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A Real-World Case

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Dynamic Pricing for User-Based Rebalancing in Free-Floating Vehicle Sharing: A Real-World Case

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Abstract. Dynamic pricing can be used for better fleet distribution in free-floating vehicle sharing (FFVS), and thus increase utilization and revenue for the provider by reducing supply-demand asymmetry. Supply-demand asymmetry refers to the existence of an undersupply of vehicles at some locations at the same time as underutilization of vehicles at other locations. We propose to use dynamic pricing as an instrument to incentivize users to rebalance these vehicles from low demand locations to high demand locations. Despite significant research in rebalancing vehicle sharing, the literature so far lacks experimental results on dynamic pricing in free-floating vehicle sharing. We propose to use an algorithm that minimizes the differences in the idle time of vehicles. The algorithm is tested in a real-life experiment that was conducted in cooperation with an FFVS provider. The results of the experiment are not statistically significant, but they clearly indicate that even slight differences in pricing and a simple algorithm can already influence user-behavior to counter supply-demand asymmetry. Improving the existing algorithm with more experimental research is advised to further uncover the potential of this strategy.

Keywords: Dynamic pricing · User-based rebalancing · Free-floating vehicle sharing · User-based operations · Living lab · Price sensitivity

1 Introduction

In recent years, one-way shared mobility has seen large growth. One-way shared mobility can be subdivided into station-based vehicle sharing (SBVS) and free-floating vehicle sharing (FFVS). The main difference between these two modes

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of vehicle sharing is that SBVS only allows pick-up and drop-off of vehicles at specific locations called stations. This mode of vehicle sharing is mostly present in bicycle sharing (BS) and the stations are often physical existing stations with a limited number of spots available for dropping off vehicles. FFVS allows the drop-off of vehicles at any locations inside a certain geofenced area. The result of this difference is that FFVS offers users more freedom and flexibility. However, balancing the fleet is easier to manage in SBVS. The large growth of one-way shared mobility in recent years is especially visible in FFVS according to a study by the Bundesverband Carsharing [1], a German carsharing organization.

Another recent trend is the usage of small vehicles, called micromobility. The term micromobility generally encompasses vehicles that weigh under 500 kg [9], including (e-)bikes, kick-scooters, and seated scooters (also known as mopeds). The potential market for micromobility has been estimated to make up for about 50% to 60% of all passenger miles traveled [11]. The same estimation concludes that these miles will translate into a potential market of between $330 billion to $500 billion worldwide, of which between $100 billion and $150 billion is in Europe alone, by the year 2030.

The successful adoption of FFVS as a part of an urban transport system requires reliability from the perspective of the user. Reliability can be achieved by ensuring the availability of a vehicle at nearly all times and places of demand. From the perspective of the FFVS operator, the availability of vehicles for customers can be increased by increasing the number of vehicles or restricting the service area. But rather than performing large investments by increasing the vehicle fleet or decreasing the number of potential customers by reducing the geofenced area, researchers have suggested a different approach to increase vehicle availability: rebalancing [7,13,16,17,19]. Rebalancing is the act of repositioning vehicles from low-demand to high-demand areas to overcome spatial asymmetry in supply and demand. This supply-demand asymmetry is a common difficulty in FFVS systems. Studies suggest that a successful rebalancing strategy can greatly increase the performance of a vehicle sharing system by increasing availability [17,19] or, in the case of ride-hailing, decreasing customer pick-up time [6,14].

Rebalancing of vehicles can be done by the operator (operator-based rebalancing) or by incentivizing users (user-based rebalancing). Dynamic pricing (DP) can be used to incentivize users to perform user-based rebalancing. Despite success with dynamic pricing to influence customer behavior in a variety of industries, it is still not common practice to apply DP to incentivize user-based rebalancing.

