Electric-Vehicle Car-Sharing in One-Way Car-Sharing Systems Considering Depreciation Costs of Vehicles and Chargers

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Abstract

In recent years, car-sharing systems have been announced as a way to increase mobility and to decrease the number of single-occupant vehicles, congestion, and air pollution in many parts of the world. This study presents a linear programming model to optimize one-way car-sharing systems for electric cars considering the depreciation costs of chargers and vehicles as well as relocation cost of vehicles. In this way, the objective function consists of imposed costs to the system due to the depreciation cost of vehicles, depreciation cost of chargers, and relocation cost of vehicles. Also, the rate of depreciation and the cost of relocation is considered constant in this study. The model was implemented on small and big test networks with 2 and 100 nodes with variable parameters and demand patterns. The results indicated that managing the fleet of vehicles by relocating the vehicles among stations increases the inventory at each station and minimizes the cost for meeting all requests. Also, the results indicated that the number of required vehicles decrease with an increase in charge levels and final cost increase with an increase in depreciation rate.

Keywords: Car-sharing systems; One-way car-sharing; Linear programming; Electric vehicles; Vehicle imbalance

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1. Introduction

The cities around the world have one or a combination of public transportation systems such as bus, tram, subway and taxi [Alizadeh, 2014]. Although these systems are helpful for many citizens, some of them still prefer to use their own personal vehicles. Accessibility of personal vehicles at any time, the ability of traveling to the country, and traveling with freight, are among the benefits of traveling with personal vehicles. Personal vehicles can also be the choice of those people who live at a long distance from public transportation stations, are not interested in traveling with strangers, or cannot travel with public transportation due to physical problems [Ellaway et al., 2003]. Use of personal vehicles incurs huge irrecoverable costs to both the individual and the society. As an instance, the cost of owning a personal vehicle including parking, insurance, etc. is too high. Also, it is the main source of increase in pollution, anxiety, and travel time in cities [Rizzi and Maza, 2017; Neves and Brand, 2018; Twari, Jain and Rao, 2016; Wadud and Waitz, 2011].

In many cities around the world, car-sharing organizations (CSO) have been grown to help urban transportation. These systems provide individuals with access to the fleet of available vehicles at designated stations [Shaheen and Cohen, 2013]. The car-sharing systems can be classified into one-way and two-way types, according to whether users should give back the rented vehicle to a different or the same location they picked it up [Illgen and Hock, 2018; Li et al. 2016]. The flexibility of one-way systems creates a complex challenge for operators due to the need to redistribute vehicles in order to respond to the demands [Boyaci, Zografos and Geroliminis, 2015; Correia and Antunes, 2012; Nourinejad and Roorda, 2015].

Nowadays, most studies focus on one-way car-sharing due to greater comfort of users. Based on this, companies have a greater tendency to present this kind of service. Most aspects of car-sharing system have been investigated in previous studies, but some dimensions still need to be further explored. Among the related issues, depreciation may be one of the most important ones that cause mistakes in decision making due to not paying attention to it. This paper addresses the question: “what is the impact of depreciation costs of different parts of a car-sharing system on the total cost and how it can be reduced?” Two main parts of the system in this study that are depreciated include cars and chargers. This means that these two parts lose a share of their value every year and this issue affects the benefit of the company. Furthermore, this study examines the impact of relocation and charge level of vehicles, as well as different demands patterns on the total cost.

This study uses electric vehicles due to climate change and the global warming problem. Nowadays, this kind of vehicles is very popular because they have less pollution and use renewable energy. The distance traveled by this kind of vehicles generally depends on their battery. The charging time of these vehicles is too long and this is the main problem of this kind of vehicles, but governments provide free charging stations in many parking lots to encourage the use of these vehicles. In near future, a large share of vehicles may use electricity for their movement all around the world [Jochem et al. 2018]).

The remainder of the paper is organized as follows. A literature review is provided in section 2. Section 3 introduces the proposed model. Then, in Section 4, numerical examples are presented for better clarification. The final section, Section 5, concludes the paper.

