Broken Bike system

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Abstract

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Keywords: bike sharing system, broken bike, static demand

1. Introduction

Due to increasing urban traffic congestion and growing awareness of green transportation, Bike Sharing Systems (BSS) are becoming increasingly popular and essential for urban transportation. These systems offer convenient public service for short-term access to the public bikes, in which bikes are made available on stations distributed throughout a city, and users typically check out a bike from any station, ride to their destination, and drop it off at a nearby station.

The first bike sharing system was introduced in 1999 in the Netherlands [1]. So far, BSSs have been widely deployed in many major cities across the world, and more than 500 shared bicycle systems with more than $1,000,000$ bicycles have been launched in about 60 countries around the world [2].

Bike Sharing Systems provide an affordable and more sustainable emission-free mode of transportation to commute across small distances without the costs and burdens of its ownership such as the regular maintenance of their bikes or risk the theft and vandalism. Additionally, BSSs are increasingly put forward as an effective complement to public transit. They facilitate one-way trips, and through integration with other public transportation systems such as bus and subway, they improve the accessibility and convenience of the "first-mile" and "last mile" problem of the resident trip.

Along with the advantages of bike sharing services and their growing widespread use, they also face numerous challenges, among which a critical one is the uneven distribution demand for rides. The demand for rides often leads to imbalanced bike distributions among stations in the system that creates some stations with the surplus of bikes while others are empty or having a deficit, which drastically affects the quality of the customer service rate due to unmet demand. To alleviate the imbalance between bike supply and demand, it is necessary to establish bike repositioning strategies. The repositioning strategies are typically performed using truck fleets and operators, which transfer the bikes according to the demand patterns.

There have been extensive research papers addressing the problem of the bike rebalancing problem, which falls into two major streams: static and dynamic rebalancing. The former considers the rebalancing operations performed during the night or off-peak hours when the system usage can be considered negligible, while the latter focuses on the fluctuations in the service demand and the repositioning process continuously occurs throughout the operating period.

In the static approach, In order to reduce the cost of travel, [3] provided a static model using a single vehicle that allowed multiple visits to each station that may serve to perform temporary operations. [4] also worked in static mode to lessen route cost by considering a vehicle and banned temporary operations to not use the stations as a temporary depot in the vehicle's multiple visits. [5] established a static model to minimize the tour length and consider the time limit for vehicles operates. [6] established a multi-vehicle repositioning allowing a single visit to each station that considers travel time and penalty function both in the objective function. Also, [7] developed a static model considering multi vehicles and visits with time limit constrain to minimize the total travel time. [8] studied the static model with two service times: the total service time and the maximum route duration of the fleet, and also a single visit to stations. In the paper, first, the positive deviation from the tolerance of the total demand dissatisfaction of the system and then the total service time of the vehicles is minimized. [9] used a bilevel programming model by considering the repositing time connected with the system providers and the vehicle owner to satisfy both of them. In the upper-level, system providers manage the optimal loading and unloading quantities with the objective function of minimizing the total penalty from unsatisfied customers. Also, in the lower-level, the vehicle owner attempts to reach the minimum travel route cost. [10] used depot inventory cost and multi-vehicle to address the tradeoff between the traveling cost and the depot inventory cost. To minimizing the daily operational cost, including the depot inventory cost and the traveling cost, two mixed-integer programming formulations were developed to attain the optimal daily decision on the vehicle routes and the numbers of bikes and vehicles applied from the depot. [11] also attempted to minimize total traveling cost and inventory cost by considering multiple depots in which multiple station visits or temporary stops are not allowed. Furthermore, [12] used integer linear programming to solve the static model in multiple periods that assumed VIP and normal bikes and several particular vehicles in their model. Also, the objective function was to minimize costs of implementing trucks, moving between stations, and carrying bikes on vehicles while rebalancing. [13] introduced the static model base on minimizing the weighted sum of the total operational time and the demand lost, which assumed a single vehicle and also a penalty cost for losing demands. Also, rebalancing was partial, which means some demand may lose due to optimization, and balanced stations can be ignored as there are no visiting or loading/unloading operations needed and also assumed that the model would distinguish the impact of different stations on user dissatisfaction by defining different unit penalty costs for each station.

The Other approach, which is the dynamic model, also has been under research in literature. [14] maximized profits while considering the different time steps in which the used vehicles perform the repositioning operations. [15] proposed a forecasting model to predict demand dissatisfaction and used it to model the dynamic relocation problem to reduce demand dissatisfaction and vehicle costs. In addition to forecasting dissatisfaction, inventory level and demand forecasting are also done in the paper. [16] goal was to determine a dynamic rebalancing scheme that minimizes user dissatisfaction while maintaining the rebalancing cost as low as possible. The scheme has been done by improving the availability of the service through minimizing the time during which stations are unable to meet user demand. To obtain the smallest amount of failed demands, [17] presented a comprehensive Markov decision process model for the stochastic-dynamic inventory routing problem for station-based BSSs. [18] similarly minimized the number of failed ride requests and proposed a formulation that explicitly integrates resource-management decisions by considering a limited redistribution budget to acquire and operate vehicles, as well as an accurate time representation of pickups and deliveries of bikes at stations.

Another thoughtful issue in the operation of a BSS is posed by unusable bikes, which none of the mentioned papers considered. Owing to the high usage frequency, open-air parking problem and the lack of care consciousness of users, the presence of unusable bikes seem inevitable. With a limited number of bikes in the BSS, that means the wastage of resources and deterioration of the system's service quality with negative consequences on the users' experience in BSSs.

To deal with the rising issue, the bike sharing operators need to collect the broken bikes from stations and return them to the depot for repairs. Therefore, it is imperative to develop an effective and efficient repositioning plan for both usable and broken bikes simultaneously to achieve a desired distribution of bikes across the stations in an integrated manner.

Despite the great importance of this issue, broken bikes have received considerably less attention in the bike rebalancing literature. [19] proposed integer linear programming formulation for relocating bikes as collect bicycles in need of repair. In order to minimize the traveling cost, it is assumed there are multi vehicles and stations that each station is visited exactly once, and all broken bikes must be returned to the depot at the end of the operation. [20] assumed there are multiple depots and heterogeneous trucks that can visit stations multiple times by the same or different trucks and, along with relocation, collect broken bikes, but the travel distance and time do not limit the trucks. To minimize the total repositioning time of the whole truck fleet, a useful greedy-genetic heuristic is formed by introducing the maximum operation number (including the loading and unloading numbers of usable bikes and broken bikes at each visited station), near station set, the operation priority strategy, and the repair strategy. [21] presented the static model with the broken bikes and multi-vehicle by using the route optimization and loading capacity ratio as constraints, and the total recycling costs were minimized. Furthermore, the k-means method for clustering with the planning recycling route for operational decisions are mixed in the paper. [22] also considered broken bikes in the model and similarly assumed that there are several depots and multi vehicles in the system, and vehicles may not start and end at the same depot. As a result, a free solver name brrp solver for the bike repositioning and recycling problem was developed. Using a Markov decision process approach, [23] also considered broken bikes in the dynamic model, but they will not be collected; however, broken bikes will be repaired in the stations.

An underlying assumption in all of the above-mentioned papers is that the repositioning operations (for both usable and broken bikes) are performed by internal combustion vehicles, which produce tremendous amounts of greenhouse gas emissions. These emissions endanger the environmental sustainability of bike sharing systems. However, most of the prior studies only focus on operational aspects, and environmental aspects are generally have been ignored. To the best of our knowledge, Wang and Szeto (2018) [24] were the pioneer work to minimize the total CO_2 emissions of all repositioning vehicles. They proposed a static model, assuming both usable and broken bikes that multi vehicles with multiple visits to the depot and stations relocate them. [25] and [26] converted carbon emission to cost and tried to minimize the total cost of the operation. [25] considers multi-energy mixed fleets and traffic restrictions in the static model that each station can be served by a vehicle only once. [26] presented a dynamic green bike repositioning problem with a single vehicle and a rolling horizon approach to breaking down the proposed problem into a set of stages in which a static bike repositioning sub-problem is solved in each stage.