Responding to the current trends that were discussed in the first two paragraphs of this paper, we extend the academic research regarding user-based rebalancing. We investigate what dynamic pricing can do for user-based rebalancing in the upcoming free-floating vehicle sharing market. The rest of this paper will focus on answering the question:

How can dynamic pricing incentivize user-based rebalancing in free-floating vehicle sharing?

To answer this question we will first define what an optimal rebalancing strategy is in free-floating vehicle sharing. This strategy will be translated into a pricing strategy. We will make suggestions on how to evaluate such a pricing strategy, and finally, show how these results translate to other free-floating vehicle sharing platforms.

2 Literature Review

Multiple research articles have proposed relocation strategies for mobility on demand (MoD) systems that can decrease the average walking distance to one of the assets or decrease the average customer waiting time. Research on rebalancing for (autonomous) MoD has already extended to even incorporate different service levels [2] or a combination of parcel and person transport [3]. However, research in vehicle sharing is less advanced. Most of the research on vehicle sharing solves a static version of the rebalancing problem in BS [7,16]. Often this is done with the use of mixed-integer linear programming (MILP).

In the field of DP in mobility, Uber is probably one of the most experienced players. The DP system of Uber is called surge pricing and research into this system shows that it can increase total welfare according to the concept in transport economics [6,8,14]. Although it ought to be noted that maximizing revenue in these ride-hailing systems with dynamic pricing also has its downsides as it has a negative influence on congestion [15,18].

Congestion issues are less important for most forms of micromobility as they do not form traffic jams as easily. Also, the total number of miles driven in a ride-hailing system is higher than that of one-way vehicle sharing caused by vehicle miles traveled to the start point of the customer [12]. Another notable difference between DP in ride-hailing services and DP in one-way vehicle sharing is that DP in ride-hailing also affects the supply side of the demand-supply asymmetry, because the pricing affects the payments of the drivers [10]. Results of research into operator-based rebalancing of ride-hailing services points in different directions suggesting either large improvements even for small fleet sizes [20] or only marginal improvements [23].

A notable attempt on solving the rebalancing problem in one-way vehicle sharing that also considers user-based rebalancing is focused on SBVS [17]. This research finds that the ideal rebalancing strategy combines operator-based rebalancing with user-based rebalancing. A limitation of this research is that it does not consider latent demand, which is the demand that is not visible in the data because there were no vehicles available at a certain place and time, but rather assumes that historical data provides a full picture of demand for the service. Also, the results are only derived by simulation and not by a real-life experiment. This requires some assumptions about human behavior, like full rationality, which do not do justice to the complexity of the real-life problem.

The methods developed in [17] are applied in an experiment in BS [19]. This research extends on [17] with several insights. For example, it is shown that most of the rebalancing actions are done by only a small group of people. Survey-based research also finds that users are in general open to the idea of user-based rebalancing and are willing to comply with different methods of rebalancing [13].

Both [17] and [19] focus on increasing the *service level* although in the latter research it is renamed to *quality of service*. The definition of a *service level* is given as follows:

$$\text{Service level} = \frac{\text{Potential customers} - \text{No-service events}}{\text{Potential customers}}. \tag{1}$$

It is important to note is that latent demand is not taken into account. The no-service events in this metric are determined by assuming that the demand will stay the same independent of the rebalancing. The results of the experiment performed by [19] are also not used to evaluate the effect of rebalancing on the service-level of the SBVS system. To the best of our knowledge, this means that no research so far has provided any insights into the effect of user-based rebalancing in one-way vehicle sharing that are based on experimental results. This is also visible in Table 1, which contains the references used in this research. A general lack of experimental research, as well as a lack of research on user-based rebalancing in FFVS in general, can be concluded from this overview.

Table 1. Analysis of articles about rebalancing in Vehicle sharing showing the different research methods applied to different types of vehicle sharing and whether the research includes dynamic pricing (DP), operator-based rebalancing (OBR) and user-based rebalancing (UBR).

