-adapted user-based relocation is the optimal strategy (R3). In summary, adapting user-based relocation by prioritizing EVs and relocations to free charging points is a promising approach for mitigating the vehicle relocation problem within the context of mixed vehicles fleets, while un-adapted user-based relocation strategies are most effective for pure EV fleets.

# 5 Discussion and Conclusion

The research project presented in this article aims to develop a user-based relocation approach tailored for the needs of e-carsharing. In the following section, we discuss the implications of the developed artifacts followed by limitations and future opportunities for the presented research.

## 5.1 Implications

DSR adds to theories by developing new design theories, in other words, by explaining *how to do something*. Correspondingly, we summarize our findings as a design theory [23] for vehicle relocation IS in e-carsharing. The resulting design theory insights are summarized in Table 3. Adapting user-based relocation by prioritizing EVs and relocations to free charging points shows an improvement of the system performance within the context of mixed vehicles fleets, while un-adapted user-based relocation strategies are most effective for pure EV fleets. Increasing the number of EV-rentals might also have a multiplicator effect, since carsharing users perceive EVs as more attractive than ICVs [31]. Furthermore, the framework is scalable to free-floating carsharing systems and more sophisticated demand-modelling approaches.

While the outcomes provide solutions for the known problem of vehicle relocation (improvement), this research also extends user-based relocation to the novel problem

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of EV relocation (exaptation). In addition to the theoretical contributions, the developed relocation algorithm also contributes to practice. The goal of design science research is to achieve practical relevance by solving prevailing problems of practitioners [21]. This study provides guidance on how to solve the relocation problems of e-carsharing, thereby providing valuable guidance for carsharing providers in the development of contextualized IS for EV relocation and rethinking currently employed relocation strategies. The suggested design includes the customer in the value creation process, which furthermore repositions a carsharing service from an access economy to a community-based access economy. This has the potential to prevent the risk of moral hazard, since value co-creators might be more interested in preserving the well-being of the community [5].

**Table 3.** Design Theory of Vehicle Relocation IS in E-Carsharing

| Component | Description |
|---|---|
| ***Purpose and Scope*** | Goal: Increasing the availability of EVs within an e-carsharing system.<br>Requirements: Charge Management (R1), EV Utilization (R2), Cost Efficiency (R3), Overall Performance (R4) |
| ***Constructs*** | Rental, Customer, Vehicle, ICV, EV, SoC, Charging point, Station, Relocation |
| ***Principle of Form and Function*** | Relocation procedures for pure EV fleets should not consider relocating to available charging points.<br>Relocation procedures for mixed vehicle fleets should prioritize EVs for relocation and also should relocate EVs to available charging points. |
| ***Artifact Mutability*** | Adaptable for free-floating e-carsharing<br>The modular architecture enables adoption of individual parts and algorithms |
| ***Testable Propositions*** | Employing the vehicle relocation procedure increases the number of EV rentals. |
| ***Justificatory Knowledge*** | Carsharing Literature |

## 5.2 Limitations and Opportunities

Our research is subject to some inherent limitations which present opportunities to address such challenges through future research.

Firstly, we tested the proposed relocation methods on simulations generated from only one medium-sized carsharing system and related data set, thereby limiting the generalizability of our findings. The next step should be to implement user-based relocation in the context of e-carsharing, following the presented design theory.

Secondly, in the simulation, some assumptions and generalizations are employed. For instance, it is assumed that every rental could be carried out with an EV and that

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users accept relocation requests. Hence, the fact that some users are unwilling to rent EVs or need specific vehicle characteristics, e.g. transporter or station wagons, is not taken into account. Moreover, users might not drop-off a car at inconvenient positions. In practice, requests that are tailored to individual customer demand might be helpful to achieve high user-acceptance rates. This includes to not only formulate requests for drop-off locations but also to incentivize pick up locations. Hence, future research should engage with the question of how these factors influence the efficiency of vehicle relocation. Furthermore, developing and benchmarking more sophisticated algorithms should be considered in future research.

## References

1. Avital, P.M., Carroll, J.M., Hjalmarsson, A., Levina, N., Malhotra, A., Sundararajan, A.: The Sharing Economy: Friend or Foe? (2015).
2. Schor, J.: Debating the Sharing Economy. J. Self-Governance Manag. Econ. 4, 7 (2017).
3. Hietanen, S.: 'Mobility as a Service' – the new transport model? Eurotransport. 12, 2–4 (2014).
4. Remane, G., Hanelt, A., Nickerson, R.C., Tesch, J.F., Kolbe, L.M.: A Taxonomy of Carsharing Business Models. Proc. Int. Conf. Inf. Syst. 1–19 (2016).
5. Acquier, A., Daudigeos, T., Pinkse, J.: Promises and paradoxes of the sharing economy: An organizing framework. Technol. Forecast. Soc. Change. 125, 1–10 (2017).
6. Clemente, M., Fanti, M.P., Mangini, A.M., Ukovich, W.: The vehicle relocation problem in car sharing systems: Modeling and simulation in a Petri net framework. In: Lecture Notes in Computer Science. pp. 250–269. , Berlin, Springer Berlin Heidelberg (2013).
7. Frey, A., Trenz, M., Tan, C.-W., Veit, D.: On Rapport Uncertainty in the Sharing Economy - Extending the Categories of Uncertainty. In: Proceedings of the 51st Hawaii International Conference on System Sciences. pp. 626–635 (2018).
8. Brendel, A.B., Mandrella, M.: Information Systems in the Context of Sustainable Mobility Services: A Literature Review and Directions for Future Research. In: AMCIS. pp. 1–10 (2016).
9. Wagner, S., Willing, C., Brandt, T., Neumann, D.: Data Analytics for Location-Based Services: Enabling User-Based Relocation of Carsharing Vehicles. In: ICIS. pp. 279–287 (2015).
10. Lusch, R.F., Nambisan, S.: Service Innovation A Service-Dominant-Logic perspective. MISQ. 39, 155–175 (2015).
11. Vargo, S.L., Maglio, P.P., Akaka, M.A.: On value and value co-creation: A service systems and service logic perspective. Eur. Manag. J. 26, 145–152 (2008).
12. Weikl, S., Bogenberger, K.: A practice-ready relocation model for free-floating carsharing systems with electric vehicles – Mesoscopic approach and field trial results. Transp. Res. Part C Emerg. Technol. 57, 206–223 (2015).
13. Wappelhorst, S., Sauer, M., Hinkeldein, D., Bocherding, A., Glaß, T.: Potential of