2. Literature Review

Companies are generally striving to reduce the costs or increase the profits of the system. This is achievable through some managing actions, where previous studies have mainly focused on the relocation of vehicles [Jorge and Correia

2013; Correia, Jorge and Antunes, 2014]. In this regard, Dror, Dominique and Roucairol (1998) were the first who considered relocation of vehicles and proposed the use of limited-capacity tow trucks to redistribute a fleet of electric vehicles.

Some studies investigated vehicle relocation from a simulation-based point of view. For example, Barth and Todd (1999) developed a simulation model with three components including 1) random origin and destination trips with random time between requests; 2) a traffic simulator including the trip-creator outputs; and 3) the relocation mechanism which could be static, predictable, or accurate. Also, Kek, Cheu and Meng (2009) proposed a novel three-phase optimization-trend-simulation decision support system for car-sharing operators to determine a set of optimal manpower and operating parameters for the vehicle relocation problem. In another simulation-based research, Wang and Regan (2002) showed a relocation model based on prediction with three major components. In the prediction model, the origin-destination requests were estimated which was used in the refilling inventory model. Jorge, Correia and Barnhart (2014) offered two methods to relocate vehicles by travelers including 1) a mathematical model to optimize the relocation operations maximizing the profitability of car-sharing system service; and 2) a simulation model to study relocation policies.

In some other studies, relocation was investigated via discrete event method. For instance, Febbraro, Sacco and Saeednia (2012) studied the vehicle relocation problem using discrete event systems which is an easy representation of the complex dynamics of the car-sharing systems. Also, Nourinejad and Roorda (2014) successfully solved a dynamic optimization-simulation model to reduce the vehicle imbalance in one-way systems using discrete event simulation. In this model, the arrival of a new user is defined as an event. The proposed model reveals a trade-off between fleet size and vehicle relocation hours. In another study, Deng and Cardin (2018) investigated the distribution of parking lots and vehicles in one-way car-sharing systems considering demand uncertainty. The presented simulation methodology is based on 1) discrete event simulator; 2) particle swarm optimization; and 3) optimal computing budget allocation.

In addition to the mentioned studies, other studies investigated the relocation with different methods with the most relevant ones presented as follows:

Nourinejad et al. (2015) considered joint optimization of vehicle relocation and staff rebalancing using two integrated multi-traveling salesman formulizations. In a different study, Li et al. (2016) presented a stochastic and dynamic continuum approximation model for locating electric vehicles in car-sharing systems and determining the fleet size of each station. Also, Huang, Correia, and An (2018) presented a mixed integer non-linear program model to investigate the location and capacity of stations. The problem considered uncertainty in demand time and space. Furthermore, it took the cost of relocation into account in presented model. In the study, a logit model was used to demonstrate the nonlinear rate of car-sharing users based on its utility. Furthermore, Burglieri, Pezzela and Pisacane (2017) also investigated the relocation problem in which the staff used folding bicycles. In the last study of this section, Jorge, Molnar, and Correia (2015) investigated the variable trip pricing to lower the imbalance of vehicles in stations through encouraging people to travel from stations with many vehicles to the station in shortage of vehicles during peak hours.

Most researchers have evaluated one-way car-sharing systems due to their flexibility. In most of the system optimization models, the use of relocators to relocate vehicles among stations is proposed as a solution to increasing the availability of vehicles and to decreasing the costs. Nevertheless, most studies have paid no attention to the depreciation costs which significantly contribute to the costs incurred to the systems. Based on this, the current study intends to investigate the impact of that on total costs. Furthermore, this study aims to examine the effect of charge level and demand pattern on the total cost.

3. Methodology

The following nomenclature identifies the sets, parameters, and decision variables used in the model.

