Proceedings of 7th Transport Research Arena TRA 2018, April 16-19, 2018, Vienna, Austria

The vehicle relocation for electric free-floating car-sharing services

Roberto Nocerino [a], Paola Tresca [a], Maurizio Bruglieri [b], Alessandro Luè [a]*, Luca Studer [b]

[a] *Poliedra-Politecnico di Milano, Via Giuseppe Colombo 40, 20133 Milano, Italy*
[b] *Dipartimento di Design - Politecnico di Milano, Via Durando 38/A, 20158 Milano, Italy*

Abstract

Free-floating is the new paradigm of car-sharing. These services enable one-way trips freely within a specified area, overcoming the need of a network of stations, that characterizes station-based services. Despite the increase of level of service for the users, free-floating poses a problem for the spatial distribution of the vehicles, due to a possible unbalance between the users-demand and the availability of vehicles. In such cases, the service provider has to develop strategies to reallocate the vehicles and restore an optimal distribution of the fleet of the car-sharing service. In case of free-floating services using electric-vehicles, the problem is even more complicated, due to the need of plug-in the vehicles to charging stations when needed. The paper presents a new model for vehicle relocation problem for an electric free-floating service, where cars are moved by operators of the service provider to keep the system balanced, generating a challenging pickup and delivery problem. The proposed algorithm has been designed and calibrated using real data from the city of Milan.

Keywords: free-floating car-sharing, relocation model, electric mobility

* Corresponding author. Tel.: +39 02 2399 2905; fax: +39 02 2399 2911.
E-mail address: alessandro.lue@polimi.it

1. Introduction

Car-sharing is a service where a fleet of cars is shared by a group of people paying only for the actual use of the vehicles. The wide variety of car-sharing services can be grouped in the following main categories (Barth and Shaheen, 2002; Le Vine et al., 2014; Arena et al., 2015):

- *Station-based*: cars can be picked up only at designated stations (round-trip or one-way);
- *Free-floating*: the service enables one-way journeys freely within a specified geographic zone;
- *Peer-to-peer*: the service provider offers a platform to bring private car owners in contact with passengers, matching supply and demand directly;
- *Community*: service targeted to specific market niches (companies, condominium, etc.).

Free-floating car-sharing services are quite more attractive for the users than the traditional station-based scheme. The balance of the fleet is one of the main issue that the service provider has to address for guaranteeing an adequate level of service, developing strategies to reallocate the vehicles and restore an optimal distribution of the fleet of the car-sharing service. Such a relocation could be based on the immediate needs in specific area, or on a historical prediction (i.e. estimating the vehicle demand in the future in order to determine when and from where a relocation event occurs). The vehicles relocation can be carried out by the service provider operators or by the users themselves. The management of the relocation of electric-vehicles is more complicated, because there is the problem to recharge the vehicles in specific charging stations.

The relocation problem of electric car-sharing services has been tackled within Sharing Cities[†], a H2020 project funded under the Smart Cities and Communities call (SCC1), which involves more than 30 partners from 6 different European Countries (UK, Portugal, Italy, France, Bulgaria, and Poland). Sharing Cities aims at creating smart districts in three lighthouse cities (London, Lisbon, Milan), where innovative and smart solutions about electric mobility, buildings refurbishment, public lighting, ICT, citizen engagement will be designed, implemented and tested, ensuring effective results and a high replicability. An integrated engagement system for personal mobility, urban logistics and housing efficiency is developed to push to a behavioural change and social innovation through reward, and to co-design the services implemented in the three cities within the project (Bresciani et al., 2016). As regards the mobility measures, the project will develop services and infrastructures regarding electric car-sharing, electric bike-sharing, smart parking, e-logistics. Optimization algorithms will help to manage the relocation for car and bike-sharing service, and to plan and manage the last-mile delivery with electric vans and bikes.

The paper presents a new algorithm for the electric-vehicle relocation problem, where cars are moved by personnel of the service provider to keep the system balanced, generating a challenging pickup and delivery problem. The proposed algorithm, developed from an initial work (Bignami et al., 2017), has been designed and calibrated using real data from the city of Milan, where the car-sharing market is very developed, with six services that cover different schemes (free-floating/station-based) and using vehicles with different propulsion technology (internal combustion engine/fully electric).

