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Profit and utility optimization through joint dynamic pricing and vehicle relocation in carsharing operations

Giulio Giorgione [a,*], Francesco Viti [b]

[a] Luxembourg Institute of Socio-Economic Research – LISER, 11, Porte des Sciences, L-4365 Esch-sur-Alzette, Luxembourg
[b] University of Luxembourg, 2 Av. de l'Université, L-4365 Esch-sur-Alzette, Luxembourg

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ABSTRACT

Pricing is one of the main determinants of a successful carsharing business plan. Companies develop different pricing strategies to increase attractiveness, profit, and service usage. Using dynamic pricing strategies can lead to service improvement in terms of profit and better customer satisfaction. This paper presents a novel research contribution to the field of transportation policy by introducing a new framework for designing dynamic pricing strategies in carsharing operations. We develop two hybrid-pricing strategies to increase profit and user utility in car sharing and analyze the service key performance indicators. These two different hybrid-pricing strategies are based upon two different approaches: one relying on demand related information (i.e., fixed price and time-based dynamic price) and one relying on supply related characteristics (i.e., maximum profit price and availability-based dynamic price). By considering both user utility and company indicators, this model features a bi-level structure that allows for rapid implementation. The framework relies on real-world data, typically available to carsharing companies, including membership data, geographic distribution of users, fleet composition, and the location of vehicles and stations. Additionally, we propose a relocation procedure that relocates vehicles on a day-to-day adjustment process. We study the impact of these strategies in an agent-based environment capable to accurately replicate a real carsharing service that operated in the city of Munich, Germany. Once these policies are in place, results show how it is possible to increase profit and customers' utility. Moreover, we show how an increment in profit corresponds to a reduction of the utility and vice versa. Overall, the effectiveness of the proposed hybrid-pricing strategies in improving key performance indicators such as profit and score in carsharing services is demonstrated through the positive impact of demand-based pricing combined with relocation operations, while supply-based pricing strategies were found to be ineffective in enhancing profit and booking time.

1. Introduction

Carsharing comes with a variety of forms, peer-to-peer (P2P), business-to-consumer (B2C) and business-to-business (B2B) (Münzel et al., 2020). Focusing on B2C, which is arguably the most popular, carsharing comes in three main formats (Ferrero et al., 2018):

Stations-based round-trip or two-way carsharing, where the pick-up and return of the vehicle must happen at the same station or location.

Station-based one-way carsharing, where customers can pick-up a vehicle in any station and return in any other station.

Free-floating carsharing, which is a format that does not rely on stations. This system employs a vast operative area in which users can pick-up and return vehicles.

Being not clear yet if this mobility service can be profitable on the long run (Lagadic et al., 2019), research is still focusing on ways to make the fleet management more cost efficient and targeting for profit or revenue maximization strategies (Di Febbraro et al., 2019; Pfrommer et al., 2014).

The adopted pricing scheme is one of the main connection points between the service provider and the final user and it is evident how its definition affects the relation between these two actors. This can affect car sharing bookings at a spatial and temporal level, influencing who, when and where the service will eventually be used (Ciari et al., 2015).

A well-structured offer can make or break a carsharing company. However, maximizing profit while providing an attractive service is challenging due to various factors, such as demand elasticity, user

* Corresponding author.
E-mail addresses: giulio.giorgione@liser.lu (G. Giorgione), francesco.viti@uni.lu (F. Viti).

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demographics, trip purposes (Cisterna et al., 2019), policy requirements (Pfrommer et al., 2014) and supply characteristics (Martínez et al., 2017). Developing a practical model that satisfies both supply and demand needs is difficult since the company's profit maximization and the user's utility often conflict.

Different pricing strategies have been proposed, but very few considered booking fares to vary dynamically, whereas it is more common to address the spatial and temporal dynamics of the demand and the supply via fleet management strategies. An exception is the work of Jorge et al. (2015) which used a mixed integer non-linear programming model to increase profit through zone and time of the day price variations in one-way carsharing. However, profit-maximizing studies typically focus on cost reduction and fleet positioning to better match supply and demand. To manage their resources at best, different methodologies have been developed to address the vehicles relocation problem (Wu and Xu, 2022). Optimization approaches primarily focus on addressing vehicle relocation problems for one-way services, where imbalances are more common than in two-way systems. For example, these approaches integrate trip pricing, vehicle relocation, and personnel assignment to develop a comprehensive optimization algorithm for pricing problems from a strategic and operational perspective (Xu et al., 2018).

In this work, the addition of a relocation strategy has been done to show that even when the location of the vehicle changes, dynamic pricing can still be used effectively to improve performance indicators. By comparing the performance of the system with and without dynamic pricing after relocation, we can assess the effectiveness of pricing strategies in different situations, which can help us determine whether it is a viable option for improving the system's performance under varying conditions.

With the goal of increasing profit, studies dealt with the problem of spatial distribution imbalance of the number of shared cars. To address this issue, Ren et al. (2020) proposed a reward mechanism called DPB, which modeled the problem as a Markov Decision Process and introduced Deep Deterministic Policy Gradient to find a solution. The DPB method guided user behavior through price leverage, increasing user stickiness, cultivating user habits, and boosting the service provider's long-term profit. Similarly, Kamatani et al. (2019) introduced a dynamic pricing scheme using reinforcement learning to improve the uneven distribution of cars in one-way car sharing services, leading to improved utilization rates. In contrast, Daraio et al., (2020) focused on the applicability of Machine Learning models to predict the availability of Free-Floating Car Sharing services, providing practical guidelines for predictive models in highly dynamic urban contexts. Despite the success of studies in reducing vehicle imbalances and increasing profits in one-way car sharing services, research on round-trip carsharing, which doesn't face this issue, is scarce. Furthermore, while machine learning approaches require weeks of training data and may not consider user utility, our proposed model can be quickly applied and incorporates user scoring to improve the system. Additionally, our approach can be easily adapted to changes in station configuration and number.

While assessing the impact of different dynamic pricing strategies, our study adopts a simulation-based approach to describe how different pricing strategies impact both the demand and the supply. Simulation based strategies are often used to address this kind of problems, where analytical methods would not be able to capture the complexity and interrelations between the different decision and system's state parameters. Today, carsharing is a quite traditional concept but, nonetheless, models and strategies able to assess its impacts and functionality are still being developed (Turoń, 2023). Based on previous studies on carsharing pricing, we compare the dynamic pricing strategies developed so far to create a hybrid pricing model (HP) aimed at increasing supply and demand main key performance indicators (KPIs) such as profit and customer's utility.

When assessing the demand response, we study multiple dynamic pricing strategies and how they impact equity (Litman, 2022) and users' travel behavior. Findings demonstrate how a dynamic pricing scheme helps to increase profit when compared to fixed pricing strategies (Giorgione et al., 2019). Continuing on the stream of research that introduced and compared two different dynamics pricing strategies (Giorgione et al., 2020), one based on the supply availability and another one based on the hour of the day, this work aims at mixing and taking advantage of the specificity of these two schemes in order to find a model that can improve KPIs for both the demand and the supply concurrently.

This paper aims to address the research gap in the area of round-trip carsharing by exploring the optimization of both profit and user utility through dynamic pricing strategies that are developed using a simulation-based approach. Specifically, the paper seeks to answer the research question: "Can a single, and practice-ready pricing model be developed that incorporates the benefits of multiple dynamic pricing strategies?". To the best of the authors' knowledge, proposing different pricing strategies can offer an additional way to increase carsharing efficiency as the business efficiency while keeping the service interesting for the population. This study focuses on the impact caused by the introduction of these different strategies in carsharing operations, both from a mobility service business and management point of view, as well as on the population (characterized by different income groups). Furthermore, to show the results in a realistic setting, the data used in this paper originates from real operations and data provided by Oply, a B2C carsharing company which operated a two-way round-trip system in different cities in Germany and the UK until 2020.

The advantage of the proposed approach is precisely its simplicity. By leveraging data and simulations, an operator can improve the car sharing service by matching supply to demand on a day-to-day basis and increase profits without the need to solve complex optimization problems. This means that the proposed approach can be easily implemented in practice, without requiring significant technical expertise or resources, and can yield tangible benefits quickly. The simplicity of the approach also means that it is scalable and can be adapted to different contexts and locations, making it a versatile solution for car sharing service providers.

The remainder of this paper is organized in five different sections. The next section provides a methodology describing the various dynamic prices and the way they are expected to affect population's behavior; furthermore, the case study taken in exam is explained. Section 3 describes the outcome of the various scenarios from a business and demand point of view. Section 4 presents an examination of the results. Finally, section 5 proposes insights for future works.

2. Methods

The abbreviations and nomenclatures used in this section and in the remainder of the paper are shown in the following table (Table 1).

Table 1
Nomenclature.

p_u	Price offered to the user u
V	Available vehicles/Supply
s	Station
t_h	Time of the day
S	Score/Utility
N	Number of activities
q	Performed activity
β_{dur}	Marginal utility of activity duration
t_{dur}	Performed activity duration
t_0	Duration of the activity since utility starts to be positive
α_I	Scale factor for the income
I_u	Income of the user u
FP	Fixed pricing
TBDP	Time-based dynamic pricing
MPP	Maximum profit pricing
ABDP	Availability-based dynamic pricing
HP	Hybrid pricing

When assessing punctual services with reduced vehicles flows, such as carsharing trips, traditional trip-based models (Cascetta, 2009) cannot capture important KPIs related to individuals (e.g. utility, intrazonal movements, spending power) and to the service (vehicles availability at a precise point in space and time). For evaluating a carsharing service, temporal and spatial resolution is crucial, and disaggregated methods are necessary. To analyze user reaction to pricing policies, a mesoscopic approach can capture emerging trends without requiring excessive modelling and calibration efforts, as finer-grained microsimulation approaches (e.g., second-by-second vehicles dynamics and interactions) may generate unnecessary detail for this study. We argue that changes in pricing policies will not significantly affect tactical strategies such as activity choices, neither affect operational aspects like driving behavior. Hence, an approach that assumes activity sequences as input, and that relies on an aggregated dynamic loading model for simulating travel costs, has an acceptable level of accuracy to simulate consistent emerging patterns deriving from individual mode choices.