Parameters

E Electric capacity of each vehicle

$|I|$ Number of stations

$|T|$ Number of time steps

$|C|$ Number of charge-levels

$f(i,j,t)$ Number of time steps it takes to travel from station *i* to *j* at time *t*

$g(i,j,t)$ Number of charge-levels it takes to travel from station *i* to *j* at time *t*

d_{ij}^{t} Demand from station *i* to *j* at time *t*

α Amortized cost of a vehicle

β Amortized cost of each charger

γ_{ij}^{t} Cost of vehicle relocation from station *i* to station *j* at time *t*

q_i Number of chargers at station *i*

Sets

$I = \{1, \dots, i, \dots, |I|\}$ Set of stations

$T = \{1, .., t, \dots, |T|\}$ Set of time steps

$C = \{1, \dots, c, \dots, |C|\}$ Set of charge-levels

M Set of nodes in the network

V Set of arcs in the network

R Set of vehicle relocation arcs

S Set of customer servicing arcs

L Set of vehicle charging arcs

Decision variables

F Fleet size

x_{ij}^{tc} Number of service vehicles at charge-level *c* from station *i* to *j* at time *t*

y_{ij}^{tc} Number of relocated vehicle at charge-level *c* from station *i* to *j* at time *t*

z_{i}^{tc} Number of vehicles being charged from level *c* to *c*+1 at station *i* and time *t*

3.1 The time-space-charge graph

Consider a one-way car-sharing system with a uniform fleet of F vehicles distributed among $|I|$ stations, with the set $I = \{1, \dots, i, \dots, |I|\}$ representing the stations. Each station *i* has a total of q_i chargers with all chargers having the same charging rate, e.g. they are all Type I or Type II chargers. The service time horizon of the car-sharing system is discretized into $|T|$ time steps with set $T = \{1, .., t, \dots, |T|\}$ representing each time step. For instance, a service horizon of 10 hours can be divided into $|T| = 20$ segments of 0.5 hour. Each vehicle in the fleet has an electric charge capacity of E measured as kW which is discretized into $|C|$ equal segments, where the energy of each segment is $E/|C|$. For example, an electric vehicle with a charge capacity of $E = 80\ kW$ can be divided into $|C| = 8$ charge-levels of $E/|C|$ =10 kW. Let $C = \{1, \dots, c, \dots, |C|\}$ represent the set of the charge-levels.

Consider a time-space-charge graph $G(M, V)$ with node and arc sets of *M* and *V*, respectively. We first explain this graph with a simple example. Consider a car-sharing system with two stations (i.e., $|I| = 2$), electric vehicles with a charge capacity E divided into three segments (i.e., $|C| = 3$), and a planning horizon of four time-steps (i.e., $|T| = 4$). The graph of this example is presented in Figure 1, where each node is identified based on the station it represents, the charge-level of vehicles, and the time-step. Let us further partition M into M_{ict} representing station *i* at time *t* and charge-level *c*. The arc set *V* is also further partitioned into S, R, and L to represent the service vehicle flow, vehicle relocation flow, and vehicle charging, respectively. An example of one arc in each of these sets is illustrated in Figure 1. As depicted, a number of fully-charged vehicles are first transferred by users from station 1 to station 2 at time $t = 1$ (this arc belongs to set *S*). These vehicles reach station 2 at time $t = 2$, where they have lost one charge-level. Thereafter, the vehicles are charged at station 2 to move from $c = 2$ to $c = 3$ (this arc belongs to set L), i.e., all vehicles are charged to their full capacity. Finally, the vehicles are relocated to their original location which is station 1 (this set belongs to set R).