Reference	Type	DP	OBR	UBR	Method
Zhou [23]	Ride-hailing	✓	✓		Simulation
Qiu et al. [18]	Ride-hailing	✓	✓		Simulation
Kroll [15]	Ride-hailing	✓	✓		Simulation
Korolko et al. [14]	Ride-hailing	✓	✓		Simulation
Castillo et al. [6]	Ride-hailing	✓	✓		Simulation
Chemla et al. [7]	SBVS		✓		Simulation
Pal and Zhang [16]	SBVS		✓		Simulation
Spieser et al. [20]	AMoD		✓		Simulation
Wen et al. [22]	AMoD		✓		Simulation
Pfrommer et al. [17]	SBVS	✓	✓	✓	Simulation
Singla et al. [19]	SBVS	✓	✓	✓	Experiment
Herrmann et al. [13]	FFVS	✓		✓	Survey

3 Methodology

3.1 Optimal Rebalancing Method

The methodology of this research was outlined in the last paragraph of the introduction and starts with defining what the ultimate rebalancing strategy is for FFVS. The answer to this question is mainly based on the research done by [17]. The optimal strategy is the one that minimizes the deviation from the optimal distribution of vehicles. [17] use historical origin-destination pairs of rides to determine the departure and arrival rates of every station at different times and days. Based on this they build a simulation in which they attempt to positively affect the *service level* by applying a rebalancing strategy.

Following the lines of academic research so far, we construct a simulation based on historical origin-destination pairs from which we can draw demand patterns for different areas in the service area. We discretize the spatial data by clustering the rides to certain areas and model the system as an SBVS system. The data is divided into week/weekend days and one day is sliced into time frames of 1 h. The simulation draws random samples from the data based on the different data sets and simulates these rides. However, the simulation does not provide realistic results especially in areas in which the number of rides taken is relatively low. A reason is that origin-destination pairs ignore the latent demand of the system and, thus, areas that lack supply in particular do not give a good representation of the demand. For this reason, we refrain from using origin-destination pairs of rides to determine the demand. We propose to use a different metric instead as a basis for the rebalancing strategy: idle time.

Idle time is the amount of time between two consecutive rentals of one vehicle that is available for rent. Hours that are outside of the FFVS opening hours or the time during which a vehicle's battery has been empty are not part of the idle time of a vehicle. We assume that the preferred rebalancing strategy, from the customers' point of view, balances the vehicles such that the idle time of vehicles is equal across the whole service area. In this scenario the utilization of vehicles is equal across the service area, which is good for the service level. However, it does not take into account differences in ride length, and for that reason, might slightly differ from the most profitable scenario from the operators point of view. Rebalancing actions that have a positive utility are those for which the expected idle time of the vehicle is lower in the targeted area compared to the vehicles current area.

These definitions lead to a slightly altered version of the minimization problem that was set up in [17]. We use a as an index for a certain area that is part of the total service area A. The parameter v is an index of a certain vehicle. The idle time that a vehicle has spent in a certain area is $\theta_{a,v}$. The average idle time of an area is $I_a = \frac{1}{V} \sum_{v \in V} \theta_{a,v}$, where V is the complete set of idle times measured during a certain time interval. The expected idle time is derived from historical data and denoted with $\tilde{I}$, and the average idle time of the complete area $\overline{I}$. The average profit made per vehicle per unit time is denoted with R and the monetary incentive for a certain ride is p. In the experiment, the monetary incentive p is a reduction of the per minute price. Multiple different levels of reduction are tested in the experiment. The difference in idle time resulting from an applied incentive p is denoted by $\Delta I(p)$. We can define the following optimization problem:

$$\min_{p(v)} \quad \sum_{a\in A}\sum_{v\in V_a}(I_{a,v}-\overline{I})^2+\alpha\sum_{a\in A}\sum_{v\in V_a}p_{a,v} \tag{2a}$$

$$\text{subject to } \Delta I_a(p)R-p>0 \qquad \forall\ a\in A \tag{2b}$$

$$\Delta I_a(p)<\tilde{I}_a \qquad \forall\ a\in A \tag{2c}$$

The objective function (2a) minimizes the differences between the real scenario and the optimal scenario (in which idle time is equal across the whole service area) and the total sum of the costs of the incentives given. The factor α can be set in accordance with the importance of suppressing the costs of incentive payout. Constraints (2b) ensure that the result of a certain incentive payout has a positive influence on the operator's profit. Constraints (2c) take into account the upper limit of a decrease in idle time by an incentive p.

