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The vehicle relocation problem for the one-way electric vehicle sharing: an application to the Milan case

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Abstract

Traditional car-sharing services are based on the two-way scheme, where the user picks up and returns the vehicle at the same parking station. Some services allow also one-way trips, where the user can return the vehicle in another station. The one-way scheme is more attractive for the users, but may pose a problem for the distribution of the vehicles, due to a possible unbalancing between the user demand and the availability of vehicles or free slots at the stations. Such a problem is more complicated in the case of electric car sharing, where the travel range depends on the level of charge of the vehicles. In a previous work, we introduced a new approach to relocate the vehicles where cars are moved by personnel of the service operator to keep the system balanced. Such relocation method generates a new challenging pickup and delivery problem that we call the Electric Vehicle Relocation Problem (EVRP). In this work we focus on a method to forecast the unbalancing of a car-sharing system. We apply such method to the data yielded by the Milan transport agency taking into account the location and capacity of the present charging stations in Milan. In this way, using a Mixed Integer Linear Programming formulation of EVRP, we can estimate the advantages of our relocation approach on verisimilar instances.

Keywords: electric vehicle; vehicle relocation; car-sharing unbalancing forecast; pickup; delivery problem.

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1. Introduction

Car-sharing, understood as an organized form of shared use of the car, began to grow in Zurich in 1948 (Harms and Truffler, 1998). The original idea has been gradually replaced by an offer structurally organized according to strict business criteria, in order to achieve economies of scale, which resulted in increased benefits to users in terms of low rates and diversification of the available fleet.

The process of designing a car-sharing service pose several optimization problems, which have been tackled in the literature (e.g. Du and Hall, 1997; George and Xia, 2011; Barth and Todd, 1999), in particular to determine the optimal size of the fleet and identify the location of the parking stations.

Some car sharing services (such as Car2Go - www.car2go.com) permit one-way trips, which allow the user to pick up the vehicle in one station, and return it in another one. The one-way system is quite more attractive for the users, but may pose a problem for the relocation of the vehicles, due to a possible unbalancing between the demand and availability of vehicles (for example, near the railway stations at the beginning of a working day) or vice versa between the request for return of the vehicles and the availability of free slots. In such cases, the service provider has to develop strategies to relocate the vehicles and restore an optimal distribution of the fleet of car-sharing service. Such strategies depend also on the available data and the main goal of the relocation. Barth and Todd (1999) propose the following classification:

- *static relocation*, based on the immediate needs of a particular parking lot. Thresholds can be defined, corresponding for instance to a minimum and a maximum number of vehicles present at each station, in order activate the mechanism for relocation;
- *historical predictive relocation*, based on an estimation of the requests made using historical data of the service or techniques of travel demand estimation. The objective is to estimate what will be the deficiency or excess of vehicles at each station, in order to activate in advance the relocation mechanism. The time horizon depends on the technique used to estimate the travel demand;
- *exact predictive relocation*, if you have the perfect knowledge of the requests. This is the case of a car-sharing service on reservation. In this kind of situation, the relocation mechanism can be organized in an optimal way, so as to minimize the waiting times for customers.

The activities of vehicle relocation can be carried out by the user itself or by the service provider (Barth et al., 2004). In the first case, the user is incentivized to car pool or to choose another location or reservation time; in the second case, which is the most common in the real services, the vehicles are physically transported using trucks or personnel. In the literature, also the platooning of the vehicles has been considered (Daviet et al., 1996), where the platoon is composed by a chain of technologically innovative vehicles, led by vehicle head.

Chauvet et al. (1997; 1999) propose algorithms to optimize the use of a fleet of trucks to move the cars between the stations. Duron et al. (2000) present a heuristics based on the immediate needs at the stations, i.e. the next station to be visited by the auto transport truck is chosen according to the current state of the system. In such a way, the algorithm gives priority to visit the stations that have the greatest likelihood of running out of vehicles. Di Febbraro (2012) represents the complex dynamics of the system, using a discrete event system simulation. The paper consider both the relocation made by both users and staff, simulating different scenarios, with the objective of reducing the number of required staff, and minimizing the number of car sharing vehicles to satisfy the system demand.

