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INSIGHTS INTO CAR SHARING RELOCATION POLICIES USING A SIMULATION-OPTIMIZATION APPROACH

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ABSTRACT

One-way carsharing allows customers to pick up a vehicle from one location and drop it off at another one. While this approach is gaining acceptance over two-way or free-floating carsharing for small populations, it suffers from vehicle imbalances: excess vehicles at some stations and shortages at others. Proper investigations are necessary to minimize these imbalances. This paper compares two relocation policies in a Jordanian pilot case study using discrete event simulation: user-based (adjusting service prices to influence demand) and staff-based (hiring external resources). Results show that the staff-based policy outperformed the user-based policy by 55.4 % in vehicle utilization and by 3.4 % in cycle service level. However, the user-based policy achieved higher overall gains.

1 INTRODUCTION

With business revenue and number of users of $13.85 billion, and 57.85 million, respectively, in 2024, and of $16.43 billion and 66.08 million in 2028 (Statista 2024), carsharing business brings the attention of the car rental companies to an important and growing market. From the environmental point view, carsharing can reduce carbon dioxide (CO_2) emission between 3 % and 18 % (Amatuni et al. 2020).

Carsharing is a transportation scheme where a vehicle can be rented by a customer for a short period. On the one hand, customers eliminate major vehicle expenses such as vehicle ownership, maintenance, and insurance. On the other hand, customers will avoid unnecessary trips, which can reduce the number of operating vehicles on the road, leading to a lower carbon emission and less road congestion. Carsharing service is a complementary service for other existing ones such as public transportation, Taxi, or Uber, and, not a substitute.

There are three different carsharing models: free floating, two-way, and one-way. In the free floating carsharing model, the customer makes an online reservation through the rental company application, where the available cars and their locations are shown to choose the suitable one. After approval, he or she picks the rented car from the designated location. In the two-way car sharing, sometimes called round carsharing, the customer picks and drops the car from the same station, while in the one-way carsharing the customer picks the car from one station and drops it at a different one. A comparison among the three models of the carsharing in terms of flexibility, parking lots, vehicle density, vehicle imbalance distribution, and brand visibility was reported by INVERS (2024), who have also mentioned that one-way carsharing is the most suitable choice for a small-size population and low vehicle density. Unfortunately, the one-way carsharing model still has an issue of the imbalance distribution of the cars among the stations.

The imbalance issue in one-way carsharing means that vehicles are overstocked in certain stations, while in other stations there are shortage in vehicles. This serious problem can be solved by relocation, moving cars from overstocked stations to shortage stations. This relocation solution can be staff- based or user-based. In staff-based relocation, external staff is hired to drive the vehicles back to the shortage stations, while in user-based relocation, the customer demand will be manipulated through changes in the offered service price, sometimes called dynamic price strategy.

The contribution of this work can be summarized in the following items:

- It provides a comparison between relocations policies: staff-based and user-based.
- In the user-based relocation policy, a more flexible dynamic pricing model is proposed, which can be tuned by manipulating three parameters, compared with one parameter in the traditional dynamic pricing models.
- The three key performance indices (i) vehicle utilization, (ii) customer service level, and (iii) service profit were used to compare the efficiency of the proposed policies.

The remainder of the paper is organized as follows: Section 2 highlights the previous work performed in this domain. Section 3 presents the as-is case study investigated with the two relocation policies staff-based and user-based. Section 4 presents and compares the results obtained from simulation-optimization models of these scenarios. Section 5 concludes the work.

2 LITERATURE REVIEW

In recent years, car sharing has become a common sustainable mobility option, offering customers to share vehicles temporarily (Eliyan and Kerbache 2024). Previous research in carsharing can be categorized based on mode of transportation, methodology, objective, and vehicle type.

Table 1 highlights the major recent related work in carsharing, in which profit, vehicle utilization, and number of bookings were used as the main objectives to enhance, while discrete event simulation, optimization, and agent-based modeling were used as a methodological approach. More work was done to investigate the Electric vehicles (EV) type upon the fossil fuel vehicles (FV), because of the recent enhancement in the electric vehicle battery capacity. In terms of the relocation policy, most work used the dynamic pricing policy as the major solution to the vehicles' imbalance issue. Up to the authors' knowledge, no previous work was done regarding the relocation policies comparison that can be used to reduce the imbalance issue, or when should it will be used.