On the other hand, due to lower pollution emissions and significant energy savings, electric vehicles (EVs) are regarded as another promising sustainable transportation mode for use in cities. Bike sharing systems tend to employ electric vehicles (EVs) to be more environmentally friendly. More recently, in Feb 2020, Lime announced that the company is committing to replacing all of their owned and leased operations vehicles with electric vehicles. However, despite recent technological advancements, employing EVs poses additional challenges to the repositioning problem that must be faced carefully to guarantee service efficiency. The challenges come from the limited driving range of EVs, battery capacity, and high initial cost. Recently, EVs have also been observed in the literature. [25], as mentioned, used multi-energy mixed fleets with both EVs and ICVs that EV's battery discharging rate is related only to the distance. Additionally, [27] assumed a static rebalancing in which both broken bikes and EVs are used. In the model, vehicles can visit stations and the depot multiple times and have a constant battery discharging rate unrelated to the vehicle load.

This paper presents new modeling of bike sharing rebalancing and recycling problem (BRRP) by considering a single-vehicle allowing the multi visit to stations and using them as a temporary depot. Moreover, due to increasing conserving about a clean environment and launching several global plans support this goal, such as "Vision Zero"[28], EV is employed. Also, there are assumed several penalties such as demand losing penalty and not collecting broken bike penalty which allows system providers to implement different policies by changing penalties value. The introduced MIP model will determine the routes and the number of usable and broken bicycles that must be relocated among stations in a way that, while observing the limitations, also maximize profit. Also, the result of applying the model to real data of san Francisco is demonstrated.

The remainder of the paper is organized as follows. "Model Formulation" presents a problem definition and the mathematical model. "Case Study" describes the numerical studies and discusses the results.

2. Model Formulation

The BRRP in this paper is formally defined as follows. There is a bike sharing system that operates in an area of the city. There is a central station that acts as both a depot and a repair station for repairing broken bikes. The depot itself may have several usable bikes to be relocated and used to meet the demands of the stations. Broken bikes from the stations may also be transported to the depot for repairs. There are also n station with initial p_i number of bikes. A percentage of them may be broken b_i, and due to the extra capacity they occupy from the station and reduce the useful space, they are better to be collected and carried to the depot during the operation horizon - T -. The rest of the bikes which are usable and available at the stations can be used to meet the demand q_i of each station. The number of usable bikes may be unbalanced with the predicted demand q_i at each station. This means that the number of usable bikes at the multiple stations may be less than the predicted demand, which should be compensated from other stations, or the number of usable bikes at the multiple stations may be more than the predicted demand, so extra bikes should be transferred to the stations that are deficient. Hence, one EV or ICV - both are considered - that starts and ends its tour at the depot, with a specific capacity Q performs loading and unloading among stations in order to respond to the demands and bring back broken bikes to the depot. All these repositing and recycling get done during the night that demand is approximately zero. The system operator has a limited time (e.g., 1 a.m to 4 a.m). If the actual time of operation exceeds the operation horizon, a penalty per minute must be paid.

The total time of operation t consists of loading and unloading times as well as the vehicle travel time. The travel time of the vehicle between two stations i and j is calculated according to the speed of the vehicle v and the distance between the two stations i and j - d_{ij} -. By using the following formula, the travel time between two stations i and j is obtained in minutes:

$$t_{ij} = \left(\frac{d_{ij}}{v}\right) \times 60 \tag{1}$$

The model is considered from a system provider's viewpoint that means the goal is to maximize profits by considering revenue and operational cost.

For the ICV, each route that traverses has a fixed cost fc, and also, it has a variable cost c based on the length of the route and the difficulty of the route. There is a coefficient h_{ij} that indicates the difficulty of the route. The route's difficulty affects the variable cost so that for routes that are more difficult to travel, the driver is reluctant to travel on these routes due to the difficulty of operation, more fuel consumption, depreciation of the vehicle, etc. Therefore, it is necessary to spend more money than the smooth and comfortable route to increase the driver's desire to travel this route. For example, if the route is uphill, the coefficient is more significant than one downhill.

For the EV, the only cost is the cost of energy consumption. For each route that traverses, energy consumption depends on distance, the route's difficulty, and the number of loaded bikes. Moreover, for each kWh energy consumption, there is ec cost.

It is also assumed there is a penalty cost for each demand lost dp because a shortage causes a cost increase, a reduced service level, and a reduced likelihood of future rental requests. In addition, due to the limited capacity of the vehicle and the limited time to perform operations, the operator can leave the broken bicycles at the station if necessary and collect them in the next period, so bp costs for each broken bike that is not collected because it causes to fill the station capacity and also decreased quality of service due to lack of usable bicycles and delayed repair of damaged bicycles. Further, there is a penalty cost tp as mentioned before for operation time exceeding each minute that passes from a certain amount T.

Another cost that is considered is the cost of labor α that operates for loading and unloading the bicycles. The l_i and u_i symbols indicate the number of loads and unloads at each station, respectively.

In the other hand, the revenue r we get from each satisfied demand s_i is assumed to be a fixed number per demand q_i according to [29].

2.1. Notations

Sets

$N = \{0, 1, 2, \ldots, N\}$	Set of stations and depot $= \{0\}$

Indices

i, j, k	Indices of stations

Parameters

p_i	Initial number of bikes in the station i at the beginning - both usable and broken.
b_i	Number of broken bikes in the station i at the beginning
T	The operation horizon
Q	Vehicle capacity
dp	Value of penalty for demand lost
tp	Value of Penalty for passing every minute of T
bp	Value of Penalty for each broken bike is not collected
α	The unit cost of loading/unloading a bike
β	The unit time of loading/unloading a bike
ec	The energy consumption cost
fc	The fixed cost of the vehicle
c	The variable travel costs per kilometer
r	The revenue from each satisfied demand
v	The average speed of the repositioning vehicle.
B	The battery capacity of the EV.
b_0	The battery consumption rate when the EV load is empty.
b^*	The battery consumption rate when the EV load is full.
t_{ij}	Time of vehicle travel from the station i to j
q_i	The Demand of the station i
d_{ij}	The Distance between station i and j, $\forall i, j \in N$
h_{ij}	Road hardness from the station i to j

Decision variables

Z	Objective function
x_{ij}	Integer variable that represents the number of the trip must be done for each route from the station i to j
z_{ij}	Integer variable that represents the number of usable bikes must be in the vehicle on the route from the station i to j
zb_{ij}	Integer variable that represents the number of broken bikes must be in the vehicle on the route from the station i to j
E_{ij}	A variable that represents the amount of the energy consumption for each route from the station i to j
s_i	Integer variable that represents the number of satisfied demands at the station i
bc_i	Integer variable that represents number of broken bikes collected at each station i
u_i	Integer variable that represents the number of unloaded bikes in station i
l_i	Integer variable that represents the number of loaded bikes in station i
t	Positive variable that represents the total time of operation
τ	Positive variable that represents difference between operation time and operation horizon

2.2. Mathematical Model

The problem can be mathematically stated as follows:

$$\begin{aligned} Maximize Z = \quad & r \times \sum_{i=1}^{N} s_i - \\ & (\sum_{i=0}^{N} \sum_{j=0}^{N} fc \times x_{ij} + \sum_{i=0}^{N} \sum_{j=0}^{N} c \times h_{ij} \times d_{ij} \times x_{ij} + \\ & dp \times \left(\sum_{i=1}^{N} q_i - \sum_{i=1}^{N} s_i \right) + bp \times \left(\sum_{i=1}^{N} b_i - \sum_{i=1}^{N} bc_i \right) + tp \times \tau + \\ & \alpha \times \left(\sum_{i=0}^{N} u_i + \sum_{i=0}^{N} l_i + 2 \times \sum_{i=0}^{N} bc_i \right)) \end{aligned} \tag{2}$$