In this paper the agent-based simulator MATSim is used (Horni et al., 2016). The choice of this specific framework is given by the fact that, currently, is the most suited in providing a disaggregated representation of carsharing operations and use (Ciari et al., 2013). Furthermore, the integration of the microscopic land-use simulation system (SILO) (Ziemke et al., 2016) makes this simulator the best fit for our needs given the possibility to recreate the synthetic population of our case study area, the city of Munich, Germany. Furthermore, the creation of the activity chains has a sufficient level of detail and heterogeneity to faithfully reproduce the usage of the car-sharing vehicles and the generated profit for the company serving the area (Giorgione et al., 2022).

MATSim is a co-evolutionary simulation where agents optimize their daily activities, including start–end times and mode of transportation, while competing against other agents towards a system equilibrium, as measured by average scoring, which reflects an agent's utility for specific travel choices and activities.

Regarding the introduction of the carsharing mode in MATSim, all agents, including carsharing members, do not have carsharing as their predefined transportation mode. During every iteration, a specific "random trip to carsharing" module assigns the carsharing mode to a member with a probability of 20%. This means that this specific strategy prompts agents to use the carsharing service by randomly substituting a leg mode that should not be a chain-based mode with a carsharing mode. At the end of the iteration, the scoring is calculated, and the modal choice is determined through a multinomial logit model selection between plans (Horni et al., 2016). At the end of the simulation, we obtain the final plan for every agent. This strategy takes advantage of the co-evolutionary algorithm of MATSim in which agents compete for resources and develop their strategies to maximize the average system score. Since the score is a function of pricing, and it may dynamically change throughout the day due to booking events, agents will be motivated to adapt their schedules in order to maximize their convenience.

2.1. Methodology

In this section, we compare four pricing strategies developed by Giorgione et al. (2022, 2020, 2019). These can be ascribed to two general groups: demand-based and supply-based policies. After that, we describe the novel approach to generate the hybrid version of these strategies, called Hybrid Pricing Procedure.

2.1.1. Demand-based pricing

We define as demand-based pricing schemes, all those prices that can be obtained from demand information, obtained for example with market surveys based on preferences or revealed behaviors.

2.1.1.1. Fixed pricing. The Fixed Pricing (FP) is the simplest pricing scheme, often evaluated through market surveys or competitor analysis, and included in demand-based pricing for the purposes of this paper due to its independence from vehicle request rates. It is the most common pricing used in car-sharing services.

2.1.1.2. Time-based pricing. Time-Based Dynamic Pricing (TBDP) is a price that changes in function of the time of the day. The pricing model aims to increase resource costs during peak demand times and is based on the TBDP model derived from the FP scheme's usage demand profile (Fig. 1).

As the previous figure indicates, more booked cars result in higher prices. This pricing strategy follows the logic of exploiting demand competition in relation to limited supply availability. Regarding Fig. 1, the red line describes the demand for the carsharing service of Oply on an average weekday when the FP is offered. The dashed blue line represents the number of vehicles booked, which naturally follows the demand. It should be noted that the number of vehicles shown as booked takes into account that bookings for round-trip services are typically lower than those for free-floating and one-way services. Finally, the purple line shows the trend of the ABDP that corresponds to the vehicle consumption.

2.1.2. Supply-based pricing

Prices based on supply, such as dynamic pricing, are established according to the option value of future sales (McAfee, 2006) and commonly used in the airline industry to address incomplete markets and steer demand. This type of price can be used to address incomplete markets or steer demand behavior. Our study developed two city-level and station-level dynamic prices based on supply availability.

2.1.3. Maximum profit pricing

The idea behind this price model is that it is possible to model profit as a function of the supply and to identify a maximum profit for a specific price given the number of car-hours the operator can offer given a fixed stock of vehicles. Using different supply-price values couples, it is possible to find an expected profit that variates in function of these two inputs. Furthermore, is possible to plot these outputs on a three-dimensional graph (Fig. 2) and, using a metamodel, it is possible to find a Maximum Profit Price (MPP) (Giorgione et al., 2022) interpolating these points.

Once these points are connected, we obtain a concave surface where it is possible to define the highest profit reachable for any given price once the supply is known. Given the concave shape of the surface, it is possible to define the price that gives back the highest profit calculating the first derivative of the surface in Fig. 2 and setting that equal to zero. The result for the area and service under analysis gives the price shown in Equation (1).

$$p_u = 4.28 + \left[0.0001929 * V_{city} * (24 - t_h)\right] \quad (1)$$

It is important to note that this equation is valid for the specific service of the company Oply in Munich. In the case the context would change (a different city, another composition or distribution of the fleet) we would expect a similar equation but with different parameters, which are likely to vary with the average distance of the stations, the distribution of the members in the area around the stations, and the number of vehicles per station, among other factors. A functional relationship defining such parameters is out of the scope of this study and left for future research.

The price displayed is dynamic and subject to change based on the remaining car-hours available until the end of the day. Such pricing is determined during the planning phase and requires multiple simulations, as well as knowledge of demand factors such as members' characteristics and supply factors such as the number and location of cars.

2.1.3.1. Availability-based dynamic pricing. Similar to the one

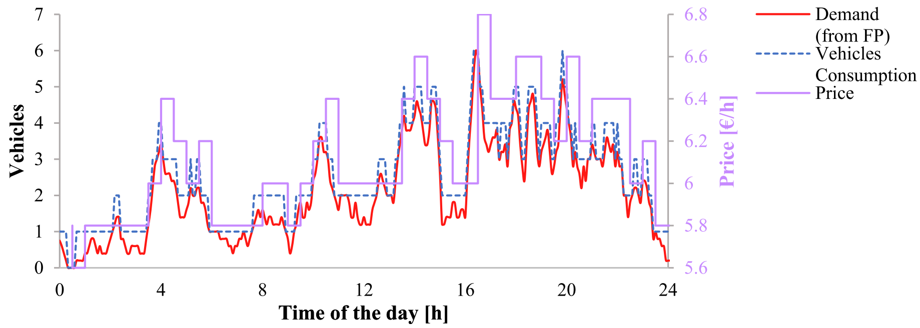


Fig. 1. Example of TBDP creation.

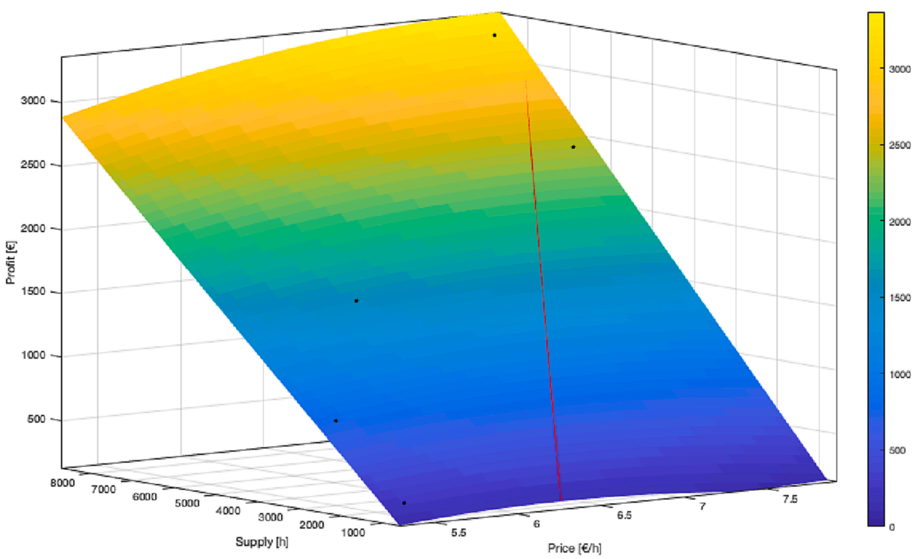


Fig. 2. Example of three-dimensional plane of Profit-Supply-Price.

introduced in the previous section, availability-based pricing strategy is based on the idea that a vehicle becomes more expensive as fewer cars are available at the moment of booking. Fig. 3 shows an example of an Availability-Based Dynamic Pricing (ABDP), the function is a power line where on the x-axis we have the number of vehicles available at the station while on the y-axis there is the price multiplier. The price multiplier is the function that, when multiplied by the base price (i.e., FP), forms the ABPD function.

2.1.4. *Hybrid pricing model*

Demand- and supply-based policies result in different responses and have been shown in a previous study to yield different benefits in terms

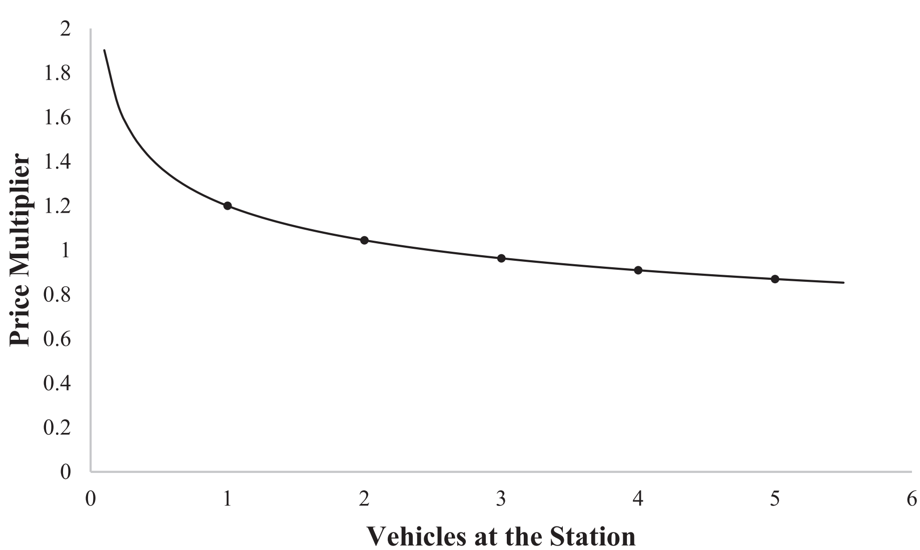


Fig. 3. Example of ABDP strategy.

of company's profit and users' satisfaction (Giorgione et al., 2022). For instance, demand-based policies result in increasing the profit but generates more inequity as car-sharing members with higher spending power (higher income) are likely to increase and/or extend vehicle bookings with respect to lower income members, whereas supply-based policies result in a more balanced vehicle utilization in time and space. The ideation of the Hybrid Pricing (HP) policy intends to answer the problem raised in the introduction: "is it possible to develop a single pricing model that incorporates the benefit of different dynamic pricing strategies?". The HP is conceived as a sequence of different stages in which a specific pricing is applied as shown in Fig. 4.