Table 1: Summary of previous work on carsharing.

No	Reference	Mode of Transportation	Methodology	Objective	Vehicle Type	Major Results
1	(Li et al. 2021)	One-way	Discrete event simulation	Maximize the net revenue	Electric Vehicle (EV)	57.03 % enhance in net revenue was attained by utilizing dynamic pricing. Applying the optimum configuration succeeded in avoiding the car accumulation at the stations and significantly improved the level of cleaner production by reducing CO_2 emissions.
2	(Guo et al. 2024)	One-way	Multistage simulation-optimization integrated methodology	Maximize the profit	Electric Vehicle (EV)	Daily profit can be increased by implementing the proposed policy. In addition, enhancing the stability of the system can be achieved as well.

3	(Lu et al. 2021)	One-way	Mathematical programing model	Maximize the profit – Minimize the cost	Fossil Fuel Vehicles (FV)	Integration of reallocation and pricing policy achieves the balance between the resources' profit and the customers' expense.
4	(Illgen and Höck 2018)	One-way	Discrete event simulation	Maximize the profit	Electric Vehicle (EV)	Utilization of electric automobiles in car sharing framework has been verified.
5	(Gambella et al. 2018)	One-way	Mathematical programing model	Maximize the profit	Electric Vehicle (EV)	Higher profit can be achieved when implementing the reallocation policy in the car sharing frameworks, considering the balance between the vehicles' capacity and the travelers' demand.
6	(Qin et al. 2022)	One-way	Branch-and-price-and-cut	Maximize the profit	Electric Vehicle (EV)	The outcomes validate the efficiency of the proposed algorithm.
7	(Shui et al. 2024)	Free-floating	Mixed-integer linear pro-gramming model	Maximize the profit	Electric Vehicle (EV)	The acceleration methods have proved to be effective in solving large-scale scenarios.
8	(Giorgione et al. 2021)	Two-way and One-way	Agent-based Simulation	Maximize no. of bookings	-	The paper shows that the two-way car sharing type is utilized as an alternative for personal vehicles, however one-way mechanism is chosen by travelers who utilizes several modes throughout the day.
9	(Brendel et al. 2018)	One-way	Discrete event simulation	Maximize vehicle utilization	Electric Vehicle (EV)	The suggested framework results in enhanced utilization and performance of electric vehicles batteries.
10	(Huang et al. 2022)	One-way	Two-stage stochastic program	Maximize the profit	Fossil Fuel Vehicle (FV)	An enhancement in the profit up to 20.49 % can be accomplished by implementing the suggested stochastic method in com-parison with the result attained from the historical approach.

3 METHODOLGY

In order to provide a better understanding of the relocation policies used in one-way carsharing, three simulation models, the basic (as-is) model, the staff-based relocation model, and the user-based relocation model were built for a pilot carsharing scenario in Jordan. Key performance indicators (KPIs) such as customer service level (CSL), vehicle utilization, and service profit for each station are reported and compared for the three models.

A simulation-optimization based approach was used to tackle the addressed problem. Discrete event simulation model was built to mimic the one-way carsharing processes (Figure 1). An optimization tool (OptQuest), which is based on scatter search, tabu search, and evolutionary algorithms such as genetic algorithms, has been used to optimize cycle service level and car utilization.

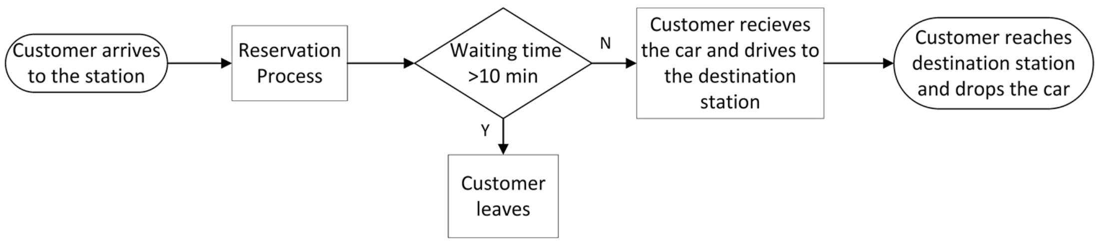

Figure 1: Carsharing flow chart.