Subject to

$$\sum_{i=1}^{N} x_{0i} \geq 1 \tag{3}$$

$$\sum_{i=1}^{N} x_{ij} = \sum_{k=1}^{N} x_{jk}, \qquad \forall j \in N \tag{4}$$

$$\sum_{i=0}^{N} \sum_{j=0,i=j}^{N} x_{ij} = 0 \tag{5}$$

$$p_i - l_i + u_i - b_i \geq s_i, \qquad \forall i = 1, \ldots, N \tag{6}$$

$$s_i \leq q_i, \qquad \forall i \in N \tag{7}$$

$$\sum_{j=0}^{N} zb_{ji} + bc_i = \sum_{k=0}^{N} zb_{ik}, \qquad \forall i = 1, \ldots, N \tag{8}$$

$$bc_i \leq b_i, \qquad \forall i = 1, \ldots, N \tag{9}$$

$$\sum_{i=1}^{N} zb_{i0} = \sum_{i=1}^{N} bc_i \tag{10}$$

$$\sum_{j=0}^{N} z_{ji} - \sum_{k=0}^{N} z_{ik} = u_i - l_i, \qquad \forall i \in N \tag{11}$$

$$z_{ij} + zb_{ij} \leq Q \times x_{ij}, \qquad \forall i, j \in N \tag{12}$$

$$t = \sum_{i=0}^{N} \sum_{j=0}^{N} t_{ij} \times x_{ij} + \beta \times \left(\sum_{i=0}^{N} l_i + \sum_{i=0}^{N} u_i + 2 \times \sum_{i=1}^{N} bc_i \right) \tag{13}$$

$$\tau \geq t - T \tag{14}$$

$$\sum_{i=1}^{N} zb_{0i} = 0 \tag{15}$$

$$l_0 \leq p_0 \tag{16}$$

$$\sum_{i=1}^{N} z_{0i} \leq l_0 \tag{17}$$

$$x_{ij}, z_{ij}, zb_{ij} \geq 0, \qquad integer, \qquad \forall i, j \in N \tag{18}$$

$$s_i, bc_i, u_i, l_i \geq 0, \qquad integer, \qquad \forall i \in N \tag{19}$$

$$\tau \geq 0 \tag{20}$$

The objective function (2) maximizes the profit that is a function of revenue from satisfying demand and costs, which include the fixed and variable costs of the ICV travel, the cost of labor to carry out operations, the cost of losing demand, the cost of not collecting broken bicycles and the cost of exceeding the operation time from the operation horizon. Note that having a coefficient of 2 behind bc_i because broken bicycles will be removed and placed in the depot. One of the most important things to note about this model is that it is very flexible. This means that by changing the value of penalties, it can be decided that the system's provider prefers to collect broken bikes or relocate usable bikes to meet the demand due to time constraints. Either both are equally important and allow the model to make a decision, or the system's provider prefers that the operation time exceeds the time limit and the operation is completed. Constrain (3) makes sure that the vehicle abandons the depot in the first place. Constrain (4) is the flow conservation that equalizes the number of entries and exits to each station and the depot. Constrain (5) prevents the creation of a route at each station by itself. Constrain (6) states that the number of satisfied demands should be less than the number of initial bicycles available at each station in addition to the number of usable bicycles brought from other stations, except for broken bicycles and the number of bicycles removed from this station. In this constraint, by changing the larger sign to a smaller or equal sign, the assumption of the problem will change slightly. So that while the sign is larger than, extra usable bicycles will remain in the stations, while if the sign is smaller or equal, extra usable bicycles will be taken to the depot. Constrain (7) indicates that the maximum number of satisfied demands for each station i is at most equal to the number of demands in the station i. Constrain (8) ensures that when the vehicle arrives at a station, it must pick up the specified number of broken bicycles. Constrain (9) make sure that the number of broken bikes the vehicle wants to collect must be less than or equal to the number of broken bikes at the station. Constrain (10) states that all broken bicycles collected from the stations must be brought to the depot. Constrain (11) makes sure that the flow of usable bicycles in and out of each station must be equal to the number of usable bicycles loaded and unloaded in the station. Constrain (12) is made for two purposes. First, it states that a bicycle can be moved between two stations if the vehicle travels this route, and also states that the number of bicycles – both broken and usable- moved between two stations each time traveling between them should not exceed the capacity of the vehicle. The Constrain (13) calculates the total operation time. This time includes the vehicle's travel time between the stations and the time of the operation of loading and unloading the bicycles by the labor. Constrain (14) calculates the difference between the operating time and the operation horizon. So that $\tau = \max\{t - T, 0\}$ and $\tau \geq 0$. So if the operation time exceeds the operation horizon, $\tau = t - T$. However, if it is less than that, it becomes zero since τ is positive. Constrain (15) prevents broken bicycles from leaving the depot and constrain (16) and (17) ensure that the number of usable bicycles leaving the depot should be less than the initial number of bicycles in there. The variables domain are established in (18)-(20).

2.3. EV Model

The introduced model considered an ICV operates the relocating; however, this section introduces a model considering an EV in the relocating. First, a part of the objective function, which is related to the relocation vehicle, will be changed due to the different way of calculating costs. Ev's cost depends on the amount of energy consumed, so the objective function changes as follows.

$$\begin{aligned} MaximizeZ = \quad & r \times \sum_{i=1}^{N} s_i - \\ & (\sum_{i=0}^{N} \sum_{j=0}^{N} E_{ij} \times ec + \\ & dp \times \left(\sum_{i=1}^{N} q_i - \sum_{i=1}^{N} s_i \right) + bp \times \left(\sum_{i=1}^{N} b_i - \sum_{i=1}^{N} bc_i \right) + tp \times \tau + \\ & \alpha \times \left(\sum_{i=0}^{N} u_i + \sum_{i=0}^{N} l_i + 2 \times \sum_{i=0}^{N} bc_i \right)) \end{aligned} \tag{21}$$

The objective function (21) maximizes the profit like (2) but instead of the fixed and variable costs of the ICV travel, the cost of energy consumption is replaced. The energy consumption E_{ij} is obtained by adding following constraint in the model.

$$E_{ij} = (x_{ij} \times b_0 \times d_{ij} \times h_{ij}) + (d_{ij} \times h_{ij} \times (\frac{b^* - b_0}{Q}) \times (z_{ij} + zb_{ij})), \qquad \forall i, j \in N$$

(22)

$$\sum_{i=0}^{N}\sum_{j=0}^{N} E_{ij} \leq B \tag{23}$$

$$E_{ij} \geq 0, \qquad \forall i, j \in N \tag{24}$$

Constrain (22) calculates the amount of energy consumption for each route. The first term of the equation demonstrates the amount of energy consumption related to the vehicle itself that depends on distance and road hardness. The second term is related to the vehicle load, which in addition to distance and road hardness, the number of bikes loaded on the vehicle is considered effective on energy consumption. Constrain (23) makes sure that the total amount of energy consumption does not exceed the vehicle battery capacity. The variable domain is established in (24).

