SIMULATION AND OPTIMIZATION OF A CAPILLAR THIRD GENERATION CAR SHARING SYSTEM

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ABSTRACT

The paper concerns a capillar third generation car sharing system for urban pedestrian environments. The following specific services are provided: instant access, open ended reservation and one way trips; vehicles can be accessed not only at stations, but also along the roads. All these features provide users with high flexibility, but create a problem of uneven distribution of vehicles. Therefore, relocations of vehicles must be performed. Different relocation procedures exist in literature. In this paper, a management scheme is proposed where vehicles automatically relocate and reach the users positions, thanks to their degree of automation. In order to provide transport managers with a useful tool to test the proposed system in different realities, an object-oriented simulator has been developed. An optimization algorithm has also been developed for assessing the fleet dimension and the transport system parameters. The proposed car sharing system has been simulated for Genoa historical city centre, Italy.

Keywords: third generation car sharing, capillarity, object oriented micro simulation, optimization

1. INTRODUCTION

The paper concerns a new generation car sharing system for urban pedestrian environments, which involves a fleet of automated personal vehicles, called PICAV. PICAV vehicles are specifically designed for areas where usual public transport services cannot operate because of the width and slope of the infrastructures, uneven pavements and interactions with high pedestrian flows. Some details on characteristics and performances of PICAV vehicles are reported in Cepolina and Cepolina (2014a).

New generation car sharing systems overcome some restrictions of traditional car sharing (first generation) where members need to book cars beforehand and the time the car will be dropped off should be specified (fixed-period reservation); besides, cars must be returned to the same station where they were picked up (two-way trips).

New generation car sharing systems are aimed at providing users a higher degree of flexibility, and in particular the following specific services:

- instant access: users can access directly to an available vehicle, without the need to make a reservation;
- open-ended reservation: users can keep the PICAV vehicle as long as needed;
- one way trips: users can drop the vehicle off at any station.

The main problem of these systems is that they may quickly become imbalanced with respect to the number of vehicles at the stations. Due to uneven demand, some stations during the day may end up with an excess of vehicles whereas other stations may end up with none.

New generation car sharing systems often resolve the balancement problem through operator based relocation. But operator based relocation has shown to be extremely expensive in terms of staff and management costs, therefore some systems have turned out into a failure, while others only remained pilot projects and have never been settled on a wide scale. A full description of the main characteristics, advantages and problems of new generation car sharing systems has been provided in Cepolina and Farina (2012b) and Cepolina et al. (2014b).

The *third generation of car sharing systems* aims to add capillarity to the new generation car sharing systems. The capillarity of the system, i.e. the possibility of having shared vehicles available at several points of the area, ideally at any point, improves the quality of the service provided to users. In this scenario vehicles can be accessed and returned not only at stations but also along the roads.

Several third generation car sharing systems, such as Car2go, DriveNow and Greenwheels, have been planned, and some of them have also been applied on the field. Users have an interactive map where they can reserve, with short advance, the vehicle closest to their position. This however can create some impedance to users because they may have to travel also for long to reach the closest available vehicle. In these systems, a large number of vehicles and a balanced demand are required, in order to keep limited the user waiting times.

2. THE PROPOSED RELOCATION STRATEGY

A trip by PICAV vehicle may have, as origin or destination, either a station or any position along the roads within the intervention area. When in the origin of the user's trip there are no available PICAV vehicles, a PICAV reaches the user position in a fully automatic way.

In the proposed transport system, relocations are required:

1. In the stations, when the number of vehicles available at stations is below the low critical threshold. This criterion is adopted to prevent user waiting times. In this case, the request for a vehicle could be addressed:
   (a) firstly to the stations where the number of vehicles is above the low buffer threshold. Among the stations to which the vehicle request could be addressed, the providing station is selected according to two criteria: the closest station (shortest time criterion) and the station having the highest number of vehicles (inventory balancing). The shortest time criterion relates mainly to service levels, while the inventory balancing mainly focuses on cost efficiency. Therefore, an appropriate choice of relocation technique should be made according to the current system situation: in periods of low usage, the most appropriate relocation technique is by inventory balancing while in periods of high usage, then the shortest time technique performs best.
   (b) secondly, to the available vehicles parked along the road. In this last case, the nearest vehicle automatically relocates towards the station in shortage.
2. Not in the stations, when a user calls for a vehicle. In this case, the criterion is to limit the user waiting times along the roads as much as possible. The system manager assigns to the user the available vehicle nearest to the user's position. If the nearest vehicle is in a station, it can be provided only if the number of vehicles available in the station is greater than the low critical threshold of the station.