The minimization problem is used to determine the optimal pricing strategy. This pricing strategy is based on a set of two different predictions. Figure 1 shows how these two predictions influence the pricing strategy. Both of the predictions are drawn from historical data. The effect of pricing on the idle time can however

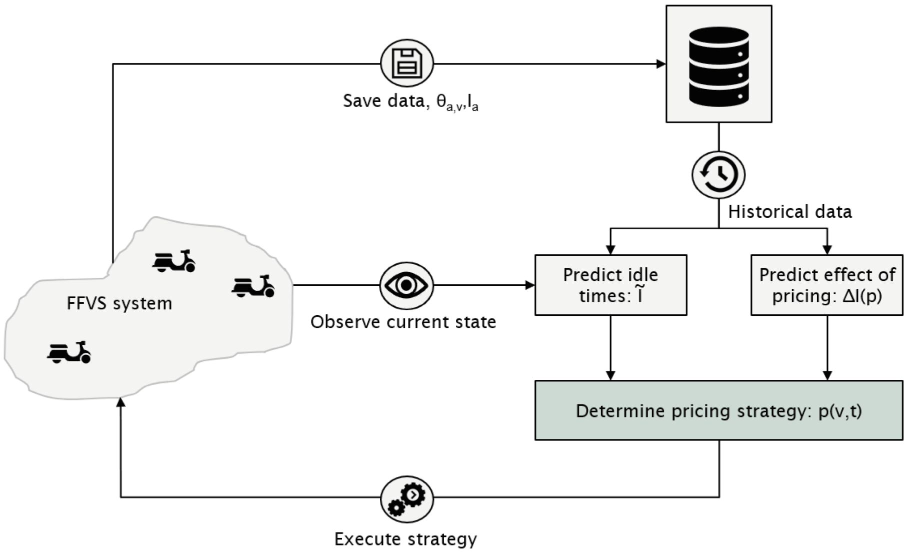


Fig. 1. The pricing strategy is determined based on historical data and the current state of the system as is shown in this block diagram. The current state consists of the amount of the current idle times of the vehicles in the system. The current fill levels should be taken into account when determining the expected idle times.

only be determined by experiment. This will be pointed out later in this paper as well.

The effect on the *service level* can be determined by looking at the average number rides in a certain time frame and the difference in idle time that was the result of applying certain incentives. If n_{rides} is the total number of rides during a certain time frame then the change in *service level* is given by the following:

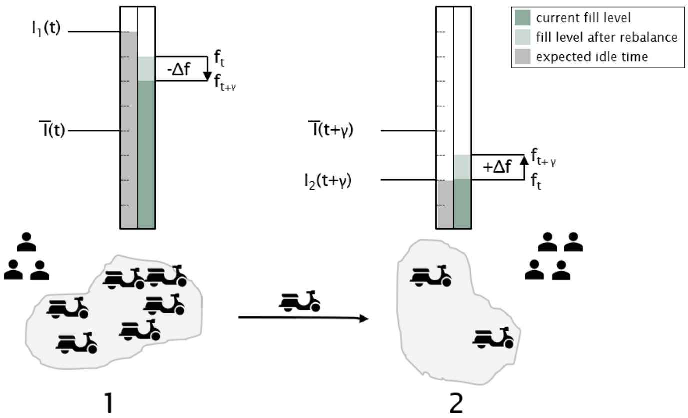
$$\Delta\text{Service level}(p) = \sum_{a \in A} \Delta I_a(p) \frac{1}{\overline{I}_A \cdot n_{rides}}. \tag{3}$$