3. Numerical Study

The proposed model is tested on the real-world dataset of the San Francisco Bay area bike sharing system [30]. The system includes 35 stations and one depot as demonstrated in Figure 1. The depot is located in the center of the stations as [18] and [31] intended. Each station contains an initial number of bikes, some of which are broken and should be collected in the depot. The data between February 1, 2015, and February 28, 2015, is chosen, and then the mean of weekdays' demand and weekends' demand are employed to build the base scenarios and represent the city's bike use demand. To demonstrate the potential of the proposed model for both ICV and EV, the following four scenarios are defined: (1) weekday when demand is high, but the breakdown rate is low (2) weekday when demand and breakdown rate are high (3) weekend when demand and breakdown rate are low and (4) weekend when demand is low, but the breakdown rate is high. Moreover, the day ahead 's demand for bikes, and the number of usable and broken bikes at each station are illustrated in Figures 2 - 5 for each scenario. In the first scenario (SC1) and the second scenario (SC2), there are 274 bikes, 242 demand, and 9 and 33 broken bikes in each, respectively. However, in the third scenario (SC3) and the fourth scenario (SC4), there are 275 usable bikes, 38 demand, and 9 and 38 broken bikes in each, respectively. The day ahead 's demand at a station is referred to as the expected number of bikes to be hired from that station the next day. Also, a sensitivity analysis on the type of vehicles and the policy chosen is undertaken to evaluate their impacts on system profit. The proposed mathematical model was solved by the GAMS 25.1.2 software in a dual-core system with a CPU of 1.9 GHz and 4 GB RAM.

3.1. Parameter settings

In the following experiments, ensuing parameters are considered to generate problem instances in all scenarios. It is assumed there is no initial bike in the depot at the beginning of the day. The breakdown rate is in line with other reported values form [24] which is considered to be 5% and 10% of initial bikes in each station. The capacity of the rebalancing vehicle is set to be 30 bike [21] and [22]. The operational speed of the rebalancing vehicle is assumed to be 40 $km/hour$ [22] and [32]. The time needed to load or unload a single bike is 0.5 $minute$ [9] and [22]. The repositioning duration of vehicle is 3 $hours$ or 180 $minutes$ [22], The fixed cost of the vehicle is $50 and the unit travel cost of the vehicle is 0.5 $dollar/km$ [22] and [33], and the income from each bike allocation will be $4.38 per trip on average. Moreover, the loss penalty for each demand loss is assumed to be $43.8 experimentally. Also, the road harness that affects the ICV's unit travel cost and energy consumption in EV is considered 1 for all routes due to the coastal area and the flat roads. Furthermore, it is assumed that the electric vehicle used is the Mercedes-Benz eSprinter electric panel van [34]. Finally, the energy consumption cost for the EV is assumed $0.139 [27].

3.2. Results

Table 2 compares the results of model implementation for four mentioned scenarios when using an ICV. Regarding the number of available bikes in the system, it is interesting to see that in the first scenario (Sc1), the model has preferred to lose two demands. This is because the potential cost of satisfying all demands is higher than losing two of them. In Sc2, by increasing the breakdown rate to 10%, losing three additional demands is inevitable as the number of demands is three more than the number of usable bikes in the system, so in total, four demands were lost. For weekend day scenarios (Sc3 and Sc4), all demands are satisfied. Although all broken bikes are collected in Sc3, this did not happen in Sc4. This is because the possible cost of

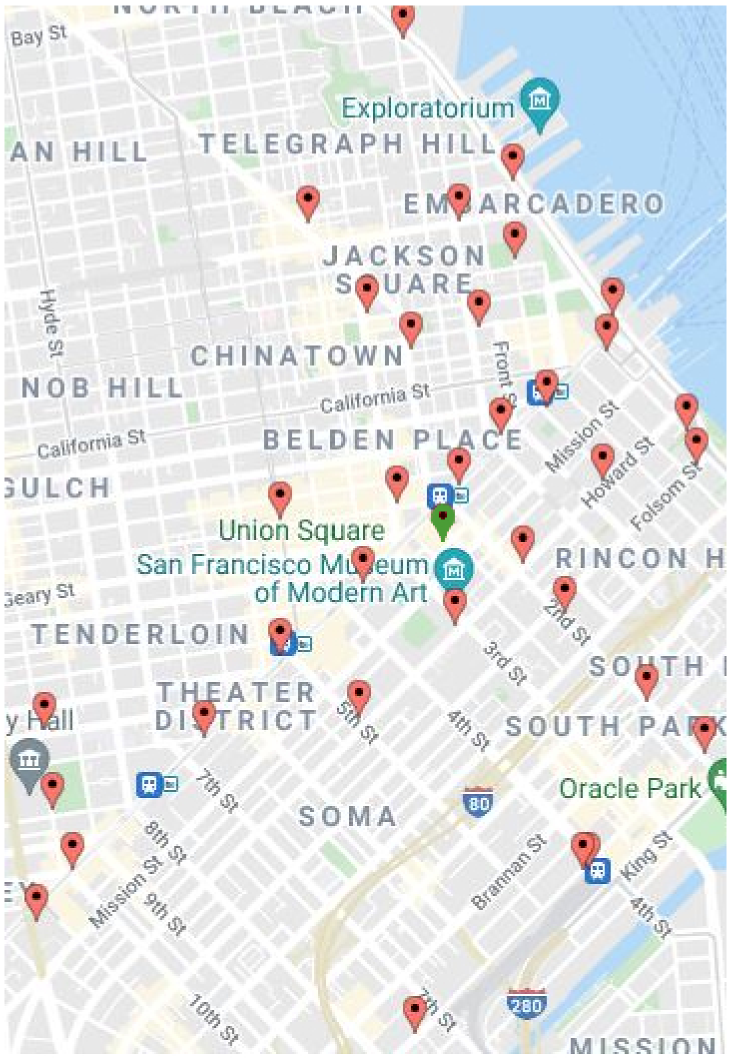

Figure 1: The location of the depot and stations in the San Francisco Bay area bike sharing system (Stations: Red marks, The depot: Green mark)