At the end of their trip, the user can leave the vehicle at any position along the roads within the intervention area. When a vehicle is returned, if the level of battery charge is below the minimum charge level, the vehicle automatically reaches the nearest station to recharge the battery. As soon as it reaches the minimum charge level, it becomes available and if not required, continues the charging process.

An object oriented micro simulator of the proposed transport system has been developed. The simulator is described in detail in section 3.

An optimization algorithm has been developed to optimize the proposed transport system's performances. The optimization algorithm is described in section 4.

3. THE MICRO SIMULATION OF THE PROPOSED TRANSPORT SYSTEM

The micro simulator receives in input: a simulation time period, a road network, a PICAV fleet, the PICAV transport demand and the parameters related to the relocation strategies (the low critical and the low buffer thresholds). The simulator allows to track the second-by-second activity of each user, as well as the second-by-second activity of each PICAV vehicle.

The micro simulator provides in output the user waiting times t_{wi} (i is the i^{th} user) and the relocation times t_{rj} (j is the j^{th} relocation).

The proposed transport system has been modelled according to an object-oriented logic. The language chosen for writing the code is Python 2.5.

3.1. Input data

The micro simulator input data are: the simulation time period, the road network, the transport demand, the PICAV fleet characteristics, the relocation strategy parameters. All these inputs are deterministic. The only stochastic input is the transport demand, as it concerns the user arrival time instant.

3.1.1. The simulation time period

The simulation time period starts when the car sharing system opens to users and ends when the last user returns the PICAV. In the following we refer to a daily simulation time period. The simulation time period could be characterised by peak and off peak phases: for each phase, an average pedestrian density k in the pedestrian area, from which the PICAV vehicles speed depends, and a PICAV transport demand, should be specified.

3.1.2. The road network

The road network includes stations, provided with charging stations, and the roads in which PICAV vehicles are allowed to travel. The road network has been defined using OpenStreetMap.

Stations have been represented through nodes. Each road is divided into sections and each section has been modeled again by a node.

Between each pair of nodes, we take into account only one path, which could be the shortest one or the one which contains a high concentration of shops, museums and other attractions. The overall length and the average upslope for each of the paths were charaterised using GoogleMaps (Cepolina et al. 2011a). These data are necessary to determine the battery discharging law: in particular the quantity of discharge is assessed from the average upslope, as it contributes heavily to the resistances to motion encountered by the PICAV vehicle. If the path is instead descending the recovery in battery charge is so slight that it is neglected, therefore for each path the downslope parts are considered as flat in the calculation of the average upslope. The overall length of a path is required in order to determine the trip duration.

The path lengths and the average upslope are assessed through a routing algorithm written in javascript, which interacts with OpenStreetMap. These data are given as input in the simulator in the form of two matrixes. The matrixes are squared and the number of rows (or columns) equals the number of nodes in the network. In the first matrix, the cell *ij* represents the path length between the origin node *i* and the destination node *j*. In the second matrix, the cell *ij* represents the average upslope of the path between the origin node *i* and the destination node *j*.

The minimum charge level is calculated as a function of the average upslope and of the length of the most battery consuming path in the road network.

The vehicle speed is assessed from the pedestrian density according to the following model:

PICAV user driven: $v = -1.45\,k + 1.58$ (1)

PICAV automatically driven, relocation trip:

$$v = -1.45\,k + 1.38 \quad (2)$$

where k is the *pedestrian density* expressed in pedestrians per square meters; v is the PICAV vehicle speed expressed in m/s. The model for assessing the vehicle speed from the pedestrian density is described in detail in Cepolina et al. (2011b). The model has been implemented in the micro simulator.

3.1.3. The transport demand

The transport demand refers to a given phase of the simulation time period and it is given to the simulator in the form of an OD matrix. Each row refers to a node of origin, and each column to a node of destination. Each cell gives the hourly number of trips from the node the row refers to, to the node the column refers to.