Fig. 4 represents a day-to-day process. This means that the information is collected using a specific strategy for the whole duration of the day, it is analysed, and used as input in a successive step. In this paper, a relatively simple hybrid pricing procedure is introduced, where the hourly rate of a booking varies according to a demand/supply-based strategy, and at the end of a day vehicles are differently redistributed on the stations to adapt the supply to the demand. The HP procedure is used to create the TBDP and ABDP profiles. These dynamic pricing profiles are then used in the case studies in Section 2.2 "Case Study".

2.1.5. *Simulation assessment*

To assess the quality of service from the operator's and user's point of view, we refer to a quantitative method of measurement based on multicriteria analysis. Here, we subdivide the measurements in two different set of KPIs, one group related to the company and another one related to the demand.

2.1.5.1. User's KPIs. We consider the score, or otherwise the utility, the main KPI related to the demand. In MATSim the score is the evaluation of the agent's daily plan, and it is divided in two fundamental parts: the former related to the activity and the latter to the performed trips as shown in Equation (2):

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)} \quad (2)$$

Overall, agents aim to maximize their personal score during daily operations, which occurs between each simulation iteration. Within an iteration, plans are executed and evaluated, and an updated plan is executed in the next iteration. The selection between plans is determined by a multinomial logit model (Horni et al., 2016). Besides this main indicator, modal split, walking time to the station and score per income group are also chosen as additional KPIs. Hence, user's KPIs allow to evaluate different aspects related to their experience, i.e., their achieved level of utility (via the surrogate measure score), the relative service gain or loss in attractiveness with respect to other mode alternatives, the service accessibility, and finally a measure of equity.

2.1.5.2. Operator's KPIs. In this paper we consider the profit as the main KPI. Profit is the result of the difference between the revenue, generated by renting cars, and the costs, both variable and fixed. Revenue is calculated by multiplying the hourly cost of the offer for the rental time. Costs (which were obtained from Oply), are divided in:

Variable costs: linked to the utilization of the vehicle, it includes maintenance, wear of the vehicle, fuel and is estimated by the company around 1.5€/h per vehicle.

Fixed costs: include insurance and leasing cost, estimated with an amount of 3€/day per vehicle.

Other indicators used to assess the goodness of the carsharing service are the elapsed booking time, and the number of bookings (which are directly related to the profit), the demand profile (needed to create the TBDP and a measure of when vehicles are used the most during the day), and the station utilization (used to assess the situation before the relocation of the vehicles). Hence, company's KPIs allow to evaluate business profitability and therefore its long-term sustainability, but also fleet utilisation in time and space, which give us an indication of how the vehicles are efficiently distributed to meet the demand needs.

2.1.5.3. Relocation phase. Even though not part of the pricing model, relocation is a step that can lead to further improvement of both the profit and the user's score since it allows to adapt the supply distribution to the demand. In this paper, we show how the simulation output enables forecasting of car requests by users, specifically identifying cases where demand exceeds supply. By utilizing the MATSim events file, we obtain daily station utilization data, which includes information on failed booking attempts and the corresponding unmet user needs. This way we are able to collect data on unused cars and where bookings were denied due to unavailability of vehicles. This is nowadays an information that can be directly obtained or estimated from the booking system. For instance, the company backend platform could collect the information about booking requests or availability searches that resulted in no availability of vehicles in some specific station.

The relocation phase used in our hybrid model is explained in Fig. 5. It starts with the evaluation of the HP procedure assessing the two main KPIs described above: profit and utility. A grade from 1 (lowest) to 4 (highest) is given to the dynamic pricing simulations ran in series to the FP and the MPP policies simulations (see Fig. 4). This grade is specifically between 1 and 4 given the number of dynamic pricing strategies we are evaluating (TBDP010, TBDP030, ABDP105 and ABDP120). This allows us to create a ranking of the four strategies. For the one that receives the highest total score, the sum of the two scores described above is made, gets the chance to be run again, this time, with the vehicles relocated. The relocation procedure consists in moving one unused car from a station to another where the service was denied due to unavailability of vehicles. Essentially, we take one vehicle from the pool of unused vehicles at any station (origin station), we assign it to the station with the highest unmet demand (destination station); the approach is repeated until there are not unused cars anymore or until the number of relocated cars is equal to the number of requests denied due to

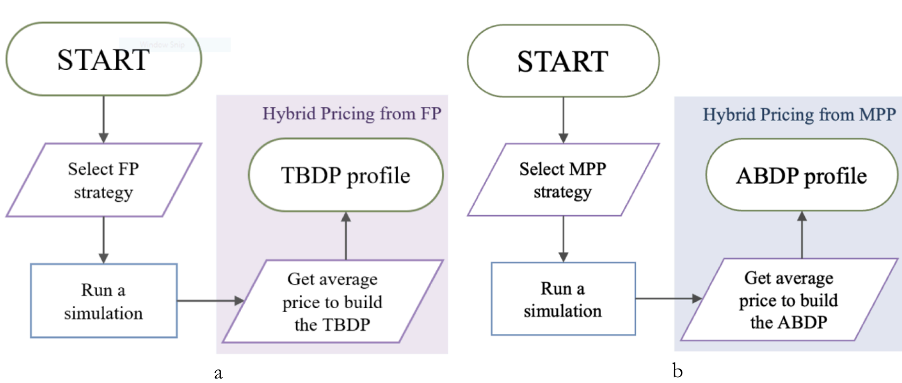


Fig. 4. Examples of HP simulation loop. a) Demand-based; b) Supply-based.

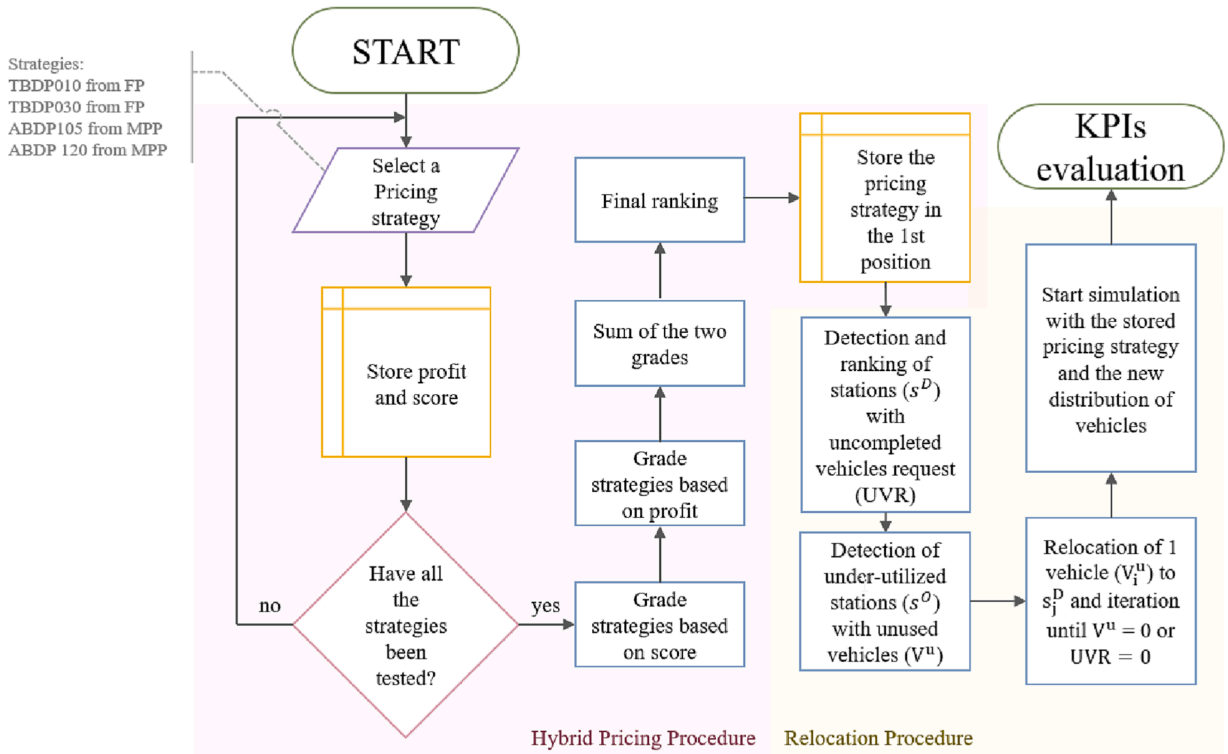


Fig. 5. Identification procedure of the best simulation and vehicle relocation.

unavailability. This procedure is introduced as an additional step after the application of hybrid pricing model.