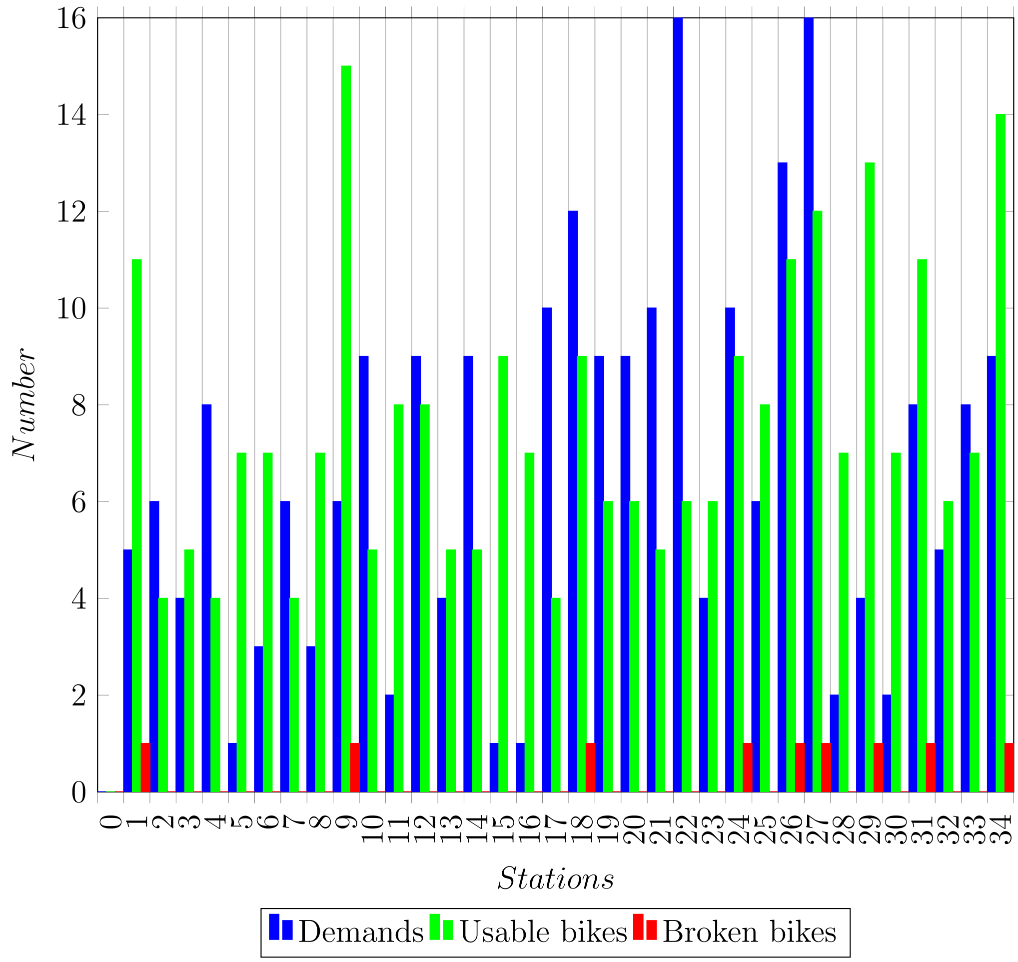

Figure 2: The number of usable and broken bikes, and the next day demand at each station in Workday with 5% breakdown rate scenario

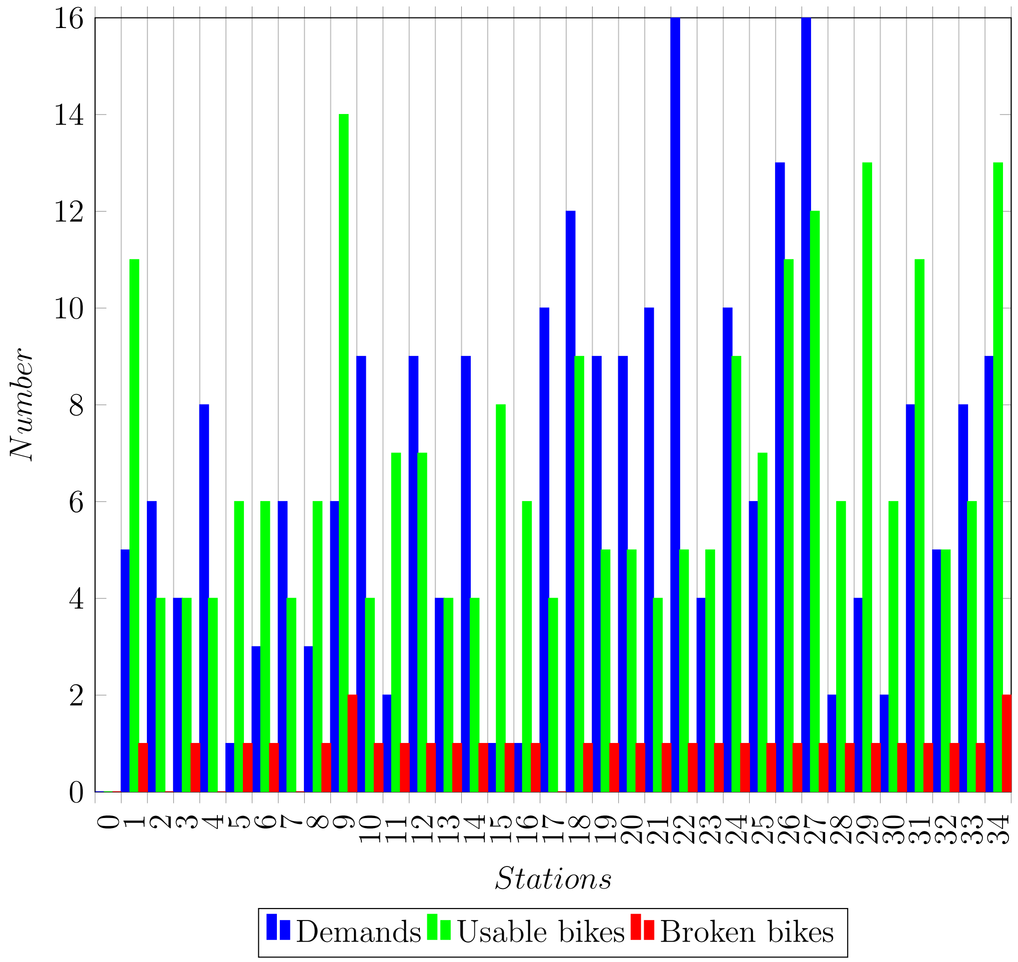

Figure 3: The number of usable and broken bikes, and the next day demand at each station in Workday with 10% breakdown rate scenario

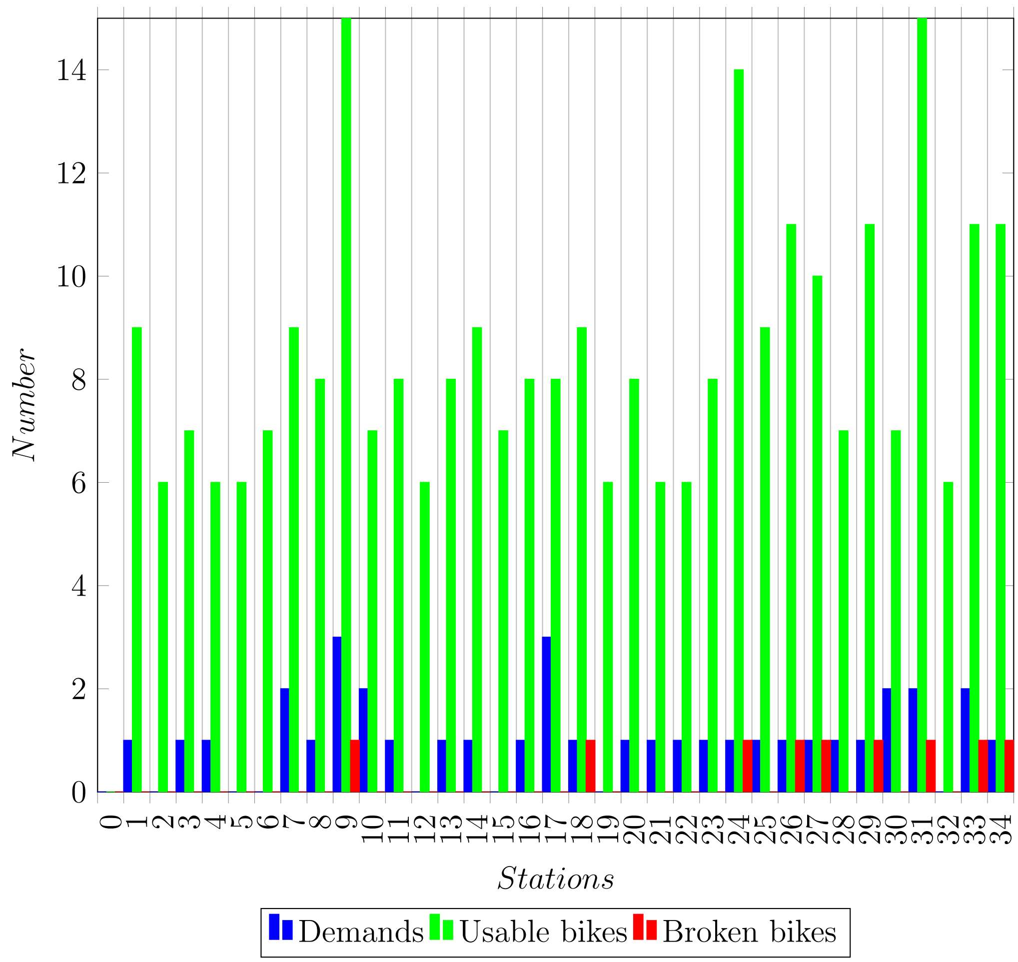

Figure 4: The number of usable and broken bikes, and the next day demand at each station in Weekend with 5% breakdown rate scenario