The problem of the relocation of electric vehicles (EVs) has been faced in Dror et al. (1998), which proposes an algorithm to manage auto transport trucks, based on a Tabu search approach and a savings. The algorithm is applied to a car sharing service with fifty EVs and five stations, offered in the French town of Saint Quentin en Yvelines. The car sharing service offered in the same location was studied also by Hafez et al. (2001), which have determined the needed number of auto transport trucks with an exact algorithm, and then minimize the total travel time of relocation, studying three different heuristics.

In our opinion the relocation approach based on auto transport trucks may be not well suitable for an urban settings, from a practical point of view, because stations may not be easily reachable by the trucks, and the operations of loading/unloading EVs is time consuming. For the EV relocation problem, we propose therefore the use of a staff of car sharing operators (hereafter called workers). They may move easily and in eco-sustainable way from a delivery point to a pickup point using a folding bicycle that can be loaded in the trunk of the EV which needs to be moved (see Fig.1). Such relocation approach generates a challenging pickup and delivery problem with features that, to the best of our knowledge, have been never considered in the literature. We call such a problem the Electric Vehicle Relocation Problem (EVRP). EVRP shares some features with the 1-skip vehicle routing problem (Archetti & Speranza, 2004) and the rollon-rolloff problem (Aringhieri et al., 2004; Bodin et al., 2000; De Muelemeester et al., 1997), i.e. the fact that just one item at the time can be picked up and delivered and routes starting and ending at a single depot cannot exceed a given maximum duration. However EVRP is more challenging than the above mentioned problems since it is complicated by the fact that the distance covered by a vehicle depends also by the item picked up, i.e. the residual electrical charge of the EV picked up. This further complication does not allow for instance to map the problem into a static bipartite graph like for the rollon-rolloff problem presented in Aringhieri et al. (2004) because the feasibility of an arc connecting a pickup request node with a delivery request node depends on the time when the pickup request node is reached since the residual charge of a parked EV increases over the time. Therefore, compared to the 1-skip vehicle routing problem and to the rollon-rolloff problem, the EVRP requires to solve simultaneously both a routing and a scheduling problem.

Fig. 1. A folding bicycle loaded in the trunk of an electric vehicle (www.decathlon.it).

2. The Electric Vehicle Relocation Problem (EVRP)

We consider a one-way car sharing service with a homogeneous fleet of EVs. Let L be the maximum distance that an EV can cover when its battery is fully charged. Such distance depends on the kind of EV considered; for instance L can vary from 50 km for a Liberty Piaggio EV to 400 km for a Tesla EV (in the experimental campaign we assume that L =150 km). Notice that when the battery of an EV is not fully charged, the maximum distance that can be covered is linearly proportional to the residual charge of the battery (i.e. an EV with residual charge at 50% can cover $L/2$ km). Concerning the recharge time Γ of a battery, the question is slightly different since typically the recharge process comprises two phases: the first one is intensity-constant, the second one is tension-constant. The first phase allows to recharge the battery almost fully and it is linear on the time. The second phase is not linear on the time and can require some hours to achieve the full charge of the battery and to ensure an uninform recharge of all the cells that compose the battery. For sake of simplicity we do not consider the second phase of recharging to model the EVRP. The maximum time needed to complete the first phase depends on the recharge technology used and can vary for instance from Γ = 1 hour for a 380V Superfast Recharger to Γ = 5 hours for a 220V Multifast Recharger (in the experimental campaign we consider Γ = 4 hours).

Fig. 2. An example of recharging station for one of the electric car sharing of Milano (www.car sharing-evai.it).