We consider two trip typologies: a direct trip, or a sequence of shorter trips (multitask trip) where one accomplishes a number of short tasks that require short term parking along the street, before finally returning the vehicle. In both cases what is of interest for the proposed study is the overall duration of the trip. Given an origin, a destination, the path between them, and an average pedestrian density, the trip duration changes according to the trip typology.

Therefore each OD matrix refers to a given phase of the simulation time period and to a trip typology. In the simulation PICAV users are generated with the following characteristics: the origin of their trip by PICAV, the destination, the time at which they appear in the origin and the trip typology. These data are assessed according to the OD matrixes. The time at which a user appears in their origin is randomly generated: if X users have to be generated between 8 and 9 a.m. in a given origin, X casual numbers are extracted within the given time interval and these casual numbers are the exact arrival instants of the X users in the origin.

3.1.4. The PICAV fleet characteristics

The PICAV fleet characteristics are: the fleet dimension, the number of PICAV vehicles at each station at the beginning of the simulation time period, the battery capacity, the battery charging and discharging laws.

A lithium-ion battery has been selected by MAZEL, the partner of the project consortium dealing with the electric engine and battery development. The battery is composed of 15 blocks connected in parallel, each composed of 27 cells connected in serial, and provides 202Ah and 48V DC.

The battery charging technique is the *opportunity charging*. The term opportunity charging refers to the charging of the batteries wherever and whenever power is available. The *minimum charge level* is the quantity of charge necessary to the vehicle to perform the longest trip or relocation journey. Every time a PICAV is returned in a station, a check on its charging level is performed. If the vehicle has a level of charge which is more than minimum charge level, it is available to users and to relocations, otherwise it starts the charging process.

3.1.5. The relocation strategy parameters

The relocation strategy parameters are described by two vectors. Their dimension equals the number of stations in the area, the value of each vector component is the station's *low critical threshold* for the first vector and the station's *low buffer threshold* for the second vector.

A high value of low critical threshold gives rise to a high number of required relocations and to low waiting times, if the fleet is consistent and therefore there are vehicles available for relocation.

The low buffer threshold is greater than the low critical threshold. If the low buffer threshold is much greater than the low critical threshold, the number of satisfied requests for relocations is low because often no stations can provide the vehicles required: this results in an increase of the users waiting times.

If the low buffer threshold is slightly greater than the low critical threshold, the number of satisfied requests for relocations is high; on the other hand, it may occur that at a given time instant a station provides a vehicle and at a following time instant the same station is in shortage of vehicles. This results in an increase in the number of required relocations.

As a result, it is necessary to optimize the low critical and low buffer thresholds values for each scenario under study.

3.2. Output data

3.2.1. Level of Service (LOS)

LOS measurement are assessed based on the statistical distribution of users waiting times. Castangia and Guala (2011) proposed a new LOS measurement scale (shown in table 1) using as reference the 50th, 90th and 95th percentiles of waiting time. The LOS measurement scale ranges from LOS from A (perfect service) to F (completely poor service). All the constraints on the three percentiles of users waiting times should be met to achieve a given LOS. LOS measurements could be assessed for each station or for the overall area, referring specifically to the waiting time of users.

Table 1: The LOS assessed according to the percentiles of users waiting time expressed in seconds

LOS	Waiting time (minutes) not greater than:		
	50th percentile	90th percentile	95th percentile
A	0.5	1	1.5
B	1	2	3
C	1.5	3	5
D	2.5	5	8
E	4	8	10
F	worse	worse	worse

3.2.2. Efficiency

An explicit expression to assess the transport system efficiency does not exist. However, according to Barth and Todd (1999) and Kek et al. (2006), we assess the efficiency according to the following variables:

- fleet dimension;
- number of required relocation trips;
- percentage of vehicles available, with reference to the total fleet dimension, at each simulated time instant.

The values of the first two variables are assessed offline at the end of the simulation; the value of the last variable is assessed online, i.e. during the simulation run.

3.3. Stochastic effects

As the input data are stochastic regarding the users arrival times, the output data, in terms of users waiting times and relocation time, are stochastic as well. According with the criteria given in Law and Kelton (1991), 30 runs of the microscopic simulator resulted sufficient to reduce these stochastic effects.