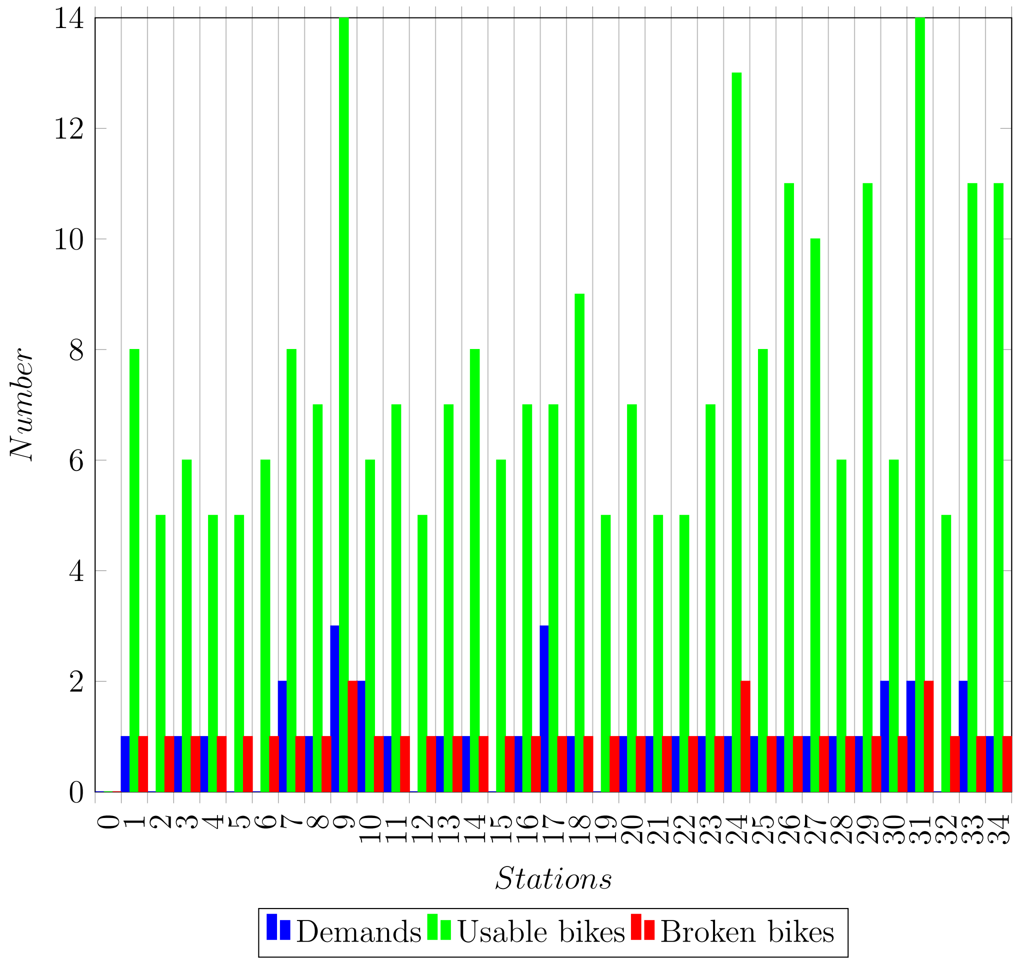

Figure 5: The number of usable and broken bikes, and the next day demand at each station in Weekend with 10% breakdown rate scenario

Parameters	Description	Value	Unit
$\boldsymbol{Q}$	The capacity of the vehicle	30	*Bikes*
$\boldsymbol{V}$	The average speed of the vehicle	40	*Km/hour*
$\boldsymbol{B}$	The capacity of the EV battery	47	*kWh*
$\boldsymbol{b_0}$	The EV empty loaded energy consumption	0.309	*kWh/Km*
$\boldsymbol{b^*}$	The EV full loaded energy consumption	0.507	*kWh/Km*
$\boldsymbol{T}$	The operation horizon	180	*Minute*
$\boldsymbol{\beta}$	The unit time to load or unload a bike	0.5	*Minute*
$\boldsymbol{\alpha}$	The manpower wages	0.2	*Dollar/load or unload*
$\boldsymbol{fc}$	The fixed cost of the vehicle	50	*Dollars*
$\boldsymbol{c}$	The unit travel cost of the vehicle	0.5	*Dollar/km*
$\boldsymbol{ec}$	The unit cost of energy consumption	0.136	*Dollar/kWh*
$\boldsymbol{r}$	The income from each bicycle allocation	4.38	*Trip*
$\boldsymbol{dp}$	The penalty for lost of each demand	43.8	*Lost demand*
$\boldsymbol{bp}$	The penalty for each uncollected broken bike	55	*uncollected broken bike*
$\boldsymbol{tp}$	The penalty for each minute exceed from the operation horizon	2	*Minute*

Table 1: Parameters.

Scenarios	SD	CBB	Z
Sc1	240	9	-470.3
Sc2	238	33	-1181.8
Sc3	38	9	-338.9
Sc4	38	30	-1739.5

Tables information: Sc1: 5% Breakdown rate in the Workday, Sc2: 10% Breakdown rate in the Workday, Sc3: 5% Breakdown rate in the Weekend, Sc4: 10% Breakdown rate in the Weekend, D: Number of demands, UB: Number of usable bikes, BB: Number of usable bikes, SD: Number of satisfied demands, CBB: Number of collected broken bikes, Z: The profit.

Table 2: Computation results in four mentioned scenarios using an ICV.

Scenarios	SD	CBB	Z
Sc-e1	242	9	1031.663
Sc-e2	239	33	879.623
Sc-e3	38	9	163.826
Sc-e4	38	38	157.115

Table 3: Computation results in four mentioned scenarios using an EV.

collecting all broken bikes is higher than the penalty of not collecting some of them. The results show that the profit of using the ICV is negative, which means that using ICV is detrimental.

Table 3 demonstrates that using an EV compared with the an ICV raises the profit for all scenarios so that employing EV improves the number of satisfied demand and collected broken bikes in all cases compared to the ICV. It is also noteworthy that using an EV immensely improves the objective function in all scenarios, meaning that using an EV instead of an ICV is profitable.

To understand the effect of the type of vehicles (EV/ICV), Table 4 and Table 5 provide detailed utilization rates of vehicles.

Comparing the utilization rates of vehicles reveals that none of the scenarios used the average vehicle capacity effectively. Intuitively, increasing the breakdown rate increases operation time and the average used vehicle capacity as the number of broken bikes increases. As a result, the number

Scenarios	MUVC	AUVC	TTO
Sc1	23	10.8	93.5
Sc2	30	14	146.9
Sc3	9	4.5	19.9
Sc4	30	10.8	59.9

Tables information: MUVC: Most used vehicle capacity, AUVC: Average used vehicle capacity, TTO: The total time of operation.

Table 4: The ICV efficiency.

Scenarios	MUVC	AUVC	TTO
Sc-e1	10	1.7	129.2
Sc-e2	27	3.1	168.3
Sc-e3	1	0.5	37.7
Sc-e4	13	2	97.5

Table 5: The EV efficiency.

of usable bikes available to meet demand decreases, so more relocation operation is required to meet demand due to the lower travel cost of EV than ICV, and so the vehicle travels longer, so both the operation time is increased ~~and the average used vehicle capacity is reduced~~. Moreover, another reason is that increasing the load of the EV has a significant impact on energy consumption; the EV has preferred to travel more but with less load.