2.2. Case study

Fig. 6 shows the network of the city of Munich that is used in the simulator. Together with the actual location of the carsharing stations managed by Oply (in blue) and the agents, members of the carsharing service (in green). This information comes from real data shared by the company, with blurred home address locations for privacy preserving reasons. The case study consists in a population of 14,747 agents and 186 cars unevenly distributed in 79 stations. The network used is derived from OpenStreetMap (OSM) data that is available under the Open Database License. The population is composed by the members of

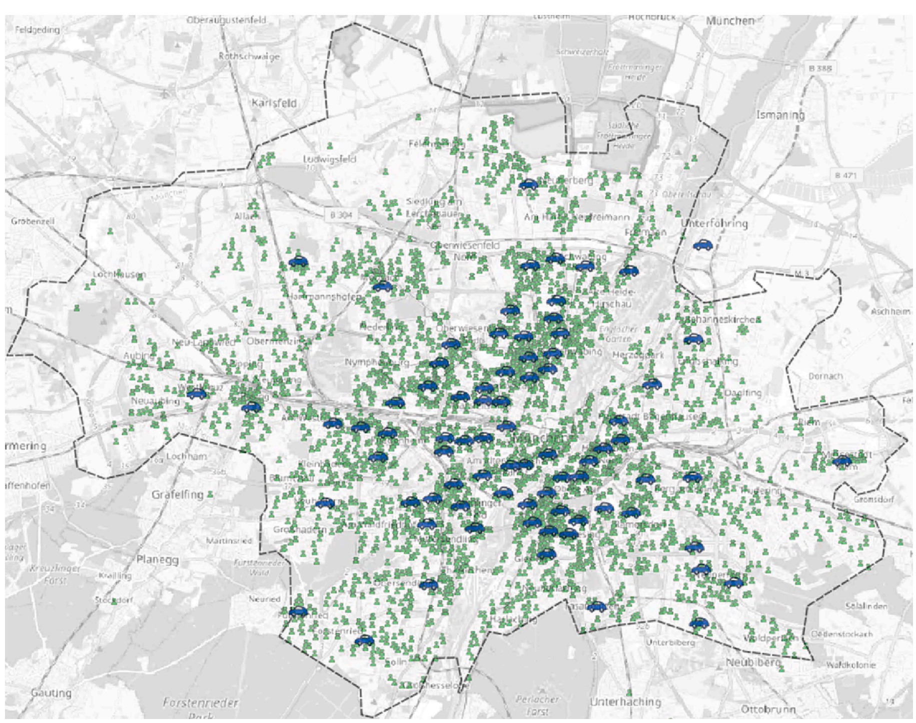


Fig. 6. Network, stations and carsharing members.

Oply and was obtained importing the location of the members using an iterative linking algorithm based on the Euclidean distance and matching each Oply member with an agent from the already existing synthetic population. This allowed us to simulate a typical day for the Oply members using MATSim. The agents generation procedure is described in Giorgione et al. (2022).

We define the different scenarios summarized and color-coded in Table 2. The dynamic pricings shown in this table (i.e., TBDP010, TBDP030, ABDP105, ABDP120) are the ones obtained through the HP procedure shown in Fig. 4.

2.2.1. *Demand-based pricing setup*

In this subsection we explain how the demand-based pricing schemes are developed. This kind of pricings are based on location and density of the population, travel behaviour and market analysis.

2.2.1.1. Fixed pricing. Oply charges a flat rate of 6 €/h, paid by the hour without division. A grace period of five minutes is introduced to avoid full-hour payment for minor delays, allowing bookings closed within this time to avoid the full hour charge (e.g., a 64-minute booking costs 6€, while a 66-minute booking costs 12€).

2.2.1.2. Time-based dynamic pricing. The TBDP is developed based on either simulated demand or observed demand from carsharing operations. Two price schemes are created from the FP and MPP scenarios, with carsharing demand averaged using 30-minute bins and three measures are considered:

- the maximum number of cars booked in any of the 30-minute bins,
- the average number of cars booked during the day,
- the base cost, 6 €/h for the FP scenario and 5.14 €/h for the MPP.

For the FP scenario, being the price fixed, the result is 6 €/h; otherwise, for the MPP scenario the price depends on the number of vehicles available at city level, i.e., the average number of vehicles booked (for the explanation of the MPP price development for this case study refer to section 2.2.2). The FP or the MPP is the base cost, that is, the hourly cost that the *n*th vehicle booked will have. Once the base cost is assigned to the average vehicle (that is, the *n*th vehicle corresponding to the average number of vehicles booked during the day with the FP), we create two scenarios in which we vary the price of 0.10 and 0.30 € for every vehicle unit diverging from the average vehicle as explained in Table 3 and Table 4.

Fig. 7 shows the demand and price profile of the TBDP010 (Fig. 7a) and the TBDP030 (Fig. 7b) developed from the FP demand profile.

The TBDP seeks to exploit the higher competition of customers for limited supply at specific times of the day and makes the price more interesting to customers during low demand periods. Fig. 8 shows the demand and price profile of the TBDP010 (Fig. 8a) and the TBDP030 (Fig. 8b) developed from the MPP demand profile.

Table 3
TBDP from FP scenario.

Number of bookings	Variance from the mean	TBDP010 [€]	TBDP030 [€]
0	−2	5.8	5.4
1	−1	5.9	5.7
2	**0**	**6.0**	**6.0**
3	1	6.1	6.3
4	2	6.2	6.6
5	3	6.3	6.9
6	4	6.4	7.2

Table 4
TBDP from MPP scenario.

Number of bookings	Variance from the mean	TBDP010 [€]	TBDP030 [€]
0	−4	4.74	3.94
1	−3	4.84	4.24
2	−2	4.94	4.54
3	−1	5.04	4.84
4	**0**	**5.14**	**5.14**
5	1	5.24	5.44
6	2	5.34	5.74
7	3	5.44	6.04
8	4	5.54	6.34
9	5	5.64	6.64
10	6	5.74	6.94
11	7	5.84	7.24

2.2.2. *Supply-based pricing setup*

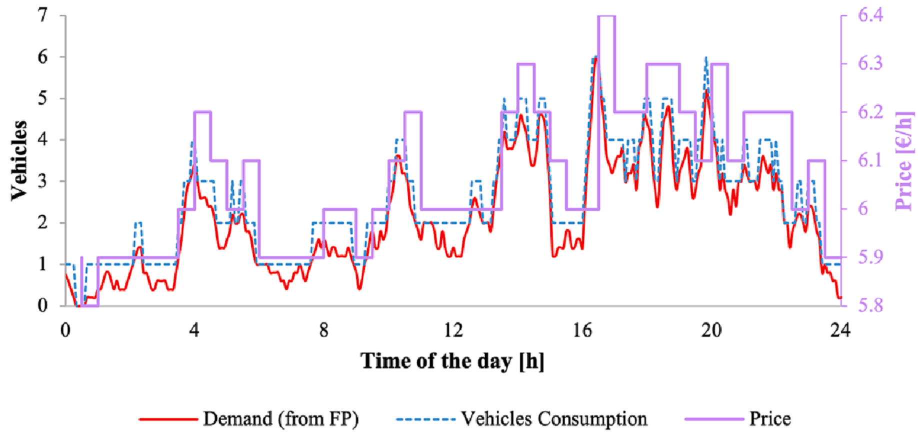
In this subsection we show the criteria behind the supply-based pricing schemes. This kind of pricings are based on different factors related to bookings rates at station and city levels, and fleet size.

2.2.2.1. Maximum profit pricing. The MPP is an efficient price, calculated *ex-post*, which can be used as an ideal reference. Once demand characteristics (i.e., location, demographics, activities executed during the day) and supply characteristics (vehicles and stations location) are known, it is possible to follow the procedure explained in Giorgione et al. (2022) to obtain Equation (1). This equation shows the variation of the price in terms of how many vehicle-hours the company can still rent until the end of the day.

Regarding Table 4, to find a price of 5.14€/h we solved Equation (3) with $V_{city} = 186$ and $t_h = 0$. These parameter values are case study specific and require calibration based on factors such as geographical coverage, station dispersion, vehicle numbers, demand distribution, and sociodemographic characteristics. Providing a parameter function is

Table 2
Scenarios Identification.

Scenario Name	Pricing Strategy	Color Code
FP	Fixed pricing	
MPP	Maximum profit pricing	
TBDP010	Time-based pricing with a 0.10 € step	
TBDP030	Time-based pricing with a 0.30 € step	
ABDP105	Availability-based pricing with a 5% price increment of the fixed price for the last vehicle	
ABDP120	Availability-based pricing with a 20% price increment of the fixed price for the last vehicle	
FPRelocation	Fixed pricing after relocation phase	
MPPRelocation	Maximum profit pricing after relocation phase	
TBDP010Relocation	Time-based pricing with a 0.10 € step after relocation phase	
ABDP105Relocation	Availability based pricing with a 5% increment of the fixed price after relocation phase	



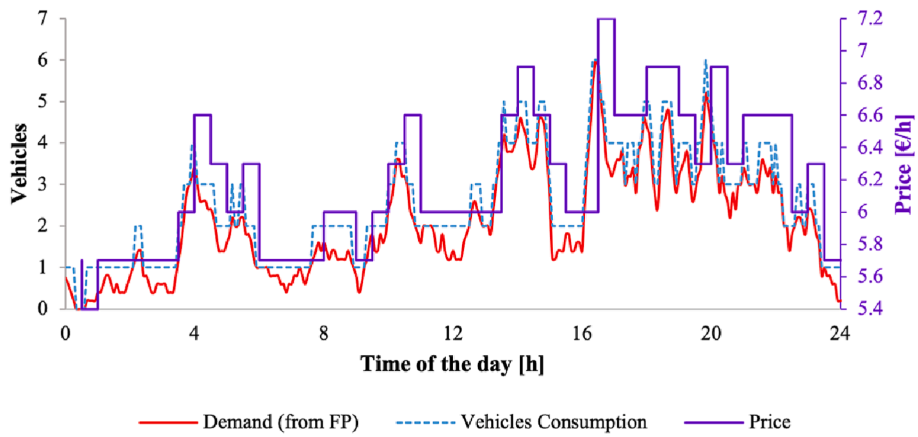


Fig. 7. (a) TBDP010; (b) TBDP030 from FP profile.

beyond the scope of this paper and is left for future research.