In Figure 1, the arcs in set L represent the vehicle charging, initiation and termination at the same station. That is when a vehicle is charged, it does not physically move between stations but only transfers from one charge-level to a higher charge-level. The arcs in sets R and S, on the other hand, show vehicle movement from one station to another. Hence, arcs L are intra-zonal, while arcs S and R are intra-zonal. Any inter-zonal trip (arcs in sets S and R) takes both time and energy. Let $f(i, j, t)$ represent the travel time from station i to station j at time t. We assume that $f(i, j, t)$ is also discretized to be compatible with the time-space-charge graph. For instance, if each time-step of the graph represents 20 minutes and the travel time between stations i and j at time t is 45 minutes, we set $f(i, j, t) = [45/20] = 2$. Also, let $g(i, j, t)$ denote the required electric energy for traveling between stations i and j at time t. This energy is discretized similarly to time $f(i, j, t)$. Hence, if each charge-level is 10 kW and it takes 13 kW to travel between stations i and j at time t, we have $g(i, j, t) = [13/10] = 1$. The arc sets can also be partitioned in another fashion. Let $\phi(i, c, t)$ be the set of arcs in S and R which ends at node M_{ict} and let $\psi(i, c, t)$ be the set of arcs in S and R which starts at node M_{ict}. For instance, $(j, b, \tau) \in \phi(i, c, t)$ represents an arc which starts at $M_{jb\tau}$ and ends at M_{ict}. Further, let $\varphi(i, c, t)$ be the set of arcs in L which ends at node M_{ict} and let $\chi(i, c, t)$ be the set of arcs in L which starts at node M_{ict}.

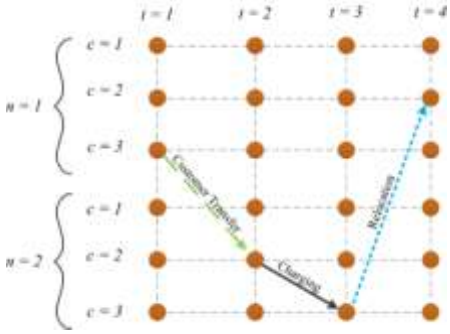


Figure 1. Time-space-charge diagram (Note: "Customer Transfer", "Charging", and "Relocation" arcs belong to S, L, and R sets respectively)

3. 2 Model Assumptions

The following assumptions are imposed:

1- All demands are to be satisfied. The CSO fleet size should be large enough to serve all users. This assumption is justified because the cost of unsatisfied demand is large as it can lead to users terminating their subscription;

2- Sufficient parking lots are available at each station, but the number of chargers at each station is limited. This assumption is justified as some CSOs such as Car2Go allow users to park at any spot on the highest floor of multi-story parking stations;

3- Vehicles are rented and returned on the same day;

4- All vehicles are fully charged at the beginning of each day. This assumption is justified since vehicles can be charged throughout the night; and

5- The number of vehicles at each station should be the same at the beginning and end of each day. This assumption should be imposed for day-to-day consistency in CSO operations.

3.3 Servicing Users, Relocating Vehicles, and Charging Vehicles

Each user in a one-way non-floating CSO has a schedule to follow which is comprised of an origin station *i*, a destination station *j*, and a departure time from the origin *t*. Let d_{ij}^{t} represent the total number of such users and let x_{ij}^{tc} represent the flow of service vehicles at charge-level *c* leaving station *i* at time *t* to arrive at station *j*. These vehicles serve the demand d_{ij}^{t}. Hence, given that all demands should be satisfied (Assumption 1), we have:

$$\sum_c x_{ij}^{tc} = d_{ij}^{t} \qquad \forall i,j,t \qquad (1)$$

The vehicles that are assigned to users of d_{ij}^{t} must have enough charge to answer the travel. For instance, if $g(i,j,t) = 3$ then $x_{ij}^{t1} = x_{ij}^{t2} = 0$.

Let y_{ij}^{tc} represent the flow of relocated vehicles at charge-level *c* leaving station *i* at time *t* to arrive at station *j* at time $t + f(i,j,t)$. The charge-level of these vehicles upon arrival at station j will be $c - g(i,j,t)$. Relocated vehicles, similar to service vehicles, should have enough charge for the travel. Finally, let z_i^{tc} be the number of vehicles at station *i* which are charged from charge-level *c* at time *t* to charge-level *c*+1 at time *t+1*. By discretizing the charge capacity *E* of each vehicle, we choose $|C|$, where each vehicle can only be charged by one charge-level at each time-step.