2. Relocation models: literature review

Over the last twenty years, with the spread diffusion of one-way and free-floating car-sharing systems, many studies focused on the vehicle relocation problem, proposing different approaches.

Barth and Todd (1999) in their seminal work proposed the following classification regarding the possible relocation strategies: i) *static relocation*, based on the immediate need of a specific station, that is the relocation activated according to a maximum and minimum number of vehicles that can be present in each station; ii) *historical predictive relocation*, based on an estimated request that is calculated using historical service data or demand estimation techniques; iii) *exact relocation*, this is only possible when we have the perfect knowledge of the users' demand, as in the case of a car-sharing service on reservation. Another classification distinguishes the

---

[†] This paper had received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N. 691895. The European Commission support for the production of this publication does not constitute endorsement of the contents which reflects the views only of the authors, and the Commission cannot be held responsible for any use which may be made of the information contained therein.

operator-based relocation, where the vehicles are moved by a team of dedicated workers (i.e. operator-based relocation), from the user-based relocation, where the users themselves contribute to the relocation, following the instruction given by the service provider about where to leave the car at the end of a use (obtaining a discount).

Hafez et al. (2001) proposed an operator-based relocation strategy where the operators move the vehicles through tow trucks. They first focus on the problem of determining when it is necessary to relocate a vehicle and then solve the problem about how relocate it. While the first problem is solved in exact way by a linear programming formulation, the second one is solved by mean of three heuristics, being NP-hard.

Bart et al. (2004) developed a static user-based relocation model. In such a model, the imbalance of each station is computed by comparing the current situation with a threshold determined from historical data. The strategy is based on two possible actions: “trip-joining” and “trip-splitting”. The first one is made when two users, whose journeys have in common both the origin and the destination, have to leave at the same time from a station characterized by a temporary lack of vehicles; in this case, users are offered to share the deal using the same car. Conversely, in case there is a surplus of vehicles in the station from which two or more users belonging to the same group want to depart, a “trip-splitting” operation is proposed, i.e. each of them is required to use separate vehicles. In both cases, advantageous prices are proposed to the users for incentivizing them to collaborate.

Ciari et al. (2012) focused on demand forecast. Their predictive model is based on a multi-agent simulation by activity. They used MATSim, an existing simulator software, to simulate a one-way car-sharing service.

Bianchessi et al. (2013) developed a user-based model that, leveraging the user’s sensitivity to service cost changing, aims to control the fleet balance by varying the cost in real time. The validity of such approach is tested through a simulator to compare the case with fixed price and that with variable prices, on the basis of performance indicators as the percentage of rejected requests, the average travel price, and the additional walking distance.

Bruglieri et al. (2013) proposed an operator-based relocation approach where the operators can move easily and in an eco-sustainable way from a delivery point to a pick-up point by means of a folding bicycle that can be loaded into the trunk of the electric-vehicle which needs to be moved. Such a new relocation approach generates a challenging pick-up and delivery problem, called E-VReP, that they solve by a MILP formulation and a simple but effective heuristic. In Bruglieri et al. (2014) the same authors generate realistic instances of the E-VReP through a simulator applied to some data provided by the Milan transport agency, AMAT, and by the main energy supplier company in Milan, A2A.

Boyaci et al. (2015) proposed an approach that simultaneously considers strategic decisions (location, number and size of stations), tactical decisions (determining the fleet size) and operational decisions (vehicle relocation), highlighting the strong interaction between the three levels of decision. The authors developed, solved, and applied to the actual data of a car-sharing service in Nice (France), a MILP model that at the same time determined the optimum values of the fleet size, number of stations and their best positioning, taking into account the dynamic relocation of vehicles.

3. Model description

The relocation process can generally be simulated into three phases and related models:

- *Demand provision model*: the future demand of vehicles can be estimated using historical data on the service about trips and data regarding unsatisfied service requests and not-recursive events (strikes, accidents, weather conditions);
- *Unbalance in demand and offer estimation model*: in this phase, a comparison between the forecasted demand and the actual cars location is made, in order to identify in which area a vehicles-deficit or surplus will occur;
- *Microsimulation vehicles model*: in this phase, the best way for reallocating cars is simulated, establishing incentives for the users (user-based relocation) or designing the best relocation strategies (operator-based relocation).