~~Results demonstrated that chosen capacity for this dataset is not suitable. Therefore, more analysis should be done in choosing the type of vehicle according to its capacity.~~

3.3. Sensitivity analysis of the vehicle capacity

~~As mentioned in the previous section, the vehicle's capacity significantly affects costs and the solution obtained from the model.~~ ~~So~~ in this section, the performances of the proposed model for four scenarios with different vehicle capacities are evaluated. The capacity of the vehicle has been changed from 10 to 50. Figure 6 illustrates the vehicle capacity effect on the value of the objective function.

According to Figure 6, in all scenarios (except Sc3) with increasing the

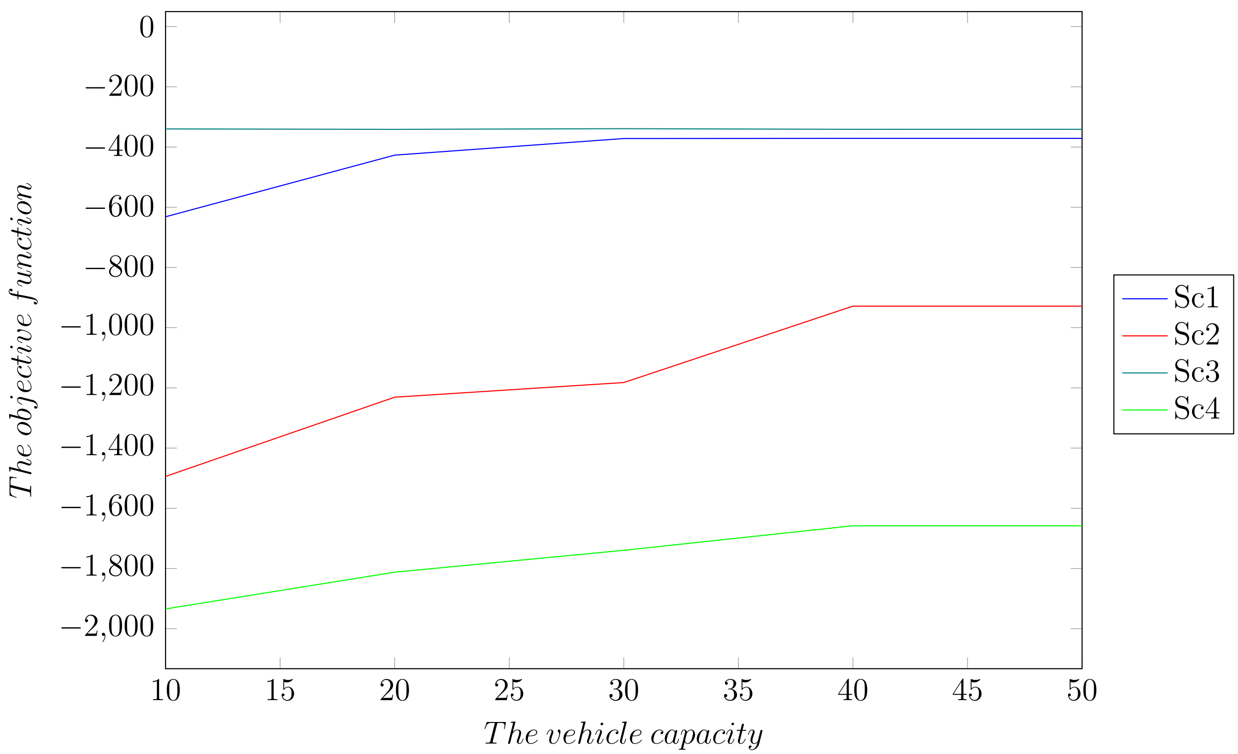

Figure 6: Sensitivity analysis results of different ICV capacity

Scenarios	$Q = 10$	$Q = 20$	$Q = 30$	$Q = 40$	$Q = 50$
Sc1	127.45	113.15	93.5	95.9	95.86
Sc2	180.59	144.70	146.9	137	142.77
Sc3	22.34	26.76	19.9	26.374	26.15
Sc4	55.93	101.43	59.9	88.84	110.37

Table 6: The total time of operations using different ICV capacity

Scenarios	$Q = 10$	$Q = 20$	$Q = 30$	$Q = 40$	$Q = 50$
Sc-e1	132.25	117.11	129.26	131.32	134.68
Sc-e2	152.78	168.11	168.39	166.61	176.01
Sc-e3	39.39	36.18	37.73	37.73	34.4
Sc-e4	86.75	118.26	97.51	82.26	121.63

Table 7: The total time of operations using different EV capacity

vehicle's capacity, the value of the objective function has increased and then has had minor changes since the capacity of the vehicle reaches a particular value. In Sc3, because the number of bikes relocated among stations is small, changing the vehicle's capacity does not affect the total time of operation.

The effect on the total operation time when using an ICV is also demonstrated in Table 6. The results show the same trends in the total time of operation.

When using the EV, as demonstrated in Figure 7, changing the EV capacity does not have a significant effect on the objective function. This analysis assumes that energy consumption cost changes linearly with the EV capacity; the profit did not change much due to the low cost of using EV.

The same deduction could be achieved regarding the total time of operation from the result in Table 7 that changing the capacity of the EV does not have a significant effect.

In the last analysis, the same EV was used in all cases; however, the number of EVs in the market is growing, and the EV must be chosen carefully. So, another analysis was done in order to show how EV's type can affect the results. Including the Mercedes-Benz eSprinter electric panel van [34], two other EVs are assumed to be employed in the model, Tesla Cybertruck [35], and Chevrolet S-10 [36]. Table 8 demonstrates a comparison between energy consumption and battery capacity of selected EVs.

Figure 8 illustrates the performance of EVs in the mentioned scenarios.

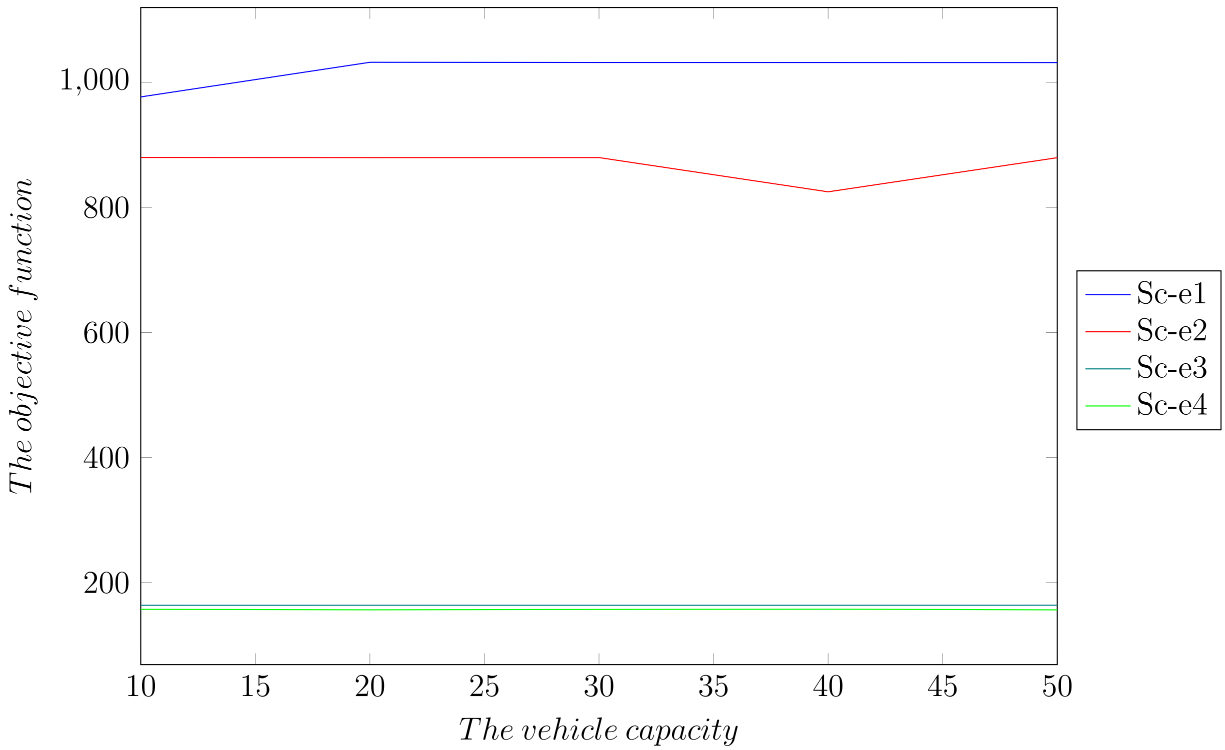

Figure 7: Sensitivity analysis results of different EV capacity

EV	Battery Capacity	Loaded Energy Consumption	Full Energy Consumption
Tesla Cybertruck	100	0.177	0.364
Mercedes-Benz eSprinter	47	0.309	0.507
Chevrolet S-10	29	0.534	0.584

Table 8: The EVs specifications.