2.2.2.2. Availability-based dynamic pricing. The ABDP is similar, conceptually, to the price discrimination applied in airline business (McAfee, 2006). To obtain it, we calculate the average number of vehicles per station. This step is used to find the point in which the hourly cost of a booking with the ABDP will be equivalent to the price of the FP (and the MPP later).

$$\overline{V} = \frac{\sum_s V_s}{\sum s} = \frac{79}{186} = 2.3544[vehs] \tag{3}$$

To determine the price variation for our power curve, we require an additional data point. The aggressiveness of the pricing strategy is determined by the carsharing company, influencing whether they opt for a faster price increase or maintain a fixed pricing scheme resulting in a milder demand response. Referring to the price of the last vehicle, we defined two prices: one with a 5% increase (Fig. 9a) and another, more substantial, with a 20% increase (Fig. 9b). To obtain the ABDP after selecting the base strategy (FP or MPP), we multiply them by the × value shown in Fig. 9I.

3. Results

The results of the simulations will be assessed separately for the supply and the demand-based pricing. The dynamic pricings showed in this section are the ones resulting from the HP procedure shown in Fig. 4, the FP is the one described in Section 2.1.1 and Section 2.2.1, and the MPP is the one described in Section 2.1.2 and Section 2.2.2.

3.1. Demand-based pricing

In this section, FP is used as baseline for all other scenarios. Once all the simulations are over, we asses as first the resulting demand profile (Fig. 10).

Fig. 10 shows how different pricing strategies impact carsharing usage, despite all simulations start from the exact same set up and demand and supply settings. The three lines (i.e., dotted blue line, continuous blue line, and red line) show the number of vehicles booked at different levels of granularity over the course of the day. The moving average is employed to visually illustrate the booking trend and enhance the readability of the graphs. TBDP induces a peak of bookings where price is low while ABDP shows peaks after periods of low usage. This is due to the fact that the more the vehicles at the station, the lower the price. Together with Fig. 11, we can see how increasing the aggressiveness of the dynamic pricing (i.e., we refer to TBDP030 and ABDP 120) pushes away members from the service.

Fig. 11 shows how, in terms of carsharing use, the FP and the TBDP010 are the pricing strategies that manage to attract more people (relatively + 1.81% and + 1.82%). Relocating vehicles manage to increase this carsharing share up to + 2.05% and + 1.98% respectively, meaning that the relocation was effective. The same effect can be noticed in Fig. 12 where we show the score follows a normal distribution for every scenario.

Fig. 12 illustrates that, except for ABDP120, all pricing strategies lower users' score even in the relocation scenario. As a result of decreased bookings in this scenario (see Fig. 10), only users who highly benefit from the carsharing service continue to use it, leading to an increased average score. Even though this may seem a good strategy to increase user's satisfaction, the fact that the number of bookings decrease strongly makes us believe that a service using this strategy will

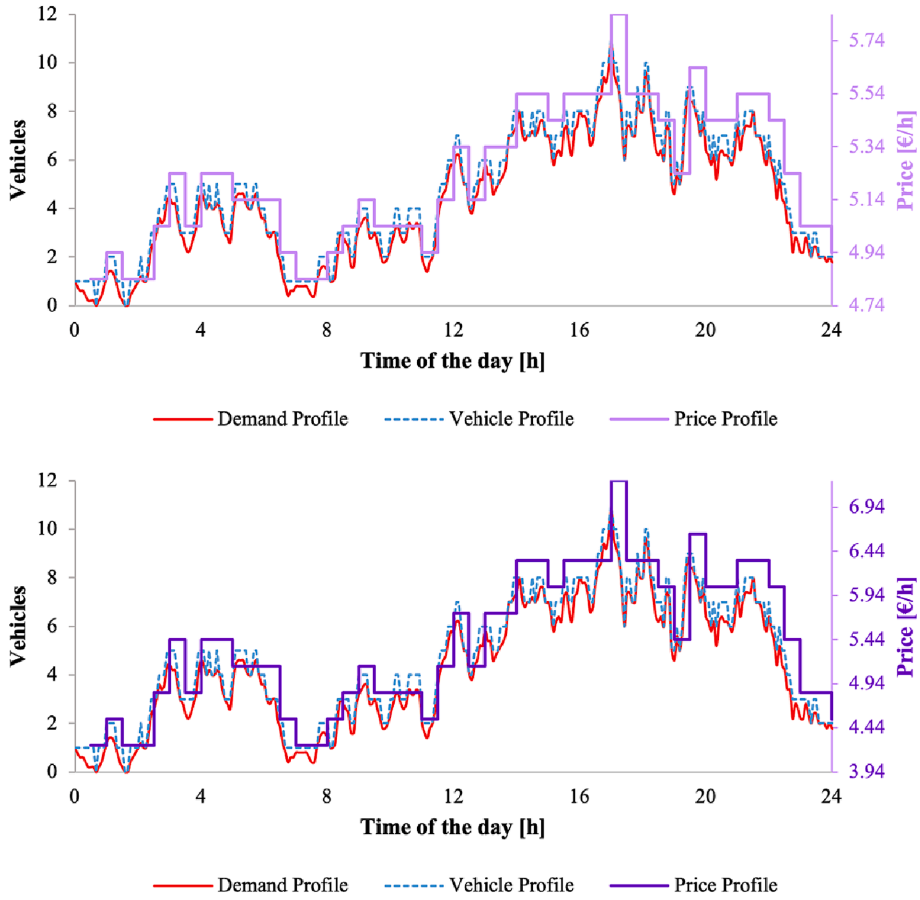


Fig. 8. (a) TBDP010; (b) TBDP030 from MPP profile.

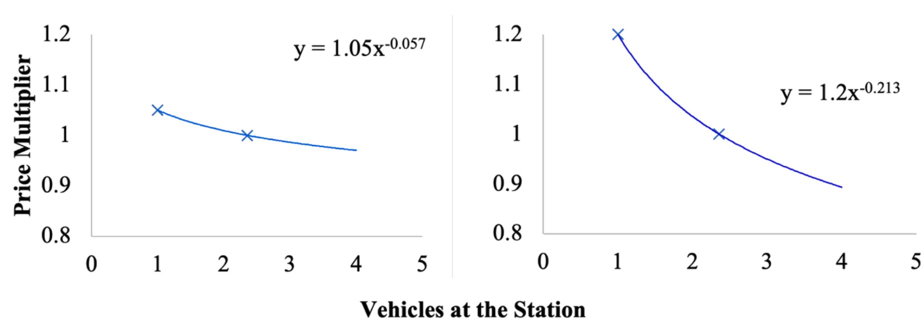


Fig. 9. (a) ABDP105; (b) ABDP120.

have the result of push people towards other modes. Fig. 13 provides an alternative representation of the score grouped by income.

In line with the results in our previous works (Giorgione et al., 2020), we see how, when compared to the other scenarios, the FP strategy is the only one in which the average score for the lowest income group is higher than the others (2.5% higher). For all the other scenarios, the score tends to increase (slightly) with the income. A similar plot can be used to explain the supply KPIs as in Fig. 14.

Fig. 14 shows how it is possible to increase the company's profit passing from a FP to a TBDP strategy. This only occurs if the selected pricing step is within a specific range. By examining the figure, it becomes evident that increasing the price by 10 cents of euro (TBDP010) increases profit, while increasing it by 30 cents of euro (TBDP030) does not yield the same result; on the contrary, it reduces profit. The same happens after the relocation. The change in strategy results in a similar amount of bookings and time spent driving, but the fact that the price adheres better to the demand leads to higher profit and overall fleet utilization. Once the vehicles are relocated, more members can find cars where and when they are needed. This additionally increases the profit. Once vehicles are relocated the average walking time to reach the station increases, this is because people leaving far from the stations, this time, can find cars once they arrive to the station and are not forced to use other modes.

3.2. Supply-based pricing

At first sight, the demand profile (Fig. 15) has an increase in the number of vehicles used during the day only for some specific scenarios. As in Fig. 10, the three lines (i.e., dotted blue line, continuous blue line, and red line) show the number of vehicles booked at different levels of granularity over the course of the day. The moving average is employed to visually illustrate the booking trend and enhance the readability of