Not all models need to be implemented: e.g., in case of services based on long-term cars booking (not allowing real-time reservation) the first model is not necessary since the future demand is known in any moment. In Fig. 1 the three phases and their interdependences are summarized.

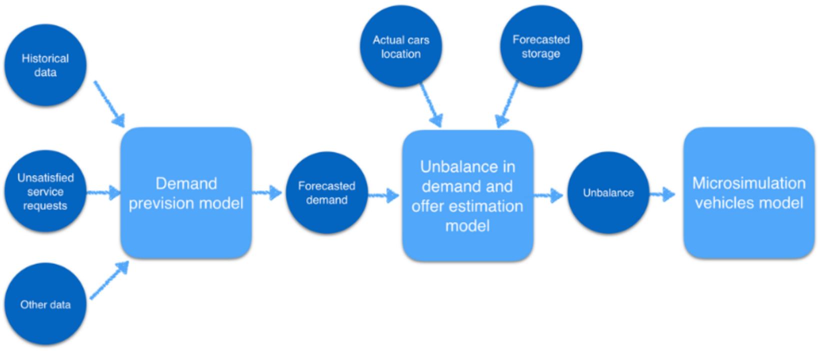

Fig. 1 block diagram of the general model structure

The following assumptions have been made in the models developed:
- the service is free-floating;
- the service uses electric-vehicles: a recharging network has to be included in the model;
- the size assumed for the fleet is of 600 vehicles, all electric;
- only operators can plug-in the e-vehicle at a recharging point;
- under a certain level of battery, the e-vehicle is not available for the users and needs to be recharged;
- long-term booking is not allowed, only real-time reservation is enabled;
- when the e-vehicle is not used no energy-loss occurs.

3.1. Demand prevision model

The future demand of vehicles can be foreseen using the historical data about users' trips: the expected demand can be calculated as the average of rentals/trips made in that area at a certain time. A probabilistic time-dependent origin-destination matrix can be estimated for a generic day of the week.

3.2. Unbalance in demand and offer estimation model

The first step is the classification of different zones of the city, dividing the service area into:
- Zone+: area where the number of vehicles needs to be increased;
- Zone=: area where the number of vehicles is aligned with the need;
- Zone–: area where the number of vehicles needs to be decreased.

Three methods have been envisioned:
- Method F: difference between the number of vehicles brought by operators and those took away in a generic zone; if F>0, the zone is a Zone+, if F<0, the zone is a Zone–;
- Method P: ratio of relocations that interest a zone; if P≃0 the zone is a Zone+, high values identify Zone–;
- Method M: mix method that uses Method P for identifying Zone– and Method F[‡] for identifying Zone+.

3.3. Microsimulation vehicles model

3.3.1. Possible occurring events during the relocation process

An electric-vehicle can be characterized by his battery level as:
- charged: when the battery level is above a certain threshold;
- discharged: when the battery level is below a certain threshold;
- in charge: when the vehicle is plugged-in to be recharged at a charging point.

Combining e-vehicle classification and zones classification described above, we define different nodes categories:

[‡] For identifying Zone+ within Method M, we use a modified version of Method F, considering the absolute number of vehicles brought by the operators

1. Discharged vehicle in Zone+
2. Discharged vehicle in Zone=
3. Discharged vehicle in Zone–
4. Charged vehicle in Zone+
5. Charged vehicle in Zone=
6. Charged vehicle in Zone–
7. In-charge vehicle in Zone+ (full charged)
8. In-charge vehicle in Zone= (full charged)
9. In-charge vehicle in Zone– (full charged)

Additionally, two other nodes categories not presenting any vehicle can be defined:

10. Zone+: node without any vehicle
11. Empty charging point, at disposal for plugging-in a vehicle

An operator can:

- Take a charged vehicle (or an in-charge vehicle that completed the charge);
- Take a discharged vehicle;
- Leave a charged vehicle;
- Leave a discharged vehicle.