3.4 Model Constraints

Vehicles are transferred in the time-space-charge diagram through vehicle relocation, vehicle charging, and service vehicle flow. Let n_{ic}^{t} be the total number of vehicles with charge-level *c* at station *i* at the end of time *t*. Given the flow conservation principles, we have:

$$n_{ic}^{t} = n_{ic}^{t-1} + \sum_{(j,c\prime,\tau)\in\phi(i,c,t)} (x_{ji}^{\tau c'} + y_{ji}^{\tau c'}) - \sum_{(j,c',\tau)\in\psi(i,c,t-1)} \left(x_{ij}^{\tau c'} + y_{ij}^{\tau c'}\right) + \sum_{(\tau,c\prime)\in\varphi(i,c,t)} z_i^{\tau c'} - \sum_{(\tau,c\prime)\in\chi(i,c,t)} z_i^{\tau c'} \qquad \forall i,c,t \qquad (2)$$

The second term on the right-hand-side of Eq. 2 is the number of relocated and serviced vehicles available at time *t* with charge-level *c*. Further, the third term is the number of relocated and serviced vehicles with charge *c* leaving station *i* at the end of time $t-1$. Then, the fourth term denotes the number of vehicles charged to the charge-level *c* at station *i* and time *t*. Finally, the fifth term represents the number of vehicles charged from level *c* to higher charge-levels at time *t*.

The number of vehicles getting charged at station i and time t is $\sum_c \sum_{(\tau,c\prime)\in\varphi(i,ct)} z_i^{tc}$. However, there are only a limited number of q_i chargers at each station i. Hence, the following constraint is imposed on the number of vehicles being charged at each station *i* and time *t*:

$$\sum_c \sum_{(\tau,c\prime)\in\varphi(i,ct)} z_i^{tc} \le q_i \qquad \forall i,t \qquad (3)$$

In addition, the flow of vehicles' relocations y_{ij}^{tc} and servicing vehicles x_{ij}^{tc} from station *i* with charge-level *c* at time *t* has to be lower than number of available vehicles at station *i* with charge-level *c* at time *t*. Hence, we have:

$$\sum_{(j,c',\tau)\in\psi(i,c,t)} \left(x_{ij}^{\tau c'} + y_{ij}^{\tau c'}\right) \le n_{ic}^{t} \qquad \forall i,c,t \qquad (4)$$

Finally, the following constraints are imposed to comply with Assumption 5 by ensuring that the number of vehicles at each station is the same the beginning and end of each day.

$$\sum_c n_{ic}^{1} = \sum_c n_{ic}^{|T|} \qquad \forall i \qquad (5)$$

3.5 Mathematical program

CSOs incur two types of costs. First is the amortized cost of assets such as fleet and station chargers and second is the cost of operations such as vehicle relocation and vehicle charging. Let *F* be the fleet size, α the amortized cost of a vehicle, and β the amortized cost of each charger. Hence, the total cost of assets is $\alpha F + \beta \sum_i q_i$. Further, let γ_{ij}^{t} be the cost of vehicle relocation from station i to station j at time t. Hence, the total cost of the CSO is:

$$\alpha F + \beta \sum_i q_i + \sum_{(j,c\prime,\tau)\in\phi(i,c,t)} \sum_{(i,ct)} y_{ij}^{\tau c'} \gamma_{ij}^{t} \quad (6)$$

In order to find the fleet size F, we introduce a "source" node with an infinite number of vehicles for every station i of the network. Let i_0 denote the source node of station i. Each station i's source node is connected to the time-space-charge network through an arc which extends from the station i's source node to station i at time $t = 1$ and charge-level $c = |C|$, i.e. $M_{i|C|0}$. An example of this arc is presented in Figure 2. The reason for connecting the source node to $t = 1$ is to ensure that all vehicles enter the network at the beginning of each day. Also, the reason for connecting the source node to charge-level $c = |C|$ is to ensure that all vehicles start the day fully charged. This complies with Assumption 4. The cost of traversing each of these links is equivalent to the marginal cost of a vehicle, i.e. α. That is, every vehicle that is added to the fleet has to traverse the arc $(i_0, M_{i|C|1})$ which costs the CSO α dollars.