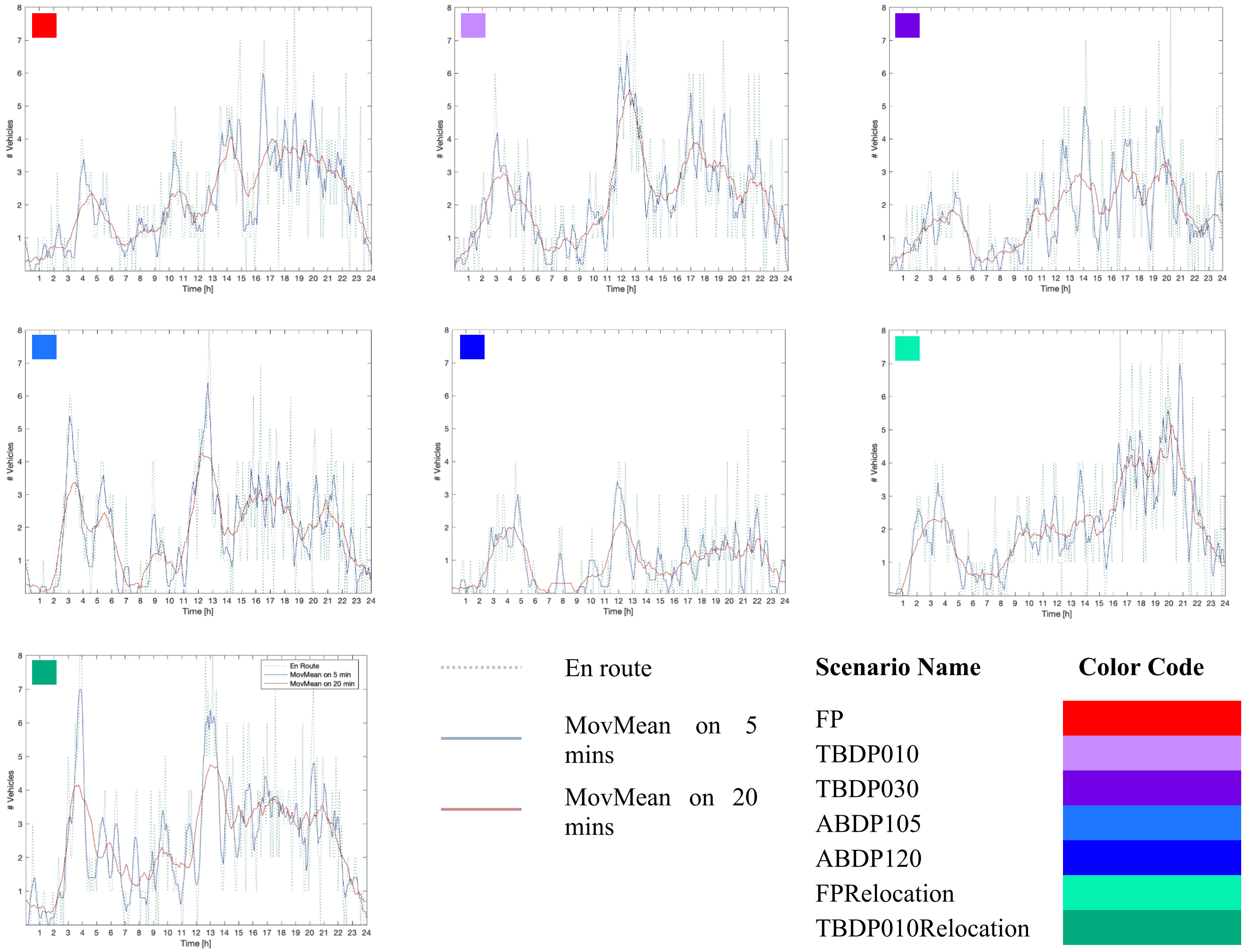


Fig. 10. Demand Profile – FP.

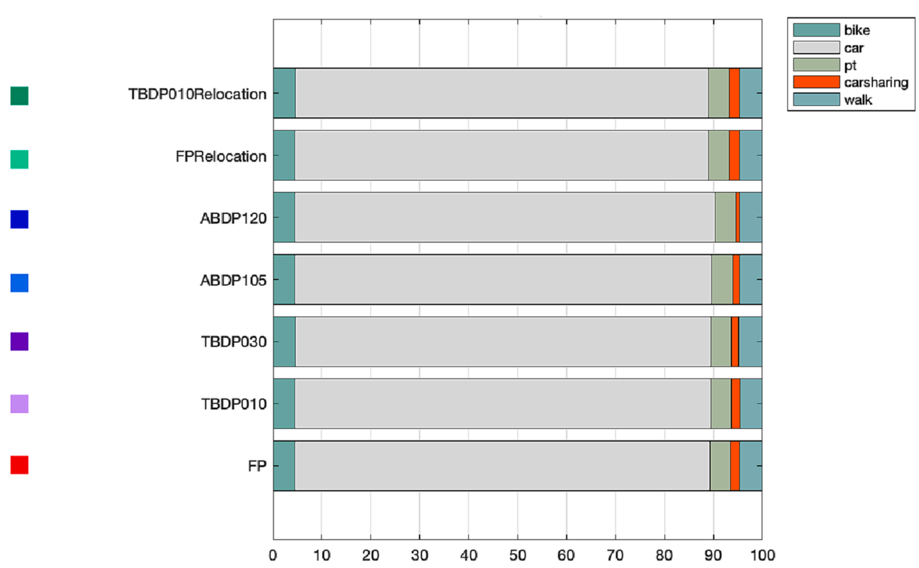


Fig. 11. Modal Share.

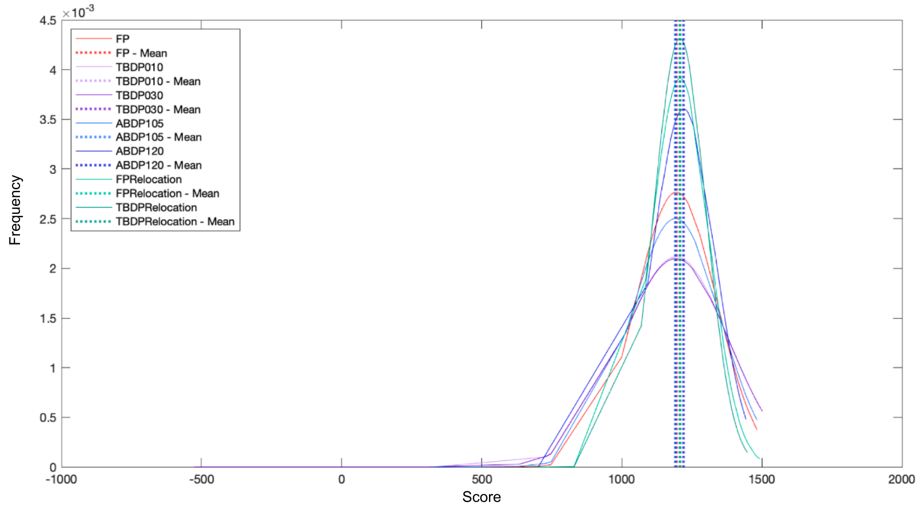


Fig. 12. Normal Distribution of the Score.

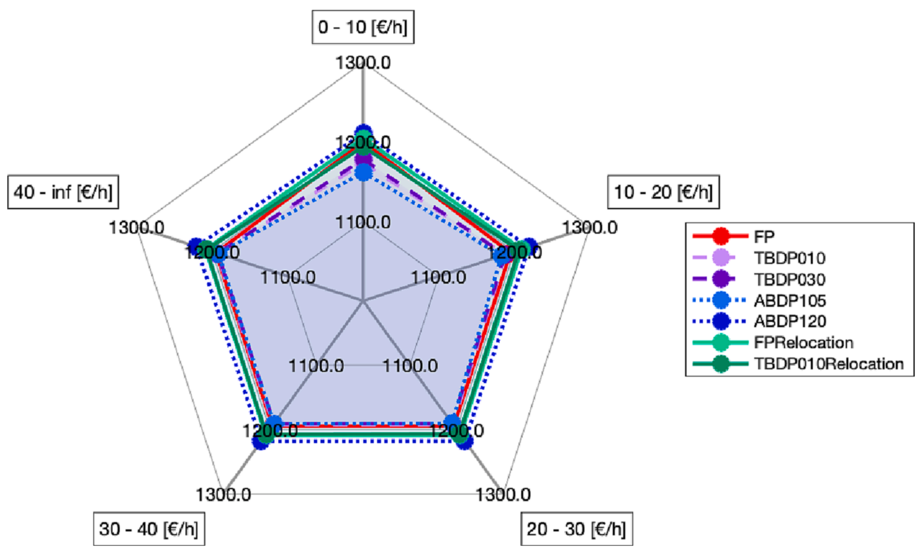


Fig. 13. Score per Income Group.

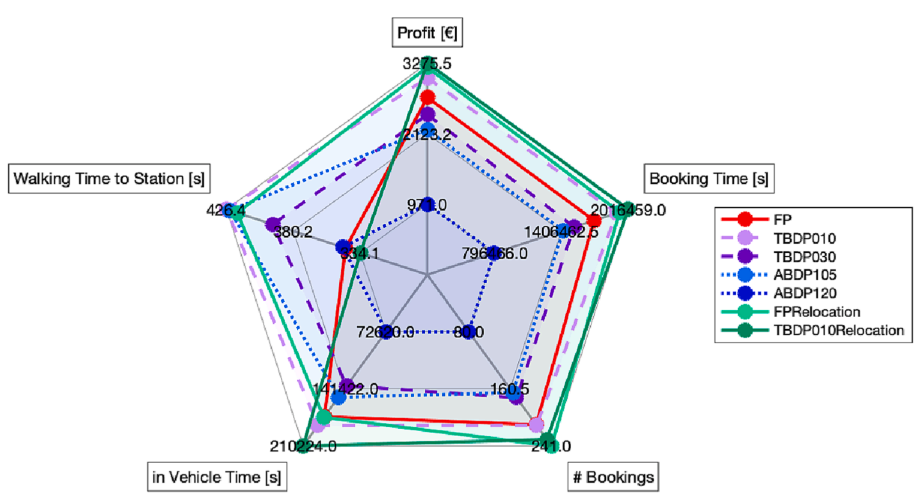


Fig. 14. Supply KPIs.