3.2 User-Based Rebalancing

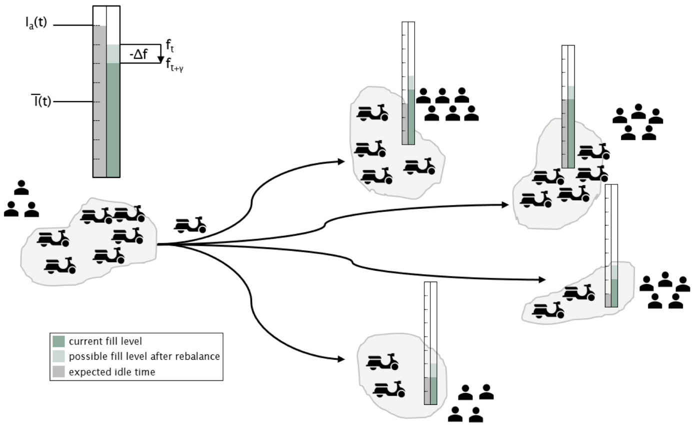
When considering the payout of incentives for certain rebalancing actions it is important to keep in mind that it might be difficult to find users to perform these actions. A rebalancing action as described in the section above is called a *complete rebalancing* in this research. There are, however, also other possible ways to rebalance in FFVS. We distinguish between three different methods of rebalancing, as listed below. The difference between complete rebalancing and pushed rebalancing is made visible in Fig. 2.

1. **Complete rebalancing** incentivizes a complete rebalancing action. In this case, a customer is presented with an incentive to reposition a particular vehicle to a certain location. It is, in fact, similar to what an operator would do when rebalancing vehicles. It can be difficult, however, to find customers that are willing to reposition a vehicle when both the origin and destination of the trip are fixed. This requires the incentive to be high.
2. **Pulled rebalancing** incentivizes users to end a ride at a certain position. This is done by [19] and also considered by [17] when an extra reward is given for leaving a bike at a (nearly) empty bike station. Giving out these incentives requires the definition of high-demand areas and high-demand times. This information then needs to be communicated to the end-user such that they can be incentivized to leave behind a vehicle in such a position. Such incentives are determined and provided by [19] during the rental period of the client, taking into account also the current number of bikes at a certain bike-sharing station.
3. **Pushed rebalancing** incentivizes users to start a ride with a certain vehicle without specifying where the vehicle should travel to. This is also performed by other free-floating car-sharing and e-scooter-sharing companies. In this case, the operator incentivizes the use of certain vehicles. Often these vehicles are positioned in a low-demand area or have not been used for a certain amount of time. When this type of incentive reduces the idle time of the vehicle the vehicle can bring in extra revenue and create extra availability. This type of rebalancing assumes that on average many vehicles departing from low-demand areas will end up in areas in which the demand is higher.

Also important to note is that the values of $\Delta I(p)$ can only be determined by modeling user behavior or by experimental research. The lack of experimental research was already indicated in Sect. 2. Experimental research can uncover better insights into how effective a certain pricing strategy is. In the rest of this research, we set up a living lab that is based on *pushed rebalancing*.



(a) In complete rebalancing, both the starting and ending position of a rebalancing move are known.



(b) Pushed rebalancing is performed from an area that is oversupplied. The vehicle will most likely end up in another area in which it is needed more.

Fig. 2. Schematic representation of different modes of rebalancing. Where f_t is the fill level of a certain are at time t, γ is the time required for a rebalancing move and Δf is the change in fill level resulting from the rebalancing.