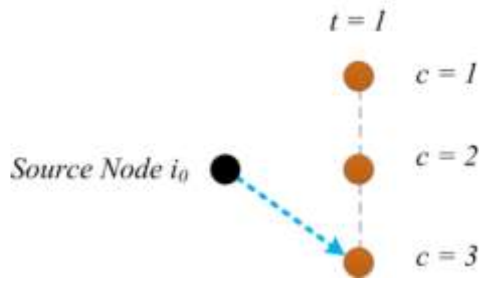


Figure 2. Source node composition

Given the presented objective function and the constraints of Section 3.4, we define the following methodical program to minimize the total cost of the CSO:

$$Minmize\ \alpha F + \beta \sum_i q_i + \sum_{(j,c\prime,\tau)\in\phi(i,c,t)} \sum_{(i,ct)} y_{ij}^{\tau c'} \gamma_{ij}^{t} \quad (7)$$

$$\sum_c x_{ij}^{tc} = d_{ij}^{t} \qquad \forall i,j,t \quad (8)$$

$$n_{ic}^{t} = n_{ic}^{t-1} + \sum_{(j,c\prime,\tau)\in\phi(i,c,t)} (x_{ji}^{\tau c'} + y_{ji}^{\tau c'}) - \sum_{(j,c',\tau)\in\psi(i,c,t-1)} \left(x_{ij}^{\tau c'} + y_{ij}^{\tau c'}\right) + \sum_{(\tau,c\prime)\in\varphi(i,c,t)} z_i^{\tau c'} - \sum_{(\tau,c\prime)\in\chi(i,c,t)} z_i^{\tau c'} \qquad \forall i,c,t \quad (9)$$

$$\sum_c \sum_{(\tau,c\prime)\in\varphi(i,ct)} z_i^{tc} \le q_i \qquad \forall i,t \quad (10)$$

$$\sum_{(j,c',\tau)\in\psi(i,c,t)} \left(x_{ij}^{\tau c'} + y_{ij}^{\tau c'}\right) \le n_{ic}^{t} \qquad \forall i,c,t \quad (11)$$

$$\sum_c n_{ic}^{1} = \sum_c n_{ic}^{|T|} \qquad \forall i \quad (12)$$

$$x_{ij}^{tc}, y_{ij}^{tc} \ge 0 \qquad \forall i,j,c,t \quad (13)$$

$$n_{ic}^{t}, z_i^{tc} \ge 0 \qquad \forall i,c,t \quad (14)$$

$$q_i \ge 0 \qquad \forall i \quad (15)$$

4. Numerical Examples

This section presents the results of solving and evaluating the proposed model on small and large networks with 2 and 100 nodes respectively. First, the features of each network and the inputs of the model are presented in Table 1. Then, the considered parameters are examined by implementing the model on each network. Finally, the sensitivity analysis is performed on the outputs.

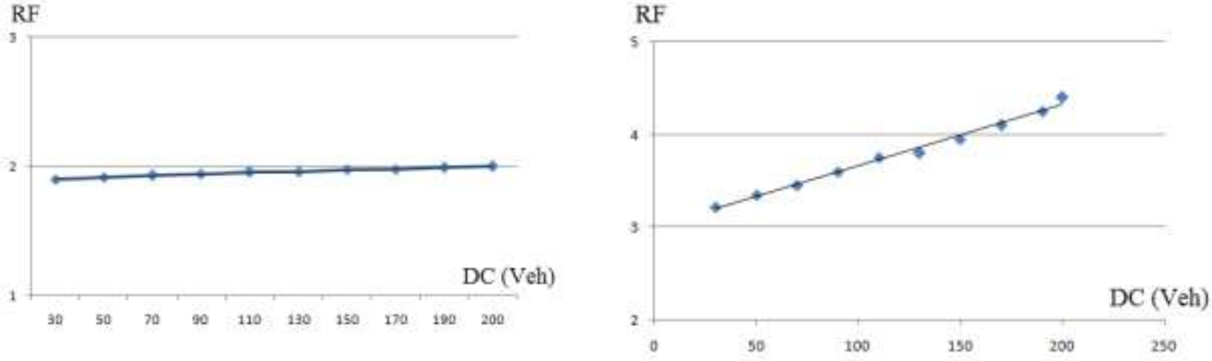
In the first network, three demand patterns have been examined as shown in Table 2. Furthermore, the results of comparing relocating and non-relocating methods are displayed in Figure 5.