3.1 Basic Model

Carsharing service has been utilized in many countries and cities to reduce congestion, pollution, and cost, while this service has not been used in Jordan yet. Therefore, the idea of investigating the carsharing service usefulness has been raised. A pilot study was considering three different stations: two stations were placed within university campuses (University of Jordan and German Jordanian University), while the other one was sited in a commercial place. The analytic hierarchy process (AHP) coupled with the set covering model were utilized to select those site locations among fifteen different locations. The hourly demand on each selected site has been estimated using agent-based modeling and survey approaches (Table 2). In this paper, the site locations with their demand is utilized from the mentioned models, without showing their details in order to reduce to focus on the main idea of this paper. Given that the stations' location with their demand and the traffic flow of vehicles (see Figure 1) were determined, the parameters in Table 3 were used to feed the simulation model.

Table 2: Customer arrivals at stations.

Periods	Arrivals at Station 1	Arrivals at Station 2	Arrivals at Station 3
7:00 - 8:00	10	7	0
8:00 - 9:00	7	5	0
9:00 - 10:00	6	6	0
10:00 - 11:00	3	3	0
11:00 - 12:00	5	5	2
12:00 - 13:00	4	4	4
13:00 - 14:00	6	6	6
14:00 - 15:00	7	7	7
15:00 - 16:00	8	8	8
16:00 - 17:00	6	6	6
17:00 - 18:00	2	3	1
18:00 - 19:00	1	2	1

The carsharing service starts when the customer arrives at the picking station and starts the registration process (i.e., provides the required information such as driving license, and credit card information), or he or she might use a carsharing application to provide the required information and check the car availability. Once the registration process is completed, the customer receives the car if it is available at the picking station, or waits for a maximum of ten minutes. If no car is available within the ten-minutes waiting period, the customer cancels the registration and leaves. If the car is available, the customer picks the car, drives to the destination station, and drops it there.

Table 3: Carsharing basic model parameters.

Parameter	**Value**
Working hours	12 hrs. (7:00 am-7:00 pm)
Working days	5 days (Sunday-Thursday)
Price ($/hour)	8
Number of replications	30
Number of cars	Five
Initial position	Two vehicles at Station 1 and 2, and one vehicle at Station 3
Distance between Station 1 and Station 2	20 km
Distance between Station 2 and Station 3	10 km
Distance between Station 1 and Station 3	30 km
Average vehicle speed in congestion	40 km/hour
Average vehicle speed without congestion	60 km/hour
Waiting time before customer lost	10 minutes
Parking space in stations	unlimited
Time required to deliver the car to customer	N~ $(5,2^2)$ min

3.2 Staff-Based Relocation Policy

The staff-based relocation policy can be defined as using external resources (drivers) to move the vehicles from stations with excess vehicles to stations with short vehicles in a certain period. To determine the number of drivers required in each time slot, a simulation-optimization model was built as follows.

Let y_{ij} be the decision variable representing the number of drivers at station i in period j, where i belongs to the set of stations, i.e., Station 1, 2, or 3, and j belongs to the set of time slots available each day, then the optimization model used with the basic simulation developed previously is

$$Maximize\ CSL_1 + CSL_2 + CSL_3 \tag{1}$$

$$S.t.:$$

$$0 \leq y_{ij} \leq 2, \qquad \forall i, j \tag{2}$$

$$\sum_{j} lost\ driver_{ij} \leq 10, \qquad \forall i \tag{3}$$

$$Average\ Vechicle\ Utilization \geq 0.5 \tag{4}$$

where the objective function (1) represents the sum of customer service level of each station, in which each term can be calculated from Equation (8). The simulation model is used to represent the nonlinear relationship between the decision variables y_{ij} and the customer service level. Constraint (2) denotes the lower and the upper limits of the number of drivers that need to be hired in each station at each period. Constraint (3) states that the total number of lost hired drivers should be less than 10, i.e., drivers who leave because they show up at the station and wait for 10 minutes without a car becoming available. Constraint (4) shows that the average vehicle utilization should be more than 0.5, where vehicle utilization can be calculated from Equation (9). Finally, the decision variables have been defined as an integer type variable. An assumption is made that the driver is willing to perform the trip to one of the two remaining stations.