We suppose that every EV is always picked up and returned in a slot of a parking station equipped with a recharge docking so as it is recharged when it is not used (see Fig.2). Since in a one-way car sharing service the cars can be returned in parking stations different from those ones where they are picked up, some of them need to be moved in order to prevent a station from running out of EVs or vice versa of parking slots. Let *D* the set of delivery requests (i.e. requests of EVs that need to be delivered to prevent a station from running out of them) and let *P* be the set of pickup requests (i.e. requests of EVs that need to be moved to free parking slots). Each relocation request $r \in P \cup D$ is characterized by a parking location v_r, i.e. a node of the road network, by the residual charge of the battery ρ_r and by a time window $[\tau_r^{\min}, \tau_r^{\max}]$ where $\tau_r^{\min}$ and $\tau_r^{\max}$ represent respectively the earliest time and the latest time when is allowed carry out the request *r*. For instance if *r* is a pickup request then $\tau_r^{\min}$ is the time before which the EV is not available while $\tau_r^{\max}$ is the time after which is not convenient to pick up the EV (since from $\tau_r^{\max}$ it may be used by some user in the parking station where it is). Note that for a delivery request *r*, ρ_r indicates the minimum charge level that the EV battery must have at time $\tau_r^{\max}$, therefore if an EV is delivered before $\tau_r^{\max}$ the charge level of its battery may be less than ρ_r on condition that at least the charge level ρ_r is achieved at the time $\tau_r^{\max}$ recharging the battery after the delivery. Whereas for a pickup request *r*, ρ_r indicates the battery charge level at $\tau_r^{\min}$. Since the fleet of EV is homogeneous each delivery request can be satisfied picking up every EV of a pickup request on condition that it is compatible for time windows and battery charge level.

Given a team of *K* workers which possibly at different times leave a single depot using folding bicycles, we want to determine their routes and their schedules in such a way that each route consists in an alternating sequence of pickup requests and delivery requests, the duration of each route does not exceed a given threshold *T* (i.e. the duty time of the workers), each route ends in the depot, the number of requests served is maximized respecting the time windows and battery charge level constraints of each request. We call such a problem the Electric Vehicle Relocation Problem (EVRP).

EVRP shares some features with the 1-skip vehicle routing problem (Archetti & Speranza, 2004) and the rollon-rolloff problem (Aringhieri et al., 2004; Bodin et al., 2000; De Muelemeester et al., 1997), i.e. the fact that just one item at the time can be picked up and delivered and routes starting and ending at a single depot cannot exceed a given maximum duration. However EVRP is more challenging than the above mentioned problems since it is complicated by the fact that the distance covered by a vehicle depends also by the item picked up, i.e. the residual electrical charge of the EV picked up. For this reason also the EVRP is an NP-hard problem.

The formulation of the EVRP is based on a directed graph G=(N, A) that models all the possible actions rather than considering straightly the road network. The set of nodes of G is given by $N = P \cup D \cup \{0\}$ where 0 indicates the depot node. The set of arcs can be partitioned into two sets: the *EV arcs* and the *bike arcs*. The *EV arcs* model the action of a worker when he is moving by an EV from a pickup point to a delivery point; the *bike arcs* model the action of a worker when he is moving by bike from a delivery point or from the depot to a pickup point or to the depot. Therefore EV arcs (i, j) are defined for each $i \in P$ and for each $j \in D$ such that $\tau_j^{\max} \geq \tau_i^{\min} + \frac{d_{ij}}{s'} + q' + q''$ and $d_{ij} \leq L$ where d_{ij} indicates the length of the shortest path from v_i to v_j with an EV, s' denotes the average speed of an EV, q' is the time to park the EV and take the bike from the EV trunk and q'' is the time to load the bike in the EV trunk and leave the parking lot with the EV. In similar way the bike arcs (j,i) are defined for each $j \in D$ and for each $i \in P$ such that $\tau_i^{\max} \geq \tau_j^{\min} + \frac{d_{ji}}{s''}$, where d_{ji} indicates the length of the shortest path from v_j to v_i with an EV and s'' denotes the average speed of a bike.

The operational times associated with every kind of arcs are reported in Table 1.

Table 1. Operational times of the arcs of graph G

Arcs	**Operational times**	**Involved nodes**
(i, j)	$\frac{d_{ij}}{s'} + q' + q''$	$\forall i \in P, \forall j \in D : \tau_j^{\max} \geq \tau_i^{\min} + \frac{d_{ij}}{s'} + q' + q'', d_{ij} \leq L$
(j, i)	$\frac{d_{ji}}{s''}$	$\forall i \in P, \forall j \in D : \tau_i^{\max} \geq \tau_j^{\min} + \frac{d_{ji}}{s''}$
(0,i)	$\frac{d_{0i}}{s''}$	$\forall i \in P$
(j,0)	$\frac{d_{j0}}{s''}$	$\forall j \in D$