Table 1. The hypothetical features of parameters presented in the numerical examples

	Vehicle depreciation cost	Depreciation cost of any electric vehicle charger at every charging time	Vehicle Relocation cost from station i at time t	The number of stations	The number of charge levels	The number of time periods per planning horizon	The number of need time periods to increase a charge level	The number of needed charge level for relocating between two stations
Network #1				i=2		T=4		
Network #2	α=30	β=5	γ_{ij}^{t}=15		C=2	T=5	t=1	c=1
Network #3				i=100		T=24		

Table 2. Results of demand patterns on network

		Demand value (unit)			results		
period		1	2	3	Number of vehicles	Relocation flow	Total cost
First pattern	From station 1 to 2	2	0	2	4	2	330
	From station 2 to 1	0	2	0			
Second pattern	From station 1 to 2	2	0	8	10	4	1200
	From station 2 to 1	0	6	0			
Third pattern	From station 1 to 2	5	0	15	See Figure 5.		
	From station 2 to 1	0	10	0			



a) The first demand pattern b) The second demand pattern

Figure 3. The diagram of changes in the Relocation Flow (RF) compared to Depreciation Cost of the vehicle (DC (Veh))

As expected, considering the demand patterns of the first and second states, the number of required vehicles, the relocation flow among stations, and total cost of the system grow with the increase of demand and misbalancing between stations.

The first demand pattern is such that the demand for system users within time period 2 of station 2 is met by vehicles relocated by users from station 1 toward station 2 at the beginning of time period 1. Because of that, vehicle relocation in this demand pattern does not matter and the flow of relocated vehicles does not differ significantly with the increase in depreciation cost of vehicles (see Figure 3a). On the other hand, the demand distribution of the second state is such that the relocation flow increases with the rise of depreciation cost of vehicles (see Figure 3).

With the increase in the depreciation costs of vehicles, the final cost will change more considerably in the first state compared to the second one (Figure 4), as part of the rise in the depreciation costs is offset by relocation in the second state. It suggests the importance of vehicles' relocation in systems where their demand does not overlap during various periods.

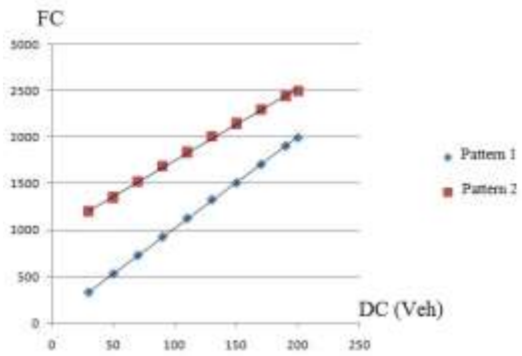


Figure 4. The diagram of changes in the Final Cost (FC) in two demand patterns compared to Depreciation Cost of vehicles (DC (Veh))

To evaluate the developed model and the effect of relocations on the system performance, the proposed model is compared to a base model. In the base model, all conditions are the same as those of the developed model. In addition to that, the relocation is also considered in this model. In this problem, the third demand pattern is used with the results illustrated in Figure 5.