3.3 User-Based Relocation Policy

The user-based relocation policy is based on using the demand elasticity phenomena to manipulate the demand on certain time slots. There is no need to use external drivers to overcome the vehicles imbalance problem as in the staff-based policy; instead, the service price is used to adjust the demand to the required level.

Equation (5) represents the suggested relationship between the service price and the demand, which can be tuned by using the equation parameters $\theta_1, \theta_2, \theta_3$. For example, θ_1 can be used to determine the threshold demand that cannot be exceeded regardless the service price, while $\theta_1 - \theta_2$ is used to determine the intercept point on the demand axis and $\theta_3$is used to control the gradient (i.e., sensitivity) of the curve (Figure 3), using $\theta_1, \theta_2, \theta_3 = 5.0, -3.0, 0.8$ as the parameters.

$$D = \theta_1 - \theta_2 e^{-\theta_3 * price} \quad (5)$$

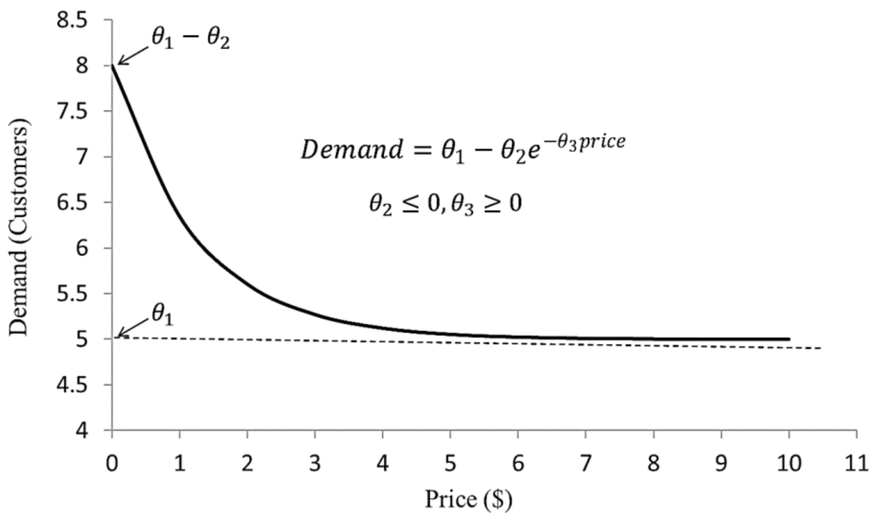

Figure 3: Demand elasticity behavior.

In order to choose the right parameters $\theta_1, \theta_2, \theta_3$ for each period in each station, the basic price of $8 per hour (benchmarked from carsharing service websites in other countries) is used to give the basic demand. For example, for Station 1 in the first period the parameter θ_3 has been tuned to a value of -0.135 to provide a demand value of ten customers at a price of eight dollar, while $\theta_1$has been adjusted to a value of 5, which represents the minimum number of customers that will arrive at Station 1 at first period regardless the service price (Figure 4). The value of θ_2 is set to –15 to represent that the demand of thirteen customers will occur at the lowest possible price of five dollar. Table 4 summarizes the parameters used in each station at each period.

After demonstrating the price demand relationship applied in this study, an optimization model has been used to find the values of the prices that optimize the objectives values.