Not all the operations are sensible: compatibility matrix between nodes and operations is reported in Fig. 2.

node \ operation			Take a charged vehicle	Take a discharged vehicle	Leave a charged vehicle	Leave a discharged vehicle
1	Discharged vehicle in zone	+		✓	✓	
2		=		✓	□	
3		-		✓	□	
4	Charged vehicle in zone	+	□			
5		=	□			
6		-	✓			
7	In-charge vehicle in zone	+	✓			✓
8		=	✓			✓
9		-	✓			✓
10	Zone +				✓	
11	Empty charging point					✓

Fig. 2 compatibility matrix between nodes and operations; possible operations are marked with a grey square; efficient operations are marked with a ticked grey square

As shown in Fig. 2 not all the nodes are object of any operation: e.g., there is no reason for moving a charged vehicle from Zone+. At the same time, some nodes categories can be grouped because object of the same operations (e.g. discharged vehicle in Zone= and Zone–). The simplified compatibility matrix is reported in Fig. 3.

node \ operation			Take a charged vehicle	Take a discharged vehicle	Leave a charged vehicle	Leave a discharged vehicle
A	Discharged vehicle in zone	+		✓	✓	
B		=/-		✓	□	
C	Charged vehicle in zone	-	✓			
D	In-charge vehicle in zone		✓			✓
E	Zone +				✓	
F	Empty charging point					✓

Fig. 3 simplified compatibility matrix between nodes and operations; possible operations are marked with a grey square; efficient operations are marked with a ticked grey square

From a node with a vehicle all the operations can be made by a single operator. Instead, the operator can leave Zone+ and Empty charging point, that do not present any vehicle (except the one left by the operator), only together with another operator. In Fig. 4 the possible transition from one node category to another and the number of operators needed for this transition are represented with a compatibility matrix and a graph. The transition from E to B, e.g., needs two operators whereas from A to F one operator is enough.

		Discharged vehicle in zone + A	Discharged vehicle in zone =/– B	Charged vehicle in zone – C	In-charge vehicle in zone D	Zone+ E	Empty charging point F
Discharged vehicle in zone	+ A				1		1
	=/– B				1		1
Charged vehicle in zone	– C	1				1	
In-charge vehicle in zone	D	1				1	
Zone+	E		2	2	2		
Empty charging point	F		2	2			

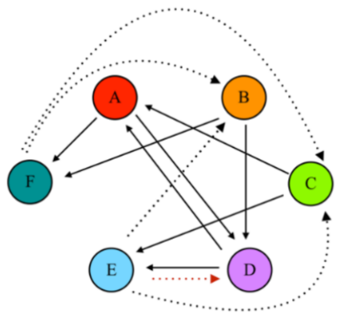

Fig. 4 (a) compatibility matrix between nodes that highlights the possible transition from one node to another and the number of operators needed for this transition (one operator: 1; two operators: 2); (b) and related graph (one operator: solid line; two operators: dashed line)

3.3.2. Possible relocation strategies

A *greedy heuristic (nearest neighbour) algorithm* has been implemented to identify the itineraries able to maximize the number of relocations made by the operators. The algorithm calculates the itinerary one by one, adding the closest node that can be reached by the operator(s) from the one where the operator(s) is(are): the time for reaching the node is calculated and subtracted to the residual time at disposal for the operator(s). When a node is reached by the operator(s), it cannot be visited by other operator(s); the algorithm stops when all the nodes have been visited by the operators and/or when the time at disposal is finished. Different options have been tested in order to identify the best relocation strategies:

- Operators working alone (single operators);
- Operators working in couples (couples of operators);
- Operators working alone with the support of other operators (single operators plus supporting operators).

With *groups of single operators* strategy, the itinerary of each operator is calculated adding at each iteration of the algorithm the closest node that can be reached. A single operator can reach a node only if this is connected by two arcs to the one where the operator is: this reduces the itinerary to an alternation of type A and D nodes (except the first and the last node).