4 Experiment in a Living Lab Setting

4.1 Setting up the Living Lab

The key principles of a living lab are *continuity*, *openness*, *realism*, *empowerment of users* and *spontaneity*, according to [21]. Examples of setting up a living lab are given by [4] and [5]. We take the most important lessons of these works into account to set up an effective living lab experiment for our use case. A notable difference between how the living lab has been set up in this research and that of [5] is that the concepts in our research are developed with very little co-creation (i.e., service design process with input from customers). The development of the concept, however, was the result of research into different possibilities that were all viewed from the customer's perspective. After this, the concepts are evaluated in a living lab setting. The main focus of this living lab experiment is to make the experiment very realistic and evaluate the concept in a user-centered way. The lessons learned from the experiment described below should take into account co-creation for the development of follow-up concepts. These co-creation characteristics of a living lab are not emphasized in this paper and should be set up as a continuation of this research.

To ensure *continuity* and *realism* we implement our pricing system in an existing FFVS system without making any changes to the service area, fleet size, or users. The pilot is communicated to the users only as it begins. Qualitative feedback is asked for directly, adhering to the *spontaneity* principle. The pricing system is visible and available to use for all users.

In the service area, we define a set of *low demand* areas L for which $L \subset A$ and $\overline{I}_{a,t} > \tilde{\overline{I}}_t + \gamma$ where gamma is a factor that controls the size of the low demand area. In addition, we define a set of *control* areas C that have an idle time that is close to the average of the service area for which $C \cup L \subset A$ and $C \cap L = 0$. Both in L and C for a certain period, a set of vehicles is discounted. This reduction in price will be the same for different vehicles at the same moment in time, so there is only one level of discount tested at a certain moment in time. The experiment runs for a couple of weeks and tests multiple levels of discount.

As indicated in Fig. 3, the experiment bases its pricing strategy on a prediction of the idle time: $\tilde{I}$. The strategy that is executed only discounts a subset of the vehicles and does not discount the other vehicles. Both of the measurements I (of discounted and not discounted vehicles) are compared with the prediction made beforehand. Their relative differences can be calculated to show the effect of a price discount under the same external influences, $\frac{I-\tilde{I}}{\tilde{I}}$. The difference between discounted and not discounted vehicles will provide insight in the value $\Delta I(p)$.

A fixed incentive is applied to vehicles in these areas. After a certain time period the incentive is changed and the effects on the idle time of the vehicles for different incentives and different areas is compared. In total, two different incentives are applied: p_1, a 10% reduction in price and p_2, a 15% reduction in price. In both of the areas only 50% of the vehicles are discounted. The vehicles

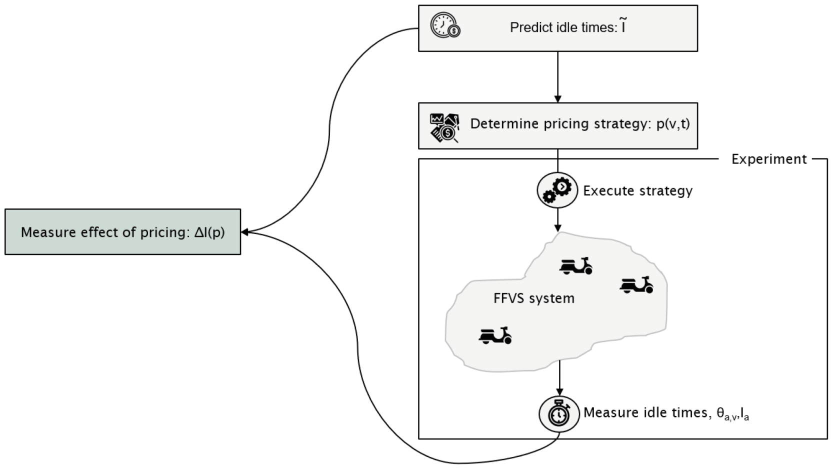


Fig. 3. The expected idle times are used to determine a pricing strategy. The execution of this strategy will then result in idle times which can be compared with the expected idle times. The comparison of the resulting values and expected values will show the effectiveness of a strategy.