Let x_{ij} be the decision variable that represents the price value at Station i at Period j, where i belongs to the set of stations, i.e., Station 1, 2, or 3, and j belongs to the set of time slots available each day, then the optimization model used with the basic simulation is:

$$Maximize\ CSL_1 + CSL_2 + CSL_3 \quad (6)$$

$S.t.$:

$$5 \leq x_{ij} \leq 12, \qquad \forall i, j \quad (7)$$

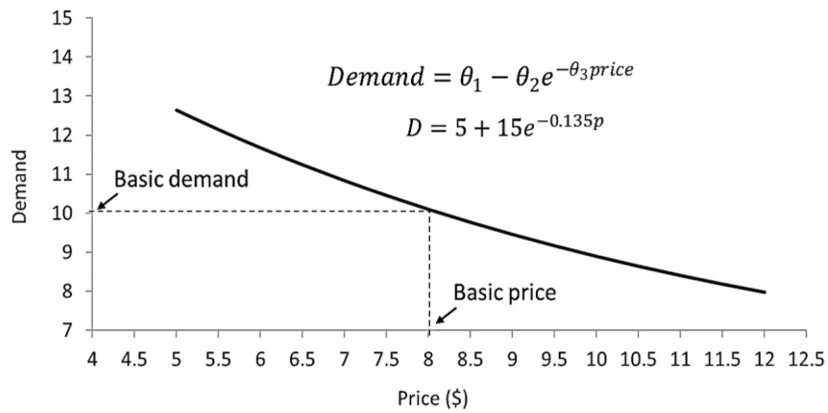

Figure 4: Demand elasticity parameter tuning.

where Equation (2), the objective function, represents the sum of customer service level of each station, which can be obtained from Equation (4). The simulation model is used to represent the nonlinear relationship between the decision variables x_{ij} and the customer service level. Constraint (3) denotes the lower and upper limits on the service price. The decision variables have been set as variables of discrete type of step equal to 0.5.

Table 4: Price demand relationship for user-based model.

	D1*	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12
Station 1												
θ_1	5	5	5	1	1	1	5	5	5	5	1	0
θ_2	-15	-15	-15	-15	-15	-15	-15	-15	-15	-15	-15	-15
θ_3	-0.13	-0.25	-0.33	-0.25	-0.16	-0.2	-0.33	-0.25	-0.2	-0.33	-0.33	-0.33
Station 2												
θ_1	5	1	5	1	1	1	5	5	5	5	1	1
θ_2	-15	-15	-15	-15	-15	-15	-15	-15	-15	-15	-15	-15
θ_3	-0.25	-0.16	-0.33	-0.25	-0.16	-0.2	-0.33	-0.25	-0.2	-0.33	-0.25	-0.33
Station 3												
θ_1	0	0	0	0	1	1	5	5	5	5	0	0
θ_2	-15	-15	-15	-15	-15	-15	-15	-15	-15	-15	-15	-15
θ_3	-0.9	-0.9	-0.9	-0.9	-0.33	-0.2	-0.33	-0.25	-0.2	-0.33	-0.33	-0.33

*D1: period 1 from 7:00-8:00 am

4 RESULTS

In order to evaluate the current performance of the staff-based and user-based models against the basic model, key performance indicators for the served customers and vehicle (or resource) utilization has been reported in Table 5, based on Equations (1) and (2),

Customer service level (CSl):

$$CSl = 1 - \frac{Number\ of\ lost\ customers}{Total\ number\ of\ customers} \tag{8}$$

Vehicle utilization (V_{uti}):

$$V_{uti} = \frac{Time\ vechicle\ is\ busy}{Vechicle\ time\ \ scheduled} \tag{9}$$

where the vehicle time scheduled equals the twelve working hours per day the vehicle is available.

The analysis was performed on a processor Intel(R) Core (TM) i5-8265U CPU @ 1.60GHz, 1800 MHz, 4 Core(s), 8 Logical Processor(s), with 8 GB Ram. The Arena 16.2 simulation software was used to develop the required models, with OptQuest as the optimization tool.

4.1 Key Performance Indicators for the Basic, Staff-Based, and User-Based Models

Key performance indicators, such as customer service level, vehicle utilization, and computational time for the basic, staff-based, and user-based models are presented in Table 5. In terms of customer service level, it increased by 16.2 % and 12.3 % when applying the staff-based and user-based policies respectively, compared with the same indicator of the basic model. Vehicle utilization increased by 35.4 % for the staff-based policy and decreased by 12.8 % for the user-based policy compared with the vehicle utilization of the basic model. The computation time was around 4, and 2 minutes for both the staff-based and user-based policies respectively, since the population size is small and the vehicle density is low which is the suitable condition for adapting one way scheme.