There are two main advantages to deal with the graph G rather than directly with the road network. The first one is that to every feasible route of a worker corresponds always an elementary cycle on graph G, whereas this is not true in the original road network when there are multiple requests in the same parking and modeling non

elementary cycles is by far harder (see Dror et al., 1998). The second advantage, even in the case of a single request for each parking, is that a formulation based on graph *G* requires by far less variables than a formulation based on the road network, because variables are defined on the arcs and nodes of the used graph. The dimension of graph *G* depends only by the number of requests ($|N|=|P|+|D|+1$ and $|A|<|N|^2$) and not by the number of the physical nodes (road intersections) and road links (e.g. the Milan road network considered in section 4 contains more than 23000 road links which are by far greater than $|A|$ even if 100 EVs need to be redistributed).
Let us introduce the binary routing variable x_{ijk} equal to 1 if the *k*-th worker visits node $j \in N$ immediately after node i, 0 otherwise. Let us also introduce the continuous variables t_{ik} to model the visit time of node *i* by part of the *k* -th worker. We stated in Bruglieri et al., 2012 and more in detail in Bruglieri et al., 2013 that using such variables the EVRP can be modeled by way of a Mixed Integer Linear Program.

3. Estimation of the relocation requests

Considering the classification reported in Section 1, we are in the case of the historical predictive relocation (Barth and Todd, 1999), where the objective is to estimate what will be the deficiency or excess of vehicles at each station. We estimated the electric car-sharing demand, exploiting the survey on the mobility of people in the Milan area, carried out by the Agency for Mobility, Environment and Territory of the Municipality of Milan (AMAT, 2005). The data concerns the private car movements and are represented by the Origin-Destination (O-D) matrix from/to different zones of Milano, with movements having different aims (business, study, occasional trips, etc) and in different time-slots of the day: morning (7:00 to 10:00), not-peak (10:00 to 16:00) and evening (16:00 to 20:00). We used the data regarding the "occasional trip" aim.

As regards the car sharing parking stations, we used the current charging infrastructure: the electric charging slots installed in the municipal area from A2A, the main energy supplier company in Milan, within the project E-Moving (A2A, 2013). Figure 3 depicts the location of such stations (5 stations with 4 slots and 21 with 2 slots), and in red the delimitation of the zoning used for the O-D matrix.

We intersected the O-D zones with a circular boundary of 500 meters around each charging station, which represent the area easily reached on foot by the station. The intersection let us estimate the potential number of movements that could be carried out with the car sharing service, instead of the private car. Then, we multiplied such values by 0.5%, to consider that only a percentage of the potential demand will end using the service. Such value is consistent with the present usage of the Milano car sharing service.

In order to estimate the requests of the relocation staff, we estimated the unbalances due to the projected travel demand. A car sharing simulator has been developed in Matlab to emulate the operational logic of the electric car sharing service. We feed the time-stepping simulator with the operational data of the stations (e.g. station capacities), travel time between stations, and travel demand. At every simulated minute, the simulator updates the inventory of each station and both position and charge level of the vehicles. If in the simulation a station *s* runs out of EVs and a user asks for an EV then a delivery requests *r* for the EVRP is generated with v_r equal to the node of the road network corresponding to *s*, $\tau_r^{\min}$ equal to the minute when such an event happens, $\tau_r^{\max}$ equal to the earliest minute when an EV arrives to *s* (or $\tau_r^{\max}=\infty$ if the latter event never happens) and ρ_r is a random level of charge such that the user can reach its destination. In similar way a pickup request for the EVRP is generated when in the simulation a parking station is full and a user wants return an EV in such a station.