https://doi.org/10.30844/wi_2020_n4-prinz

Electric Carsharing in Urban and Rural Areas. Transp. Res. Procedia. 4, 374–386 (2014).
14. Franke, T., Cocron, P., Bühler, F.: Adapting to the range of an electric vehicle–the relation of experience to subjectively available mobility resources. In: Proceedings of the European Conference on Human Centred Design for Intelligent Transport Systems. pp. 95–103 (2012).
15. Di Febbraro, A., Sacco, N., Saeednia, M.: One-Way Carsharing. Transp. Res. Rec. J. Transp. Res. Board. 2319, 113–120 (2012).
16. Carlier, A., Munier-Kordon, A., Klaudel, W.: Optimization of a one-way carsharing system with relocation operations. In: Proceedings of 10th Internation Conference on Modeling, Optimization and Simulation. pp. 1–7 (2014).
17. Barth, M., Todd, M.: Simulation model performance analysis of a multiple station shared vehicle system. Transp. Res. Part C. 7, 237–259 (1999).
18. Jorge, D., Correia, G.: Carsharing systems demand estimation and defined operations: A literature review. Eur. J. Transp. Infrastruct. Res. 13, 201–220 (2013).
19. Brendel, A.B., Brennecke, J.T., Kolbe, L.M.: Applying Econophysics in the Context of Carsharing - Development of a Vehicle Relocation Algorithm and Decision Support System. Int. Conf. Inf. Syst. 39, 1–17 (2018).
20. Sonneberg, M.-O., Kuehne, K., Breitner, M.H.: A Decision Support System For The Optimization Of Car Sharing Stations. In: ICIS 2015 Proceedings (2015).
21. Hevner, A.R., March, S.T., Park, J., Ram, S.: Design Science in Information Systems Research. MISQ. 28, 75–105 (2004).
22. Hevner, A.R.: A Three Cycle View of Design Science Research. Scand. J. Inf. Syst. 19, 87–92 (2007).
23. Gregor, S., Jones, D.: The anatomy of a design theory. J. Assoc. Inf. Syst. 8, 312–334 (2007).
24. Brendel, A.B., Brauer, B., Hildebrandt, B.: Toward User - Based Relocation Information Systems in Station-Based One-Way Car Sharing. In: AMCIS. pp. 1–10 (2016).
25. Rai, A.: Diversity of Design Science Research. MISQ. 41, iii–xviii (2017).
26. Gregor, S., Hevner, A.R.: Positioning and Presenting Design Science - Types of Knowledge in Design Science Research. MISQ. 37, 337–355 (2013).
27. Brendel, A.B., Rockenkamm, C., Kolbe, L.M.: Generating Rental Data for Car Sharing Relocation Simulations on the Example of Station-Based One-Way Car Sharing. In: HICSS. pp. 1–10 (2017).
28. Brendel, A.B., Lichtenberg, S., Brauer, B., Nastjuk, I., Kolbe, L.M.: Improving Electric Vehicle Utilization in Carsharing: A Framework and Simulation on an E-Carsharing Vehicle Utilization Management System. Transp. Res. Part D. (2018).
29. Brendel, A.B., Lichtenberg, S., Nastjuk, I., Kolbe, L.: Adapting Carsharing Vehicle Relocation Strategies for Shared Autonomous Electric Vehicle Services. In: ICIS. pp. 1–20 (2017).
30. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, É.: Scikit-learn: Machine Learning in Python. J. Mach. Learn. Res. 12, 2825–2830 (2011).

https://doi.org/10.30844/wi_2020_n4-prinz

31. Burghard, U., Dütschke, E.: Who wants shared mobility? Lessons from early adopters and mainstream drivers on electric carsharing in Germany. Transp. Res. Part D Transp. Environ. 71, 96–109 (2019).
32. Nourinejad, M., Roorda, M.J.: A dynamic carsharing decision support system. Transp. Res. Part E Logist. Transp. Rev. 66, 36–50 (2014).

https://doi.org/10.30844/wi_2020_n4-prinz