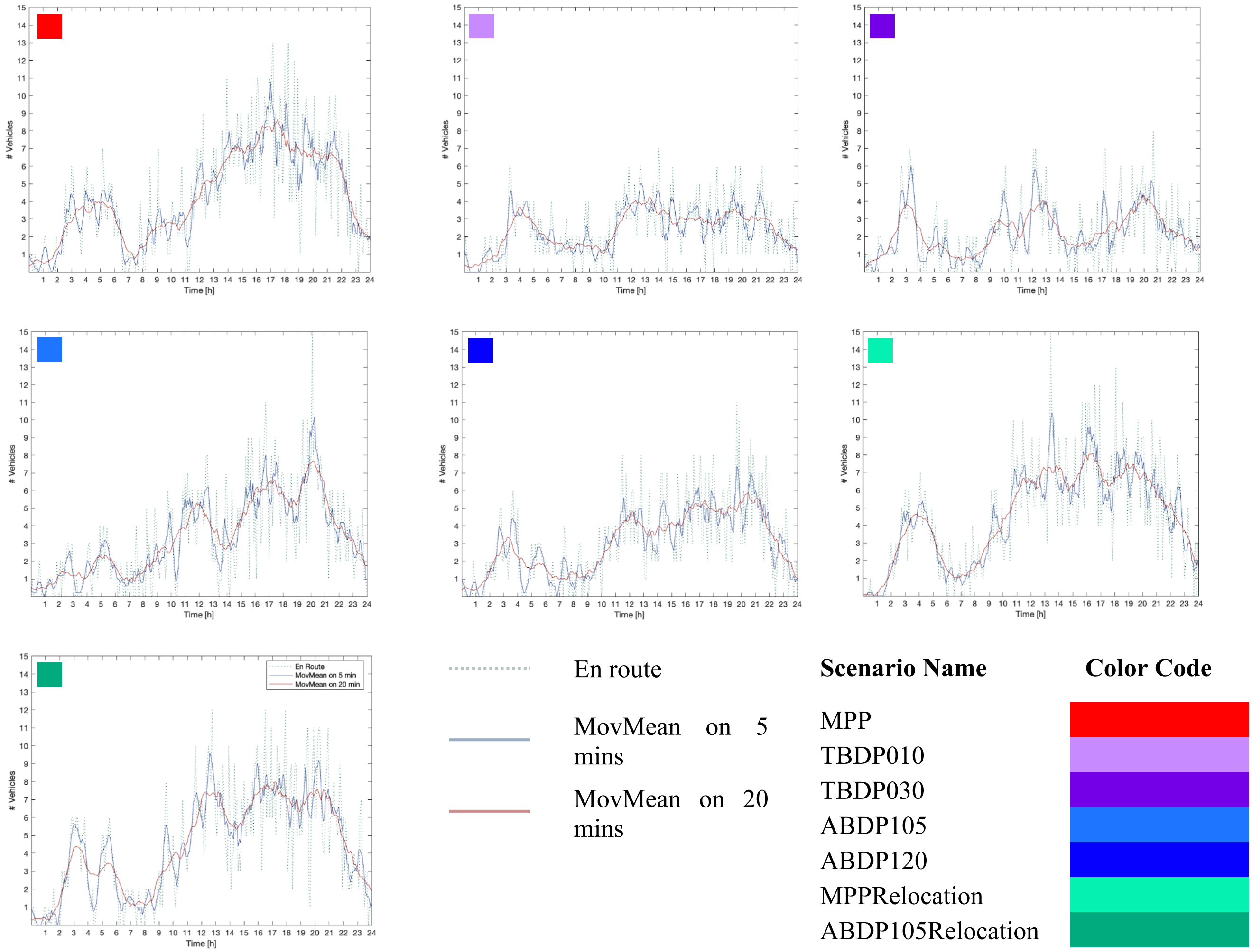


Fig. 15. Demand Profile – MPP.

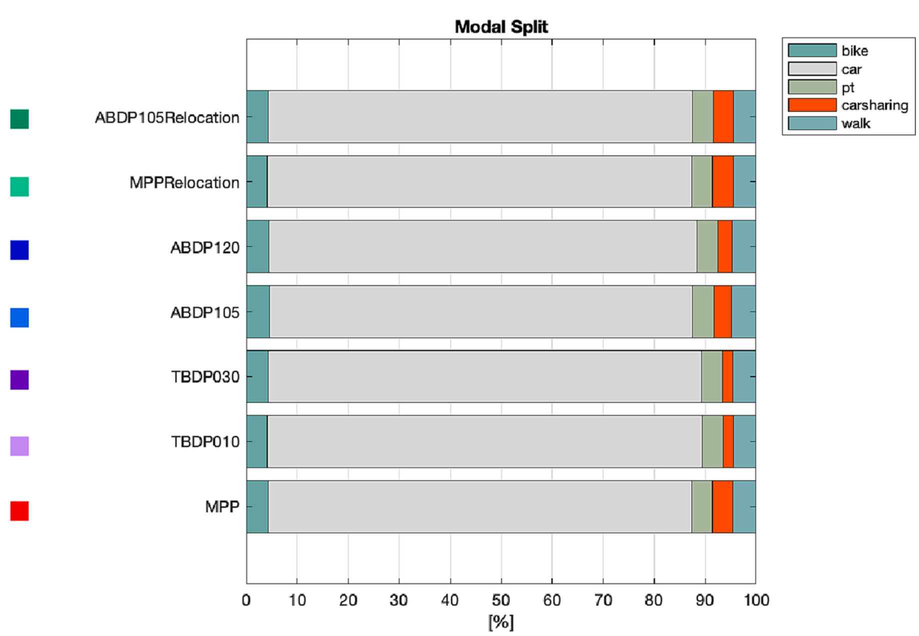


Fig. 16. Modal Share – MPP.

the graphs. In this case the price used as the baseline for this scenario is the MPP. When implementing the supply-based pricing strategy (as previously defined), reservations are highest, with a different effect compared to demand-based pricing, as the TBDP does not flatten demand and only reduces demand during peak hours. While the ABDP, particularly the ABDP105, achieves a significant number of bookings, it falls short of the MPP.

This statement becomes clearer in Fig. 16. MPP and ABDP are the strategies that result in the highest share in carsharing (relatively + 3.93% and + 3.44%). As in the other case, when relocated, the carsharing usage rises to + 4.16% for the MPPRelocation and + 4.07% for the ABDP105Relocation.

While both MPP and ABDP105 manage to increase carsharing modal share, they get a higher variance when we represent the score as a normal distribution as in Fig. 17.

MPP, both in the original version and when the relocation strategy is applied, has a bigger variance in score when compared to all the other scenarios, especially to the ABDP105. This means that the ABDP105 intercepts all those members that, at the end of the simulation, will reach a specific degree of utility. Even on average, the MPP registers a lower mean. When we analyse the score by income group, we can now see different income groups reacting to the different pricing scenarios in a more significant way than the policies based on the FP strategy (Fig. 18).

Also here, straightforwardly, the higher the income group, the higher the score. This discrepancy is stronger in the MPP where we registered score variations between + 1.5% and + 2% from the first income group. In the ABDP105 we have the same behaviour but with an average score that is systematically higher. The moment we relocate vehicles the average score drops to −3%. This happens since the new strategy allows more agents to find available vehicles at the station, resulting in a greater variety of plans. The moment the ABDP105 strategy is activated, both in the first and in the relocation phase, we see how the average score increase while the number of bookings drops as shown in Fig. 19.

In the figure we can see how the booking time, from MPP to ABDP105, decreases of −21% while getting an increment of the average score of + 1% and a variance passing from 180 to 133 min. When the relocation is done, we manage to increase the booking time of + 2.5% (from MPP to MPPRelocation), to increase the profit of + 3% at the expense of a decrease in the average score of −2%.

4. Discussion

The idea behind this paper was that it is possible to improve the main KPIs of both the supply and the demand for a carsharing service. This improvement takes place by creating dynamic prices which, being developed based on the knowledge that the operator has of the territory and its carsharing members, once hybridized, lead to a benefit for both stakeholders. These dynamic prices have been subdivided into two distinct categories: demand-based pricing and supply-based pricing. Both types are developed with a simulation-based approach and, while the former requires a basic knowledge of the territory (e.g., market surveys, revealed preferences, demand profiles) so they are less data demanding to apply in real life, the latter is created assuming that there is a thorough knowledge of the network (e.g., the vehicles status, their positioning and consumption during the day, the position and movements of the members, …). Once the scenarios are simulated, prices belonging to the same group bring a well-marked improvement in profit and/or score (Table 5).

Regarding the first block of pricing, which is based on the FP, we found that pricing strategies based on time of day (i.e., availability-based) are effective in interpreting and responding to carsharing demand. These strategies were found to increase the variance of the score while also boosting profits. Even if the number of bookings remains approximately the same, their duration increases. It is evident that changing the pricing step of the ABDP, from 10 cents to 30 cents per vehicle booked, reduces the booking time and subsequently, the profit and number of bookings. This suggests that the demand is elastic, indicating that the acceptable marginal cost for an hour of booking lies below 30 cents for users. However, this effect is not reflected in the score (as seen in the change in score between TBDP010 and TBDP030 from the FP) but only in the booking time, number of bookings, and profit. This implies that a specific group of users found the increase in cost unacceptable, resulting in them opting for alternative modes of transport, leading to a decrease in profit for the company. This phenomenon can also be observed in Fig. 11, where the modal share of carsharing slightly decreased from TBDP010 to TBDP030. The pricing strategies based on the availability of the vehicles never manage to increase profit and booking time. The pricing strategies based on vehicle availability were found to be ineffective in increasing profit and booking time. This is because the ABDP works by directing demand towards underutilized stations. The nature of the round-trip service, particularly the one provided by Oply (see Section 2.2 "Case Study"), makes it unlikely for users to have the option to choose stations beyond an acceptable walking distance. The acceptable walking distance refers to a distance that does not result in a significant reduction in the user's overall score, and where the cost savings from a lower vehicle price make up for the additional walking time required. The only other pricing strategy that manages to significantly increase both the score and the profit are those applied

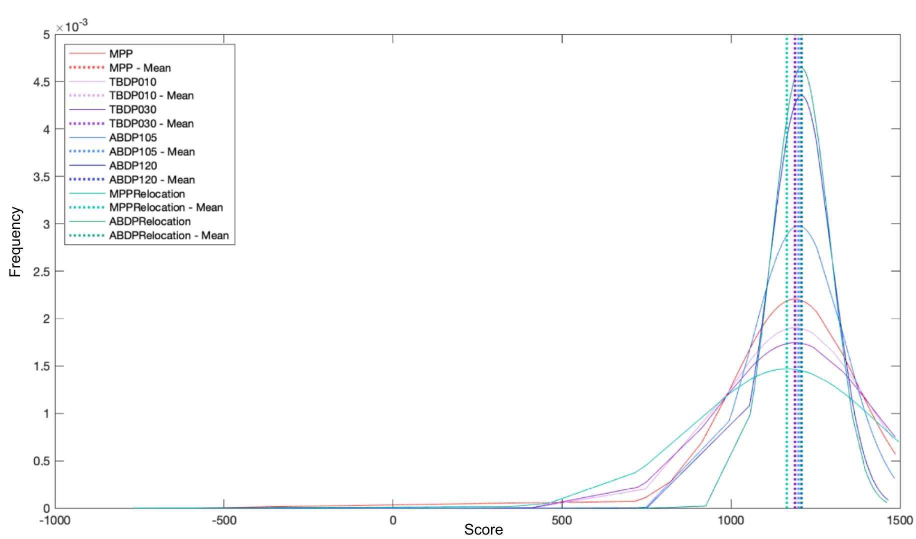


Fig. 17. Normal Distribution of the Score.