Table 5: Average key performance indicators of the basic, the staff-based, and the user-based models.

Key Performance Indicators	**95 % CI Basic Model (%)**	**95 % CI Staff-based Model (%)**	**95 % CI User-based Model (%)**
Customer Service Level			
Customer Service Level at Station 1	31.1±2.4	41.1±3.0	36.3±2.8
Customer Service Level at Station 2	35.5±3.0	47.2±2.0	39.5±1.9
Customer Service Level at Station 3	50.3±2.9	47.3±4.0	55.3±3.2
Average Customer Service Level	*38.9±2.8*	*45.2±3.0*	*43.7±2.6*
Vehicles Utilization			
Vehicle 1 Utilization	51.6±2.3	69.4± 1.0	45.0±1.8
Vehicle 2 Utilization	47.2±2.0	62.0± 3.0	41.8±1.7
Vehicle 3 Utilization	43.6±2.3	56.0± 3.0	37.1±1.8
Vehicle 4 Utilization	38.6±2.5	51.6± 4.0	33.8±2.4
Vehicle 5 Utilization	29.4±2.1	45.8 ± 4.0	25.6±1.7
Average Vehicle Utilization	*42.1*±1.3	*57.0* ± 2.0	*36.7*±1.1
Average Computational Time	-	*3 min 56 sec*	*1 min 35 sec*

Besides the technical performance indicators customer service level and vehicle utilization, a profit analysis for each alternative has been performed to take the right action.

4.2 Staff-Based Model

Table 6 presents the average number of drivers needed for each station in each period obtained from the simulation-optimization model. Choosing the university campuses as carsharing stations can be very useful in providing the stations with the necessary drivers needed with a low or reasonable price. It should be noted that the station that has zero or low demand for certain periods of the day, such as Station 3 with zero demand from 7:00- 11:00 am, requires drivers to return the vehicles back to other stations.

Table 6: Staff-based drivers required.

Periods	7:00 - 8:00	8:00 - 9:00	9:00 - 10:00	10:00 - 11:00	11:00 - 12:00	12:00 - 13:00	13:00 - 14:00	14:00 - 15:00	15:00 - 16:00	16:00 - 17:00	17:00 - 18:00	18:00 - 19:00	19:00 - 20:00	20:00 - 21:00	Total
Drivers required at Station 1	0	0	1	0	1	0	1	2	1	1	1	2	1	1	12
Drivers required at Station 2	0	1	2	1	0	0	0	1	0	0	1	1	0	1	8
Drivers required at Station 3	1	2	2	1	1	2	1	0	1	2	0	0	0	2	15

4.3 User-Based Model

The new prices with their associated demands for each station at each period obtained from the simulation-optimization model are presented in Table 7. Comparing the basic demand (BD) column values with new demand (ND) column values of any station reveals that the demand for the new values is lower than those of the old values, which can be interpreted by examining the customer service level (CSL), Equation (8), where the CSL is more sensitive to the dominator reduction, e.g., the total number of customers served, than numeration rising.

Table 7: User-based model optimum prices.

	Station 1			Station 2			Station 3		
Periods	**Price ($)**	***BD$_1$**	***ND$_1$**	**Price ($)**	**BD$_2$**	**ND$_2$**	**Price ($)**	**BD$_3$**	**ND$_3$**
Price from 7:00 - 8:00	11	10	8	10	7	6	11	0	0
Price from 8:00 - 9:00	10	7	6	10.5	5	4	10.5	0	0
Price from 9:00 - 10:00	11	6	5	10.5	6	5	10.5	0	0
Price from 10:00 - 11:00	11	3	2	11.5	3	2	10.5	0	0
Price from 11:00 - 12:00	11.5	5	3	10.5	5	4	9.5	2	2
Price from 12:00 - 13:00	11	4	3	12	4	2	9.5	4	3
Price from 13:00 - 14:00	9.5	6	6	11	6	5	10	6	6
Price from 14:00 - 15:00	11.5	7	6	11.5	7	6	12	7	6
Price from 15:00 - 16:00	10	8	7	11	8	7	12	8	6
Price from 16:00 - 17:00	9.5	6	6	9.5	6	6	10.5	6	5
Price from 17:00 - 18:00	11	2	1	10.5	3	2	10.5	1	0
Price from 18:00 - 19:00	11	1	0	10	2	2	11.5	1	0