In g*roups of couples of operators* strategy, a couple of operators can move along all the graph arches. When the couple moves from a node hosting a car, the couple is split and the two operators move using the two cars, the one just picked up and one that they used to reach the node, along the same path; instead when the couple leaves an E or F node (where there is no car) both operators move on the support car. The advantage of this configuration is the greater freedom of action, but the disadvantage is to engage always two operators, even for arches that can be travelled by a single operator.

The *groups of single operators plus supporting operators* strategy assumes that part of the staff works individually most of the time: when the closest node can be reached by a single operator, this arc is added into the itinerary; when the arc requires two operators, the algorithm verifies that an operator (with a support car) is available to travel that arc for supporting the single operator. The node can be included in the itinerary only if this availability exists. This strategy is the most complex one: at each step of the algorithm, the node closest to the last one inserted in the itinerary is searched, between those linked by an arc. If the arc connecting the two nodes can also be run by a single operator, the node is added to the itinerary and the time necessary to reach it is taken away from the time that the operator has available; if the arc requires two operators, it is necessary to check if one of the supporters is available, at the time required, to accompany the operator along the arc. If a support operator is available, the node can be added to the itinerary; if no operator is available the node cannot be added and a new node must be searched. The algorithm stops when the operator has not enough time to reach a new node or there are no more nodes that can be reached.

4. Experimental results

4.1. Data-set

The following data-set, related to the city of Milan, has been used for model calibration and test.

Car hires: we used a data-set covering one month of service, processed and anonymized by AMAT (Agenzia Mobilità, Ambiente e Territorio of Milano Municipality). The data-set belongs to an anonymous car-sharing provider and it is characterized by the following fields (all anonymized): univocal vehicle ID, univocal user ID, start and end point, start and end date (unknown year and month), start and end time, distance travelled, hire duration.

Work shifts of the operators: the operators are divided into three work shifts, in order to cover the entire day (during night shift the number of operators is three time the one during the other two shifts):

- Day shift: from 7 am to 3 pm;
- Evening shift: from 3 pm to 11 pm;
- Night shift: from 11 pm to 7 am.

Relocation made by operators: the cars-hire data-set includes trips performed by operators for relocation purpose. The data refers only to relocations for fleet balancing (and does not include relocations due to charging reasons). Of each relocation are known:

- the coordinates of the position from which the car is taken;
- the coordinates of the position where the car is left.

The time window during which the car is not used by customers is also known, but no precise information is available about the time when the relocated car is left by the operator.

Service area: covers the entire Milan territory and some neighbouring cities. The service area is included between 45.400° and 45.540° of latitude and 9.100° and 9.280° of longitude, with a total extension of around 154 km^2; it has been rasterized with cells 0.01 x 0.01° large (corresponding to 788 x 1,110 meters), for a total number of 176 cells with an extension of 0.875 km^2 each (Fig. 5).

Recharging points: current position of charging points and charging stations has been used.

Fig. 5 service area, divided into 176 cells

4.2. Zone classification

Through the three methods envisioned within the paragraph 3, different classifications have been obtained. Each method has been tested using different threshold values, not considering the relocation for charging the vehicles.

Table 1 shows a 15-days simulation results (using *groups of singles and groups of couples* strategy).
It is possible to observe the level of service enhancement; the number of unsatisfied trip requests passes from 20.10% in the system without relocation to 10.74% in the M3 method, the most performing and the one chosen for testing the relocation strategies.

Table 1 performances of different zone classification methods (around 75,000 requests)

			Satisfied requests (n.)	Unsatisfied requests (n.)	Unsatisfied requests (%)	Δ unsatisfied (n.)	Δ unsatisfied (%)	Relocation (n.)
Without relocation			59,970	15,090	20.10%			
Method	Zone+	Zone-						
F1	> 0.15	< - 0.45	64,951	10,109	13.47%	-4,981	-33.01%	3,165
F2	> 0.05	< - 0.45	65,074	9,986	13.30%	-5,104	-33.82%	3,293
P1	< 2.5 %	> 15 %	65,674	9,386	12.50%	-5,704	-37.80%	1,694
P2	< 1 %	> 10 %	65,748	9,312	12.41%	-5,778	-38.29%	1,707
P3	< 1 %	> 10 %	65,770	9,290	12.38%	-5,800	-38.43%	2,577
M1	> 0.15	> 15 %	66,526	8,534	11.37%	-6,556	-43.45%	1,519
M2	> 0.15	> 12.5 %	66,690	8,370	11.15%	-6,720	-44.53%	1,853
M3	> 0.15	> 10 %	67,001	8,059	10.74%	-7,031	-46.59%	2,500