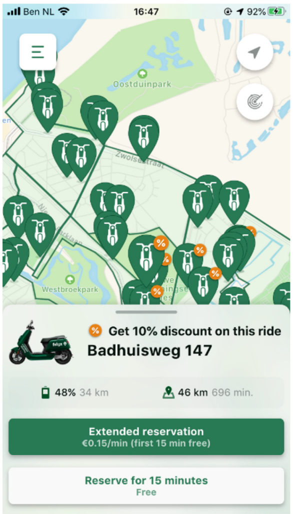


Fig. 4. Screenshot of FFVS application, showing how discounted vehicles are made visible in the application.

that are discounted are made visible in the application with a different icon. This is shown in Fig. 4. The difference between the results of the discounted and not discounted vehicles are discussed in the next section.

Table 2. Averages of idle time of the living lab experiment. $\frac{I_a - \tilde{I}_a}{\tilde{I}_a}$ is the difference between the expected value of idle time and the average of the measured idle time samples as indicated in Fig. 3. The different values for discounted and not discounted vehicles lead to the measured impact of incentive $\Delta I(p)$.

		Not discounted		Discounted		Difference	
		$\frac{I_a - \tilde{I}_a}{\tilde{I}_a}$	n	$\frac{I_a - \tilde{I}_a}{\tilde{I}_a}$	n	$\Delta I(p)_a$	n
Low demand	p_1	+26%	658	+0%	676	26%	1,334
	p_2	+15%	542	−15%	634	30%	1,176
	Total	+21%	1,200	−6%	1,310	27%	2,510
Control	p_1	+15%	284	+12%	240	3%	524
	p_2	+6%	207	−12%	241	18%	448
	Total	+11%	491	+0%	481	11%	972

4.2 Results of the Living Lab

During the pilot period, we measured the idle times of different vehicles that were discounted and not discounted. The differences between these results and the value that was expected are noted in Table 2. This table measures the resulting idle times for two different incentives: p_1 and p_2 for which $p_2 > p_1$. The values in the table are the average idle time values of both the group of not discounted vehicles and discounted vehicles. From the results in Table 2, we draw several conclusions.

The first clear effect that is visible is the difference in the effect of different incentives: $\Delta I(p)$ is larger for p_2 than for p_1 in both the low demand areas and the control areas. This means that higher incentives have a larger effect. The second effect we note is that the values of $\Delta I(p)$ are higher in the low demand areas than they are in the control areas. This can easily be seen by comparing the total values for both of these areas. This means that the pricing has a larger effect in areas with higher idle times. A reason for this could be that users need a certain time before the discount is noticed, which will result in a relatively larger effect for longer idle times.

Another clear result in Table 2 is that the expected values of the idle times are relatively low. The measured values for idle times I are therefore relatively high in comparison. This leads to very positive values of $\frac{I_a - \tilde{I}_a}{\tilde{I}_a}$, whereas a negative value would have been expected. This is investigated closer later in this section. The expected value of the idle times is, however, not of importance when looking at the difference between the discounted and not discounted vehicles, so the above conclusions still hold.

Finally, the data of the living lab experiment shows that for different areas the effects vary heavily. For example, multiple areas marked as low demand areas show very different results on the effect of pricing $\Delta I(p)$. These differences could be dependent on characteristics of these areas such as the distance to the center of the service area or other characteristics. The total number of measurements n

in some of these areas is, however, relatively low. More measurements are needed in order to get a significant result to make comparisons between these areas as illustrated in Fig. 5. These differences are not visible in Table 2, because this table contains the average of all of the incentives. The average of discounted and not discounted vehicles in the same area does not significantly decline in comparison with the average idle times before the pilot. This is visible in Fig. 6. The average line shows no significant decline and is not stable during the period of the pilot due to significant influences of the weather. Some weeks show an overlap between two different incentives because the shift between these discount levels was made during the week. A reason for the average idle time not declining could be that the offered discounts are too low. The number of vehicles that are discounted is only about 5% of the number of rides. Moreover, the idle times fluctuate heavily with the influence of exogenous variables, which makes it very difficult