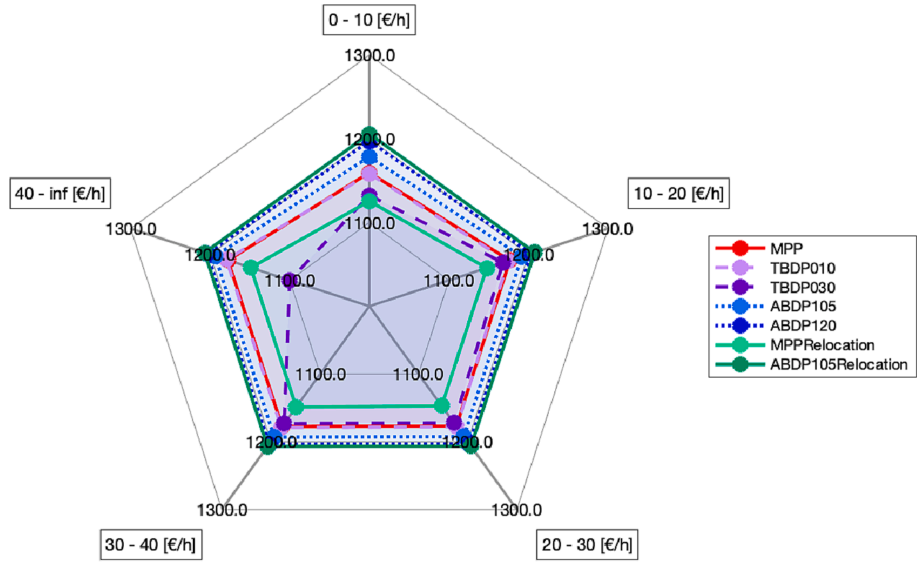


Fig. 18. Score per Income Group.

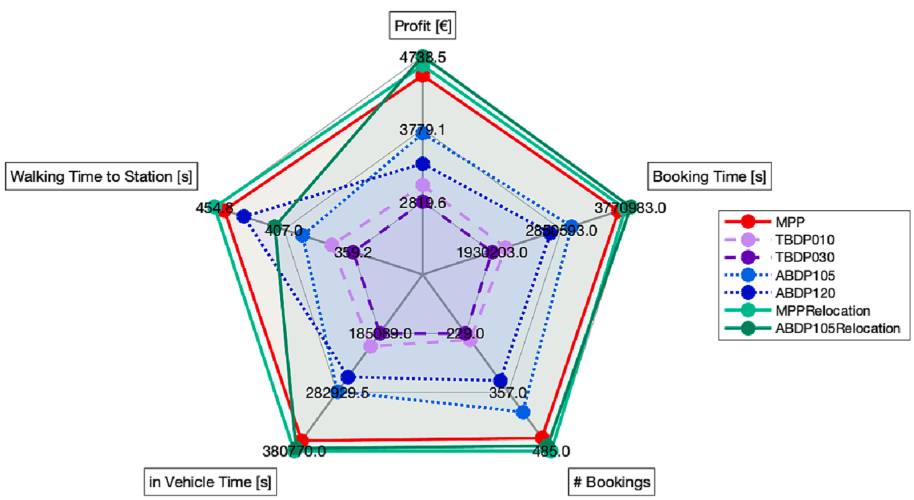


Fig. 19. Supply KPIs.

Table 5
Pricing strategies output.

	AVG Score	Var Score	Profit	Booking Time	Bookings
FP	-	-	-	-	-
TBDP010	-0.08%	23.40%	10.55%	10.78%	0.47%
TBDP030	-0.17%	24.21%	-11.48%	-11.98%	-21.97%
ABDP105	-0.17%	9.43%	-23.94%	-19.87%	-27.11%
ABDP120	2.21%	-29.73%	-179.63%	-114.02%	-163.75%
FPRelocation	1.16%	-42.57%	15.38%	12.00%	12.45%
TBDP010Relocation	1.08%	-56.52%	17.11%	15.46%	9.05%
MPP	-	-	-	-	-
TBDP010	0.08%	13.88%	-47.57%	-70.90%	-88.07%
TBDP030	0.00%	21.40%	-59.10%	-86.92%	-99.56%
ABDP105	1.00%	-35.34%	-20.52%	-20.86%	-14.25%
ABDP120	1.66%	-97.80%	-35.03%	-33.30%	-37.65%
MPPRelocation	-1.97%	33.58%	2.88%	2.46%	5.77%
ABDP105Relocation	1.57%	-111.76%	5.33%	4.32%	3.59%

including the relocation operations. The relocation procedure improves users' chances of finding cars when and where they need them. As in the pre-relocation state, applying a time-based pricing strategy leads to an increase in profit in the face, however, of a slight decrease in the number of bookings. This is not necessarily detrimental to carsharing operations. The company may aim to increase booking time while keeping the number of bookings unchanged. This results in an increase in the vehicle utilization rate, which reduces the impact of fixed vehicle costs on revenue.

In the second group of scenarios, starting from the MPP, we showed how it is not possible to increase profit by changing only the pricing strategy. This makes sense considering how the MPP is designed. Since MPP is the result of a procedure that identifies the price that maximizes profit, any other price would result in a suboptimal profit level. Nonetheless, similar to what occurs when the base price is the FP, pricing strategies based on time of day have been found to be effective in interpreting and responding to carsharing demand. ABDP is capable of increasing the overall score to a greater extent than a TBDP strategy, but at the cost of pushing away a significant number of users. As a result, this approach may lead to lower profits. When including relocating operations, the profit can be further increased. This demonstrates how MPP is a profit-optimizing price for a given network configuration that must be recalculated in the event of any changes to the fleet. However, the introduction of an ABDP strategy after the relocation can increase both profit and score. This happens because the relocation modifies the balance created during the development of the MPP, that is, making the conditions that existed during the creation of this strategy no longer holding.

5. Conclusion

In this paper we developed an approach designed to increase the profit (for the operator) and usefulness (for the end-user) of a carsharing service. The considered strategies are practical and essentially data driven. In both cases, in the application of these procedures, the data used to develop the studied pricing policies is commonly available to the carsharing companies (i.e., historical number of bookings, vehicles availability in real time, distribution of members on the territory) and hence are readily applicable in practice. In both cases, we have shown that there is still a need for a carsharing demand forecasting model to develop such schemes. Taking TBDP as an example, in a practical application, one should consult the use of carsharing cars in the previous day to decide the price of the following day using with a day-to-day approach. The ABDP, on the other hand, can be seen as an online model. This can be applied directly as it only depends on the actual consumption of resources. Furthermore, the relocation results in an increase of the main KPIs. Its simplicity is mainly dictated by the fact that what happens is the marginal calculation of the impact of moving the vehicle from one station to another. This approach is also more data driven. Using the simulator is in fact possible to evaluate the potential impact of the vehicle that will be moved. Finally, this paper is strongly practice-oriented. Any carsharing company that can collect these types of data can, in principle, apply these models in a quite straightforward fashion.

One limitation of this study is that the developed strategies are specifically designed for carsharing companies that already have access to supply and demand data, and thus may not be applicable to companies considering implementing a carsharing service without such information.

In addition, it should be noted that the results here presented specifically to round-trip carsharing services, and that the proposed approach may not necessarily increase profit or improve the end-user experience for other types of carsharing services. Further research is needed to assess the applicability of these strategies in these contexts. Although the proposed approach presented in this study has been shown to increase profit and improve the end-user experience, it should be noted that it does not necessarily return the analytical optimum for the carsharing service. Other factors, such as the cost of implementing these strategies should also be taken into consideration. Future research could explore site-specific price analysis at different stations to optimize profit and utility within a dynamic vehicle relocation framework. If the goal is to maximize the company's profit, vehicles can be assigned from stations not only based on their usage but also based on the price. For example, a vehicle can be moved from a station with the lowest price to a station with the highest price. This approach shows promise in enhancing the system's potential profitability, as it naturally allocates more resources to areas with higher demand and willingness to pay.

Possible future works can be developed around the booking forecasting system and the relocation strategies. It can help to have a fleet distribution that best adheres to member behaviour using an active approach. Another potential method for conducting research on this topic is to apply a machine learning approach to optimize profit by considering factors such as different pricing per zone, weather conditions, and seasonal patterns. Predictive systems of this kind can decrease the time it currently takes to generate a new fleet configuration based on the detected vehicle consumption. Additionally, future studies can focus on finding the optimum step used in ABDP or TBDP to maximise profit or to evaluate the best distance between two stations that maximises the utility of employing an ABDP strategy. Furthermore, the various pricing strategies applied here can be studied in view of the implementation of carsharing (or other sharing services such as bike-sharing or scooter-sharing) in synergy with other transport modes to optimize not only the single service, but this service in relation to a wider modal offer. Finally, future research mays also focus on the development of a parametric extension of the function presented in this paper. This extension may be employed to incorporate different case specific factors covering more cities, different car sharing operators, different transport services, and areas with multiple operators.

CRediT authorship contribution statement

Giulio Giorgione: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Project administration, Funding acquisition. **Francesco Viti:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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