4.3. Relocation strategies

Ten different strategies in terms of operators' configuration have been tested, keeping 15 operators for the day shifts as total number of working people, to identify the best relocation strategies. For example, in the second row of Table 2 the 15 operators are split into 9 groups with two different partitions: 3 singles and 6 couples in case of *groups of singles and groups of couples* strategy and 9 singles with 6 supporting operators in case of *groups of singles plus supporting operators* strategy.

Table 2. Different options in terms of operators' configuration

Total operators	Number of groups	Groups of singles and groups of couples		Groups of singles plus supporting operators	
		Singles	Couples	Singles	Supporting operators
15	8	1	7	8	7
15	9	3	6	9	6
15	10	5	5	10	5
15	11	7	4	11	4
15	13	11	3	13	2

The *groups of singles and groups of couples* strategy results in general better than the use of *groups of singles plus supporting operators*. In particular, holding the number of 15 operators for day shifts the best results are given by a total of 9 groups: the lowest number of unsatisfied requests is obtained adopting *groups of singles and groups of couples* strategy, with 3 singles and 6 couples, as shown in Fig. 6.

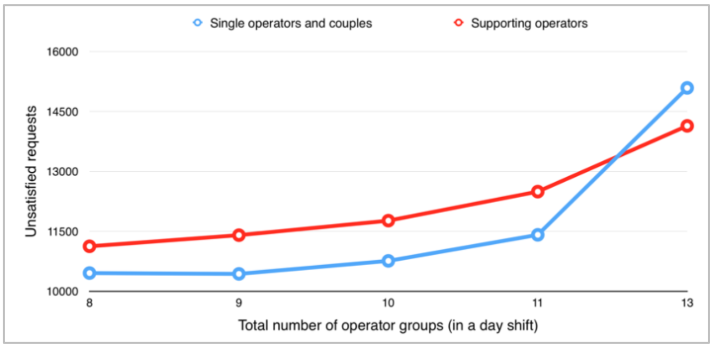

Fig. 6 performances, expressed as unsatisfied requests, of the different operators' configuration options

4.4. Size of the operator team

Finally, it was evaluated when the increase in the total number of operators (and therefore of costs) led to an improvement in the quality of the service (expressed in number of unsatisfied requests).

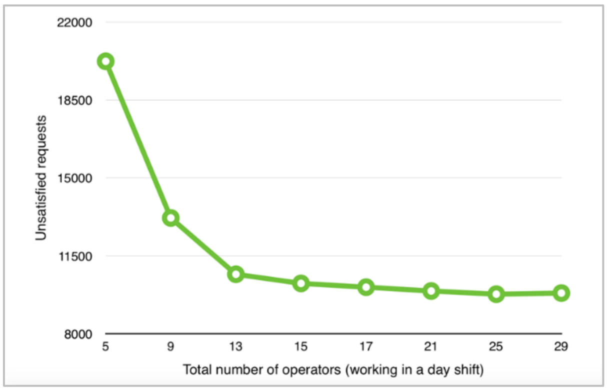

Fig. 7 total number of operators (working in day shift) and related unsatisfied requests

From the graph in Fig. 7 it is possible to observe how the number on unsatisfied demand initially decreases very rapidly, but already around the 15 operators for day-shift (the triple for night shift) this value tends to stabilize, not justifying the increase in the cost, needed to increase the team, with a significant improvement in service.

5. Conclusions

The object of this work, undertaken within the Sharing Cities project, was the development of a relocation system for the free-floating electric car-sharing service in Milan. An operator-based model for vehicle relocation has been developed, considering both aspects of fleet balancing and e-vehicle recharging.