4. THE OPTIMIZATION OF THE PROPOSED TRANSPORT SYSTEM

An optimization algorithm has been developed to optimize the proposed transport system's performances. More in detail, it optimizes:

- the low critical thresholds,
- the low buffer thresholds,
- the fleet dimension and its distribution among stations at the beginning of the simulation time.

4.1. The cost function

The cost function f to minimize is composed of:

- the user cost, given by the total users waiting time in a simulation day
- the operator cost, given by the daily amortization cost of the fleet and by the daily cost of relocation.

The cost function has the following expression:

$$f(\mathbf{s}) = n_v c_v \left[\frac{r(1+r)^{lt}}{(1+r)^{lt}-1} \right] \frac{1}{365} + c_w \sum_{i=1}^{m} t_{wi}(\mathbf{s}) + c_r \sum_{j=1}^{n} t_{rj}(\mathbf{s}) \tag{3}$$

Where:

- $\mathbf{s}$ is an array which has three components:
  - the overall fleet dimension;
  - the low critical threshold, taken the same in all stations;
  - the low buffer threshold, taken the same in all stations;
- m is the number of users; n is the number of relocations that have taken place in the simulated day;
- n_v is the fleet dimension and c_v is the purchase cost of each vehicle;
- r is the discount rate and lt is the vehicle lifetime;
- c_w is the cost of each minute of users waiting time and t_{wi} is the user i's waiting time;
- c_r is the cost of each minute of relocation and t_{rj} is the relocation time;
- j is the j^{th} relocation; i is the i^{th} user.

We have decided to consider only the total fleet dimension, and not its distribution among stations at the beginning of the simulation time, because this last aspect is not relevant as it is compensated by the relocation. Therefore, at the beginning of the simulator, the same number of vehicles is assigned to all stations.

We have taken an unique value for all stations regarding low critical and low buffer thresholds as the cost function is not very sensitive if different values are taken. This highly simplifies the procedure as a low number of variables is necessary.

The three components of the vector $\mathbf{s}$ are determined through a micro simulator.

The problem constraints are the following:

$$g(\mathbf{s}) = \begin{cases} t_w^{50\%} - 4 < 0 \\ t_w^{90\%} - 8 < 0 \\ t_w^{95\%} - 10 < 0 \end{cases} \tag{4}$$

Where $t_w^{50\%}$, $t_w^{90\%}$, $t_w^{95\%}$ are the 50th, 90th and 95th percentiles of users waiting times.

These constraints are imposed in order to avoid the system to incur into LOS F. However, the results have shown that the constraints are automatically satisfied by minimizing the cost function.

We transform the constrained minimization problem into a single unconstrained problem using penalty functions. The constraints are placed into a new objective function $h(\mathbf{s})$ via a penalty parameter $\hat{\mu} > 0$ in a way which penalises any violation of the constraints:

$$h(\mathbf{s}) = f(\mathbf{s}) + \hat{\mu} \cdot \Sigma_i \left[\max\{0, g_i(\mathbf{s})\} \right]^2 \tag{5}$$

where: g_i is the i^{th} constraint.

Since there is no analytical expression for h (**s**), we cannot exclude the need to deal with a multi-peak function and the risk of reaching a local minimum, without being able to find the global minimum, is high (Cepolina and Farina 2012a). To combat this issue and the fact that the search space is extremely large, Simulated Annealing (SA) has been chosen to solve the minimization problem.

At each iteration of the SA algorithm the cost function $h(\mathbf{s})$ is evaluated through the micro simulator.

The procedure for solving the minimisation problem through the Simulated Annealing is described in the following section.

4.2. The solution algorithm

The chosen solution algorithm is based on Simulated Annealing (SA).

The Simulated Annealing (SA) scheme is a stochastic method currently very popular for difficult optimization problems. The term Simulated Annealing is motivated by an analogy to annealing in solids searching for minimal energy states. This procedure starts with the metal at a liquid state and at a very high temperature. In this state the atoms are quite free in their movements. The temperature of the metal is then slowly lowered. If the metal is cooled slowly enough, the atoms are able to reach the most stable orientation. This slow cooling process is known as annealing and so the method is known as Simulated Annealing.

The method is an iterative process that searches from a single point moving in its neighbourhood and allows sometimes to accept worse solutions. This is meant to avoid to get stuck in a local minimum in the optimization procedure. Worse solutions are accepted according to a probability, which depends on a parameter, i.e. the temperature, which decreases with the number of steps.