	W0 | No discount	W1 | No discount	W2 | No discount	W3 | No discount	W4 | No discount	W5 | No discount	W1 | p1	W2 | p1	W3 | p1	W3 | p2	W4 | P2	W5 | p2	W6 | p2
Low demand 1	1	2	1	19	6	-64	37	42	37	26	32	-6	-13
Low demand 2	-25	12	40	9	3	21	20	22	18	-9	36	27	5
Low demand 3	29	18	3	-67	-6	8	25	36	-28	53	-10	53	13
Low demand 4	7	-16	25	21	44	34	-22	13	34	46	36	48	21
Low demand 5	34	29	32	-35	-73	1	58	73	54	66	21	4	40
Control 1	-4	-2	-3	-19	26	21	12	-20	-10	22	10	15	35
Control 2	6	31	4	-27	2	-20	-28	29	23	-16	27	-9	3
Control 3	27	3	10	36	24	13	36	-16	-46	7	-5	30	-19

Fig. 5. The $\frac{I_a - \tilde{I}_a}{\tilde{I}_a}$ values for "low demand" and "control" areas applying the strategies, *nodiscount*, $p1$, and $p2$ in different weeks. Putting expected and measured idle times into relation, these values indicate how effective a pricing policy has been in a specific area and week.

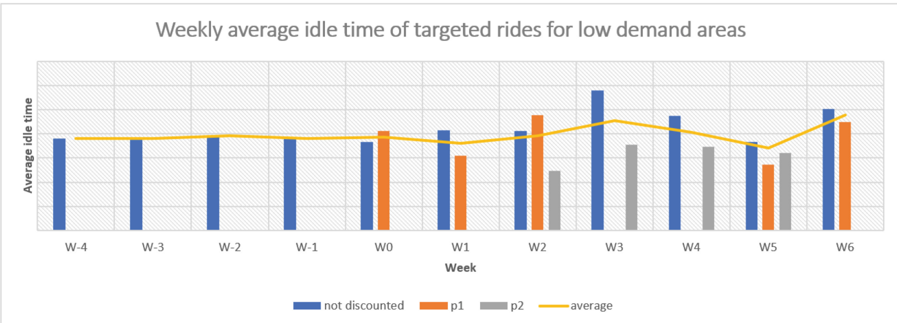


Fig. 6. The weekly averages of idle time for different vehicle groups.

to compare the results during the pilot with the historical data. This suggests that the incentives have probably triggered people to drive certain vehicles, but that these incentives might have been too low or not applied long enough to increase demand.

5 Conclusion

The success of dynamic pricing strategies for user-based operations in vehicle sharing highly depends on the users. Dynamic pricing algorithms, therefore, need to be implemented in real-world systems to fully evaluate their impact. To our knowledge, this is the first work that does this in the case of free-floating vehicle sharing. From the results, we conclude that even small price incentives and basic algorithms can be used to steer the behavior of the user. This means that dynamic pricing can be used as an instrument to incentivize user-based rebalancing in free-floating vehicle sharing. However, the effect on differences between idle times in different areas at the same time has not been significant. To reach more significant results in this regard, larger incentives might be needed or the pricing algorithm needs to be improved. Results for different living labs showed similar trends, but were still different. It could be interesting to investigate how well these results translate to other modalities of free-floating mobility, or how the effects of pricing can be different for different countries. It would also be useful to know what happens when all vehicles in a certain area are discounted. However, the resulting differences in idle time with idle times at other locations in the service area would have to be compared to times before and after applying the pricing algorithm. To make this comparison, more insight into the effect of exogenous variables on this difference would be needed. Lastly, this research does not investigate a price increase or negative incentives. Price increases are also part of dynamic pricing and can lead to an increase in revenue, but will probably not lead to an increase of *service level*.

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