*BD$_1$: Basic demand at Station 1, *ND$_1$: New demand at Station 1

4.4 Relocation Policies Profit Analysis

To gain a comprehensive insight into the impact of the investigated relocation policies, both user-based and staff-based, a profit analysis is necessary to determine the monetary value of applying these relocation policies. Table 8 shows the items included estimating the service cost and revenue. The user-based relocation policy is the most profitable alternative, despite having a lower value of customer service level and vehicle utilization compared to the staff-based relocation policy.

Table 8: Financial analysis summary for the basic, the staff-based, and the user-based models.

Item	**Basic Model**	**Staff-based Model**	**User-based Model**
Cost			
Investment period (years)	10	10	10
Effective interest rate (%)	12	12	12
Working days per year	300	300	300
Number of vehicles used	5	5	5
Cost per vehicle ($)	(30,000)	(30,000)	(30,000)
Total vehicles cost ($) = cost per vehicle*number of vehicles	(150,000)	(150,000)	(150,000)
Annual vehicles cost	*(26,574.62)*	*(26,574.62)*	*(26,574.62)*
Number of stations	3	3	3
Annual station rent ($/year/station)	(16,000)	(16,000)	(16,000)
Annual stations rent ($)	*(48,000)*	*(48,000)*	*(48,000)*
Annual registration, maintenance, and fuel ($/year/vehicle)	(10,000)	(10,000)	(10,000)
Total vehicles maintenance cost ($)	*(50,000)*	*(50,000)*	*(50,000)*
Administrative cost	*(10,000)*	*(10,000)*	*(10,000)*
Total annual expenses	(134,547.62)	(134,547.62)	(134,547.62)
Daily expenses ($/day)	***448.49***	***448.49***	***448.49***
Number of external drivers per day	-	35	-
Rate of external driver ($/hr./driver)	-	3	-
Net daily expenses($/day)	***448.49***	***523.49***	***448.49***
Revenue			
Average number of incoming customers	164.73	161.13	*132.13*
Customer service utilization (CSL) %	38.9	45.2	*43.7*
Average customers served= incoming customer*CSL	64	73	58
Price per customer ($/customer)	8	8	*See Table 7*
Daily revenue ($/day)	***512***	***583***	***613***
Net daily profit ($/day)	**63.51**	**59.51**	**164.51**

5 CONCLUSIONS

Carsharing services are considered a promising step in the direction of a sustainable logistics system, aiming to reduce pollution and congestion while providing affordable transportation options for young generations and low-income people. An investigation into the usefulness of a one-way carsharing service has been raised in Jordan, exploring strategic decisions (such as station locations and numbers) and operational decisions (such as the number of vehicles required, their initial locations, and the relocation policy).

Three different simulation models – basic, user-based, and staff-based – were built to provide insights into the number of customers that can be served out of the total customers requesting the service, the vehicles' utilization, and the recommended policy for the one-way carsharing service. The major findings can be summarized as follows:

- For small population sizes and low vehicle density, a one-way carsharing scheme is recommended.
- A staff-based relocation policy can be used to overcome the imbalance issue, but it comes with additional costs. This policy can be used throughout the entire carsharing service life.

- A user-based relocation policy can be used effectively after obtaining some preliminary data about the demand-price relationship. It is advised to use this policy when the carsharing service already has achieved real data for the demand-price relationship.
- A user-based relocation policy is based on the demand-price relationship, with the upper bound being the competitor's price and the lower bound being the service price. These bounds limit the price value and, accordingly, the demand, making this policy more suitable for small imbalance issues.

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