The algorithm evolves through an iterative cycle, in which the search space is explored. This search depends on a control parameter called temperature T which decreases as the number of the iteration of the cycle increases. In each iteration, a new point $\mathbf{s_n}$ is reached from $\mathbf{s_o}$, according to the transition rule. At the new point, the value of the cost function $h(\mathbf{s})$ is checked.

Since the cost function does not have an explicit formula, at each step of the Simulated Annealing algorithm, the microscopic simulator is recalled to calculate the users waiting times and the relocation times from which the cost function value depends.

The updating happens according to:

a) if $h(\mathbf{s_n}) \le h(\mathbf{s_o})$ → $\mathbf{s_n}$ substitutes $\mathbf{s_o}$, i.e. $\mathbf{s_o} := \mathbf{s_n}$

b) if $h(\mathbf{s_n}) > h(\mathbf{s_o})$ → $\mathbf{s_n}$ will become the current solution $\mathbf{s_o}$ with a probability given by:

$$p = \exp\left(- \frac{h(\mathbf{s_n}) - h(\mathbf{s_o})}{T} \right) \tag{6}$$

This is the core of Simulated Annealing and is known as the Metropolis algorithm. T is the value of the temperature for the current cycle (Laarhoven and Aarts 1987). Given that $r \in [0,1]$ is a pseudo random number, the updating happens according to the following:

if $r \le p$ → the new solution $\mathbf{s_n}$ substitutes $\mathbf{s_o}$,

if $r > p$ → the new solution $\mathbf{s_n}$ is rejected and therefore $\mathbf{s_o}$ will not be updated.

Therefore the algorithm needs the definition of the cooling schedule, the local search and the starting and stopping conditions.

4.2.1. The cooling schedule

The cooling schedule is defined by the initial temperature, the law of its decrease and the final temperature. The starting temperature has been determined according to Laarhoven and Aarts (1987).

An initial acceptance ratio p_0 of the worse solution, e.g. 0.5, is fixed at the first step of the algorithm. From this point, the initial temperature T_0 is determined from the acceptance ratio p_0 in this way, according to Laarhoven and Aarts (1987):

$$0.5 = p_0 = \exp\left(- \frac{h(\mathbf{s_n}) - h(\mathbf{s_o})}{T_0} \right) \tag{7}$$

The choice of the initial acceptance ratio has the purpose of performing a quite good exploration of the search space without slowing down too much the algorithm.

As in Cepolina (2005), the geometric temperature reduction function has been used: $T_{k+1} = \alpha \cdot T_k$ where T_k and T_{k+1} are the temperatures in two consecutive iterations of the algorithm. Typically, $0.7 \le \alpha \le 0.95$. In order to have a good exploration of the search space but not a too slow algorithm, α has been assumed equal to 0.9. The final temperature scheme of the cooling schedule is replaced by a stopping condition. The algorithm is stopped when 100 iterations without accepting any more new solutions is reached, according to the stopping criteria given in Laarhoven and Aarts (1987).

4.2.2. The transition rule

The transition rule regards the exploration of the search space: from a given vector $\mathbf{s_o}$, a new vector $\mathbf{s_n}$ is selected in the neighbourhood of $\mathbf{s_o}$.

The transition rule is probabilistic: it passes from $\mathbf{s_o}$ to $\mathbf{s_n}$ changing only one component of the vector $\mathbf{s_o}$. The algorithm randomly determines the component of the vector to modify. In our case, each component has the same probability to be selected. The algorithm also determines whether to increase or decrease the chosen component: it is increased with a probability of 50% and it is decreased with the same probability. More specifically, the first component of $\mathbf{s_o}$, i.e. the fleet dimension, if selected, is increased or decreased by m, where m is the number of stations in the intervention area. The second and the third component of $\mathbf{s_o}$, the low critical and low buffer thresholds, if selected, are increased or decreased by 1. Moreover, the algorithm avoids the situation where, in a given iteration, the vector component to change is the same as the one that has been changed in the previous iteration. In this way, it is guaranteed that the new vector $\mathbf{s_n}$ is taken in the neighbourhood of the previous vector $\mathbf{s_o}$. Keeping the neighbourhood that small allows to reach faster the optimum solution but, on the other hand, it cuts down the possibility of great improvements.