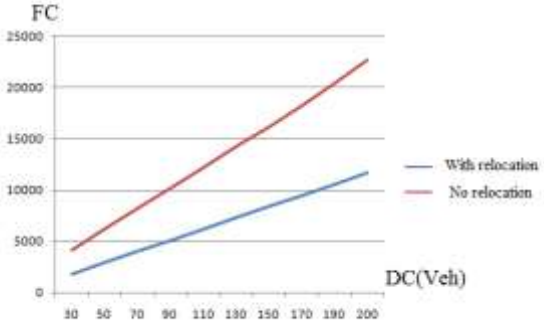


Figure 5. The diagram of changes in the Final Cost (FC) compared to Depreciation Cost of vehicles (DC (Veh)) in the proposed model compared to the base model

As shown in Figure 5, with the increase in depreciation costs, the ascending trend in the total cost will be more dramatic in the base model, while the total cost in the proposed model increases more steadily.

The first and second networks are small networks with two nodes. However, to analyze the sensitivity of the effective parameters, a network with 100 nodes has been considered. The network data are provided in Table 1. Furthermore, the demands of the first 50 stations toward the other 50 stations are considered 0 and 2 at even and odd time periods, respectively. It would act inversely for the second 50 stations.

Increasing the number of charge levels in systems with a low number of time periods (like the second network) would affect the number of required vehicles more significantly. Since the number of recharging periods increases with the rise of charge levels, there is enough time for recharging in networks with long time periods. When the number of time periods and number of charge levels grow, more time is required for recharging. Therefore, its effect is less significant compared to a network with shorter time periods (see Figure 6).

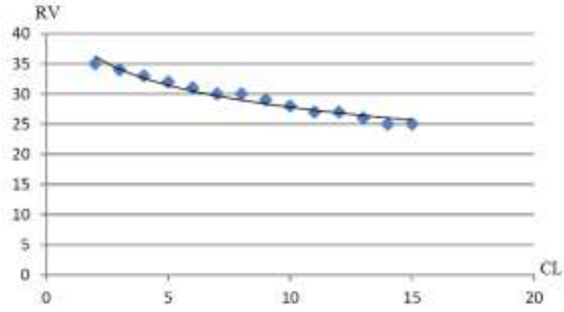


Figure 6. The diagram of changes in the Required Vehicles (RV) compared to the Charge Level (CL)

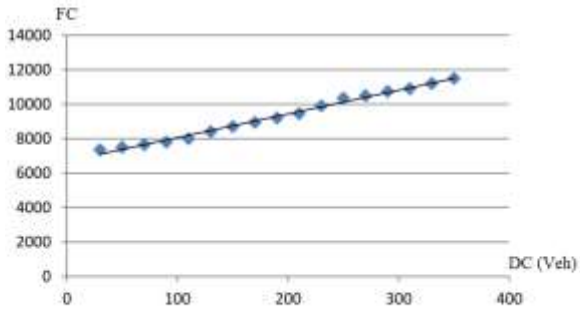


Figure 7. The diagram of Final Cost (FC) compared to the depreciation cost of vehicles (DC (Veh)) in the third network

For sensitivity analysis of the depreciation cost of vehicles, comparing Figure 7 and Figure 4, it is concluded that the final cost rises with increase in the vehicle depreciation cost with different slopes in relocation and no-relocation methods. Also, the depreciation cost may have a different impact intensity across different demand patterns on the total cost.

5. Conclusions

According to the proposed model, it is possible to increase the inventory of vehicles at each station and avoid the huge cost of purchasing a vehicle through relocation of vehicles. Furthermore, sensitivity analysis on the number of charge levels indicated that the number of vehicles decreases with the elevation of charge levels. The current model can be used for decision-makings including finding the optimal fleet size, the number of relocations, the location of vehicles, and chargers. This model can also offer a new optimal state in each time period with variable demand. Finally, due to the shortcomings of this study, some suggestions are presented in the following for further research:

1- In this study, deterministic demand has been considered, while it is better to consider stochastic demand for more accurate analysis; and

2- The balance of relocators becoming imbalanced in the system due to vehicle relocation can also be investigated.

6. References

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