A heuristic algorithm has been developed and implemented to solve the fleet balancing and e-vehicle recharging problems.

An analysis of data related to real car-sharing systems operating in the city of Milan has been conducted for identifying the areas where the number of vehicles needed to be increased (Zone+), decreased (Zone–), or the demand and the offer were balanced (Zone=).

Three different strategies in operator's management have been proposed, operators working alone (single operators), in couples (couples of operators), and alone with the support of other operators (single operators plus supporting operators).

In order to compare the different strategies, a simulation model has been developed (in MATLAB language) to reproduce the performance of the free-floating service and monitor the various performance parameters, including the number of unsatisfied requests and the total number of relocations made.

The results allow to identify the best classification method for the zone and the best relocation strategies in terms of operators' organization.

In the future, in order to improve the model there are some aspects that we would like to consider and study:

- an important aspect to be improved is the estimation of vehicles demand by considering data regarding weather conditions and not-recursive events (strikes, accidents, festivities…);
- it would be useful to analyze data related to the unsatisfied demand;
- a better analysis of the real behavior of the relocators of a car-sharing system;
- the classification of the zones has been kept static, time-variance.

Acknowledgements

We would like to thank AMAT-Agenzia Mobilità, Ambiente e Territorio of Milano Municipality, and in particular Valentino Sevino, Adriano Loporcaro, Paolo Campus, and Veronica Gaiani for their support in creating a sensible dataset.

6. References

Arena, M., Azzone, G., Colorni, A., Conte, A., Luè, A., Nocerino, R., 2015. Service design in electric vehicle sharing: evidence from Italy. IET Intelligent Transport Systems, 9(2), 145-155.

Barth M., Todd M., Xue L., 2004. User-Based Vehicle Relocation Techniques for Multiple-Station Shared-Use Vehicle Systems. Transportation Research Board.

Barth, M., & Shaheen, S. A. (2002). Shared-use vehicle systems: Framework for classifying carsharing, station cars, and combined approaches. Transportation Research Record: Journal of the Transportation Research Board, 1791(1), 105-112.

Barth, M., Todd, M., 1999. Simulation model performance analysis of a multiple station shared vehicle system. Transportation Research Part C: Emerging Technologies 7(4), 237-259.

Bignami, D. F., Colorni, A., Lué, A., Nocerino, R., Rossi, M., Savaresi, S. M. (2017). Electric Vehicle Sharing Services for Smarter Cities. Springer International Publishing

Bianchessi A., Formentin S., Savaresi S., 2013. Active fleet balancing in vehicle sharing systems via feedback dynamic pricing. In Intelligent Transportation Systems-(ITSC), 2013 16th International IEEE Conference on (pp. 1619-1624). IEEE.

Boyaci B., Zografos K.G., Geroliminis N., 2015. An optimization framework for the development of efficient one-way car-sharing systems. European Journal of Operational Research, 240(3), 718-733.

Bresciani, C., Colorni, A., Lia, F., Luè, A., Nocerino, R. (2016). Behavioral Change and Social Innovation Through Reward: An Integrated Engagement System for Personal Mobility, Urban Logistics and Housing Efficiency. Transportation Research Procedia, 14, 353-361.

Bruglieri, M., Colorni, A., Luè A., 2014. The vehicle relocation problem for the one-way electric-vehicle sharing, Networks 64 (4) 292-305

Bruglieri, M., Colorni, A., Luè A., 2014. The vehicle relocation problem for the one-way electric-vehicle sharing: an application to the Milan case. Procedia-Social and Behavioral Sciences, 111, 18-27.

Ciari F., Dobler C., Axhausen, K.W., 2012. Modeling one-way shared vehicle systems: an agent-based approach. 13th International Conference on Travel Behaviour Research.

Hafez N., Parent M., Proth J-M., 2001. Managing a pool of self service cars. In Intelligent Transportation Systems, 2001. Proceedings. 2001 IEEE (pp. 943-948). IEEE.

Le Vine, S., Zolfaghari, A., Polak, J.W., 2014. Carsharing: Evolution, Challenges and Opportunities, Report to the European Automobile Manufacturers Association (ACEA) Scientific Advisory Group.