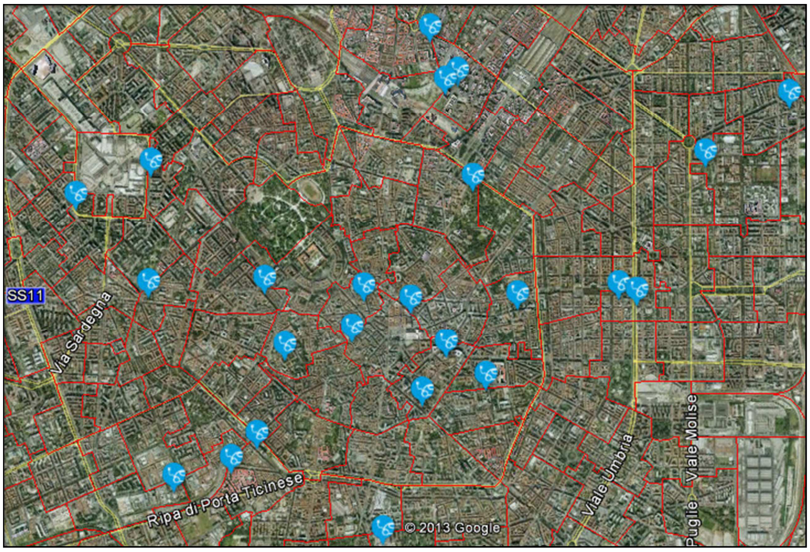

Fig. 3. Charging stations used for the numerical experiments. In red, the delimitation of the zoning used for the O-D matrix.

4. Experimental campaign

Considering a fleet of 30 EVs initially distributed in random way, we have built 30 instances of the EVRP running 30 times the car sharing simulator described in the previous section. In such instances the number of pickup requests often differ from the number of delivery requests making impossible to serve all the requests through the relocation method of the EVRP since every tour of a worker needs to alternate a pickup request with a delivery request. The maximum percentage of requests that may be served through the EVRP is given by

$$MAX\_SERVED = \frac{2\min\{|P|,|D|\}}{|P \cup D|} \cdot 100 \ .$$

The main input data values used for the MILP formulation of the EVRP mentioned in Section 2 are summarized in Table 2.

Table 2. Main input data values for the EVRP used in the experiments

Input data	T	s'	s''	q'	q''	L	Γ
Values	300 minutes	25 km/h	15 km/h	1 minute	1 minute	150 km	240 minutes

The MILP formulation has been implemented in AMPL (Fourer & Gay, 2002) and solved with the state of the art solver CPLEX12.5 on a PC Intel Xeon 2.80 GHz with 2GB RAM. A CPU time limit of 3600 seconds has been imposed. The numerical results on the 30 instances of the EVRP with values of K = 1,2,3 are reported in Table 3. The columns indicate respectively the instance name, the number of pickup requests ($|P|$), the number of delivery requests ($|D|$), the percentage value of the *MAX_SERVED* indicator, the percentage of requests satisfied (SERVED) and the CPU time in seconds (CPU) of the MILP formulation of the EVRP for the values of K reported upside. The average results are reported in boldface in the last row of Table 3.

Concerning the CPU time we note that the MILP formulation is able to solve about half of the EVRP instances in a few seconds (in particular, for K=1, 13 instances have been solved in less than 1 second and 3 instances in a time between 20 and 29 seconds) but for some instances the maximum CPU time limit (3600 seconds) has been reached (in 12 instances for K=1, in 4 instances for K=2 and in 2 instances for K=1): this behavior is due to the NP-hardness of the EVRP.

Concerning to the quality of the solutions obtained it is possible to see that already one worker is able in average to satisfy around the 72% of relocation requests and in 10 instances is able to satisfy the maximum number of requests achievable with our relocation method (i.e. the number of requests satisfied coincides with the *MAX_SERVED* indicator): these cases are emphasized in boldface in the fifth column. Since for these instances no improvement in the number of requests satisfied is possible, they are not solved with a greater value of K. With two workers the average percentage of relocation requests satisfied on the remaining instances becomes around the 86% and in 10 instances the *MAX_SERVED* value is achieved as emphasized in boldface. With three workers the number of requests satisfied improves only for two instances (AMAT 4 and AMAT 17), for one of the which the *MAX_SERVED* value is reached, and the average percentage of relocation requests satisfied on the remaining instances becomes around the 85%. Therefore K=2 seems to be the suitable number of workers to satisfy up to around 30 relocation requests on the simulated instances.

Analyzing more in detail the solutions obtained for K=2 we find that a worker bikes for about the 39% of its duty time, waits for the 37% and drives an EV only for the 24% of its duty time. Since the percentage of time spent in average by a worker for driving the EVs is reduced this shows that the impact of our relocation method on the urban traffic is very small.