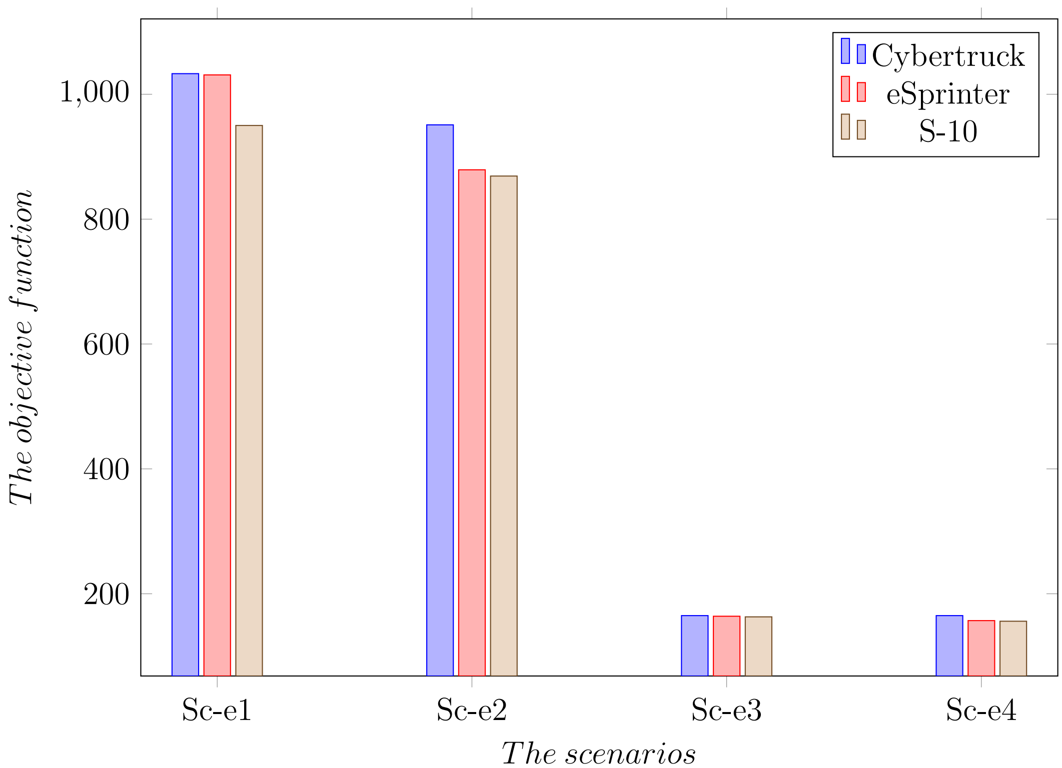

Figure 8: Sensitivity analysis results of different EV types

Scenarios	SD_{p_1}	CBB_{p_1}	SD_{p_2}	CBB_{p_2}	SD_{p_3}	CBB_{p_3}
Sc1	241	9	242	9	230	9
Sc2	239	30	239	29	238	33
Sc3	38	4	38	1	38	9
Sc4	38	31	38	2	38	38

Table 9: Sensitivity analysis results of implementing different policies using an ICV

Totally, the Tesla Cybertruck, which has more battery capacity and less energy consumption than the others, achieved better objective function than the others. However, the changes in the objective function are minor due to the low cost of using electric vehicles, as can be seen in the Figure, so the system providers should decide on selected EVs based on their budget and EV's price.

3.4. Sensitivity analysis of different policies

The proposed model is versatile and can be easily adapted to different policies. Three different policies for collecting usable and broken bikes are defined by varying the penalty parameters. The first policy (p_1) was based on the equal importance of broken bikes and demands, so $bp = dp = 50$ is assumed. In the second one (p_2), the policy was set in such a way that satisfying demands were more substantial than collecting broken bikes as the penalty of losing a demand $dp = 80$ was more significant than the penalty of not collecting a broken bike $bp = 20$, unlike the third policy (p_3) where the penalty of not collecting a broken bike $bp = 80$ was more significant than the penalty of losing a demand $dp = 20$.

Table 9 demonstrates results of employing an ICV in mentioned policies. It shows that when the penalty of losing demand increases, a higher priority is given to satisfy demands since in seconde policy, all usable bikes in all scenarios are allocated to demands. In contrast, the opposite happens in the third policy when the priority is collecting broken bikes, so all broken bikes are collected in all scenarios.

The previous section showed that the use of the EV, in addition to significantly improving the objective function, in all scenarios, all demand are satisfied and all broken bikes are collected, so changing the penalties, as expected, had a slight effect on the results as is illustrated in the Table 10. For instance, in the first policy, when the model has to decide what is optimal to be done, in the second scenario, it has decided not to collect one broken

Scenarios	SD_{p1}	CBB_{p1}	SD_{p2}	CBB_{p2}	SD_{p3}	CBB_{p3}
Sc-e1	242	9	242	9	242	9
Sc-e2	239	32	239	31	239	33
Sc-e3	38	9	38	9	38	9
Sc-e4	38	38	38	38	38	38

Table 10: Sensitivity analysis results of implementing different policies using an EV

Scenarios	**SD**	**CBB**	**TTO**	**Z**
Sc1	242	9	133.5	-466.729
Sc2	239	32	182	-1178.485
Sc3	38	9	31	-335.4
Sc4	38	37	111.3	-1696.369

Table 11: Computation results of different road hardnesses using an ICV.

bike, and also in the second policy, as anticipated, in the second scenario due to higher priority of satisfying demands, two broke bikes were not collected.

3.5. Sensitivity analysis of road hardness

In previous sections, the road hardness values for all roads were assumed to be 1. This section shows how this coefficient affects the operation performance. In this analysis, it is assumed that due to the lack of sufficient data, the road hardness coefficient between the two stations is determined based on their distance from each other, so that the minimum distance's coefficient is 0.5 and the maximum distance's coefficient is 2.5. The coefficients of the other roads were obtained linearly using the following equation.

Table 11 demonstrates the results of employing an ICV with distinct road hardness. It turns out that using this coefficient improves the objective function and the system quality slightly but increases the total operation time considerably. This is because the model selected only certain roads due to the higher cost of some roads with higher road hardness; as a result, more work must be done by laborers, which causes more operation time.

Scenarios	SD	CBB	TTO	Z
Sc-e1	242	9	226.8	939.612
Sc-e2	239	33	180.8	879.969
Sc-e3	38	9	58.2	164.64
Sc-e4	38	38	178.2	158.84

Table 12: Computation results of different road hardnesses using an EV.

Similar explanations can be given for using an EV. Table 12 illustrates that with distinct road hardness, the profit and system performance change slightly; however, the total time of operation increases significantly.

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