5. Conclusion

In this work, we exploited a new approach to redistribute the vehicles of an EV sharing service, proposed for the first time in Bruglieri et al (2012). The approach has been tested on a realistic case study, where we generated the pickup and delivery requests of EVs to be relocated using the origin-destination traffic matrix yielded by the Milan transport agency and the current location and capacity of the docking stations installed by A2A, the main energy supplier company in Milan, within the project E-Moving (A2A, 2013).

The numerical results on a test bed of 30 EVRP instances generated with the car sharing simulator show that two workers with a duty time of 5 hours are sufficient to satisfy a high percentage (about 86%) of the relocation requests (around up to 30) generated by a fleet of 30 EVs in a car sharing service of 13 hours (7:00-20:00). Moreover the time spent in average by a worker for driving the EVs is reduced (24% of the duty time) showing that the impact of our relocation method on the urban traffic is very small.

Future work concerns in investigating also the combination of our operator based relocation approach with pricing policies on the parking stations offered to the users.

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Table 3. Numerical results of EVRP formulation on AMAT data

				K=1		K=2		K=3	
Instance	**|P|**	**|D|**	**MAX_SERVED**	**SERVED**	**CPU**	**SERVED**	**CPU**	**SERVED**	**CPU**
AMAT 1	15	12	88.89	74.07	3600.00	**88.89**	1.09		
AMAT 2	15	7	63.64	**63.64**	0.03		0.02		
AMAT 3	16	6	54.55	**54.55**	0.04		0.04		
AMAT 4	15	14	96.55	75.86	3600.00	82.76	3600.00	89.66	3600.00
AMAT 5	13	11	91.67	83.33	3600.00	**91.67**	0.59		
AMAT 6	7	8	93.33	80.00	28.75	**93.33**	0.06		
AMAT 7	9	8	94.12	82.35	0.03	82.35	0.04	82.35	0.07
AMAT 8	11	10	95.24	66.67	1722.98	85.71	0.59	85.71	1.08
AMAT 9	15	7	63.64	**63.64**	0.07		0.05		
AMAT 10	11	11	100.00	63.64	3600.00	90.91	1.62	90.91	0.58
AMAT 11	10	8	88.89	**88.89**	0.22		0.09		
AMAT 12	12	6	66.67	**66.67**	0.02		0.02		
AMAT 13	13	12	96.00	80.00	3600.00	88.00	1.08	88.00	1.40
AMAT 14	6	12	66.67	**66.67**	0.03		0.01		
AMAT 15	11	5	62.50	**62.50**	0.03		0.10		
AMAT 16	16	11	81.48	74.07	3600.00	**81.48**	8.33		
AMAT 17	15	16	96.77	70.97	3600.00	90.32	3600.00	**96.77**	17.24
AMAT 18	10	12	90.91	72.73	3600.00	81.82	1.86	81.82	0.69
AMAT 19	15	7	63.64	**63.64**	0.16		0.06		
AMAT 20	17	8	64.00	**64.00**	0.05		0.09		
AMAT 21	12	16	85.71	64.29	3600.00	**85.71**	0.13		
AMAT 22	13	8	76.19	66.67	0.04	66.67	0.06	66.67	1.08
AMAT 23	9	9	100.00	77.78	20.49	88.89	0.47	88.89	0.12
AMAT 24	12	7	73.68	**73.68**	0.03		0.08		
AMAT 25	7	9	87.50	75.00	24.82	**87.50**	0.02		
AMAT 26	11	11	100.00	90.91	3600.00	**100.00**	5.26		
AMAT 27	14	12	92.31	76.92	3600.00	**92.31**	8.47		
AMAT 28	13	11	91.67	66.67	3600.00	83.33	0.49	83.33	1.01
AMAT 29	13	10	86.96	69.57	517.58	**86.96**	15.29		
AMAT 30	9	15	75.00	66.67	361.94	**75.00**	0.19		
Average	**12.17**	**9.97**	**82.94**	**71.53**	**1529.24**	**86.18**	**241.54**	**85.41**	**362.33**

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