5. APPLICATION ON THE FIELD

The proposed transport system, together with the simulation and optimization methodology, has been applied to the case study of the historical city centre of Genoa, Italy. The historical city centre of Genoa has an area of about 1.13 km^2. This area is one of the most populated in Europe and the population density is equal 19,000 inhabitants/km^2. Also the density of commercial activities is high in this area. The proposed car-sharing system successfully integrates with conventional public transport, which cannot operate in the study area because of the narrowness and slope of roads. We consider as simulation time period the PICAV service during a reference working day: the service starts at 8 a.m. and ends at midnight. From the data collected in the field (Cepolina et al. 2011a), an off-peak phase in the morning (starting at 8 a.m. until 4 p.m.) and a peak phase in the afternoon (from 4 p.m. to 8 p.m.) were identified. From 8 p.m. to midnight no PICAV trips start.

The localizations of bus stops and underground stations were identified from Genoa public transport website (www.amt.genova.it). We have identified as well the localization of hotels, museum, offices, schools and commercial activities (food shops, clothes shops, handicraft shops and other shops) from the internet and from surveys performed in the field (Cepolina et al. 2013a). We designed 7 stations, all of which are on the border of the area, placed in correspondence of the main public transport stops. Each road has been divided into 50 m long sections and therefore 120 units resulted. The characteristics of the intervention area and the position of stations are shown in figure 1.

We assume that 1% of people that currently enter the historical city centre by foot will use the PICAV car-sharing systems. From surveys performed on the field (Cepolina et al. 2011a), it has been assessed that, in Genoa historical city centre, the pedestrian density in the afternoon (i.e. peak) period is on the average 1.45 times the density in the morning (i.e. off-peak) period. The peak transport demand is therefore assumed almost 1.45 times the off-peak demand. The overall PICAV travel demand in the reference time period is 1644 trips.

Trips having an origin or destination on the area border, are assumed to have had an origin or destination at a station; whereas trips having an origin or destination inside the area, are assumed to have had an origin or destination at a road section.

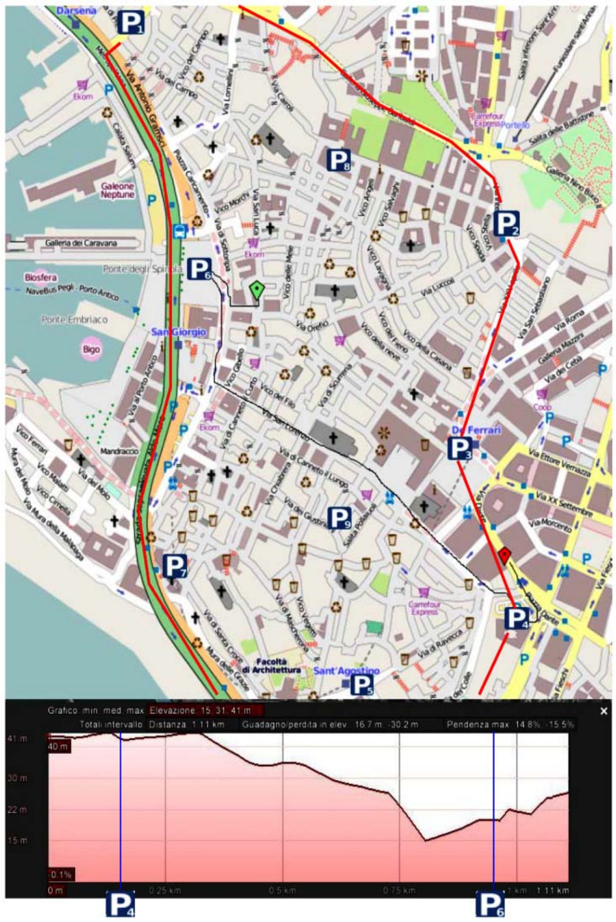

Figure 1: The intervention area and the stations positions (above). Longitudinal profile of the path between stations 4 and 6 (below).

About 100 people waiting for the bus on the area border have been interviewed (Cepolina et al. 2013a), in order to know the characteristics of the trips performed in the historical city centre. From the collected data, the duration of a multitask trip was found to be about 5 times the length of a similar direct trip.

The minimum charge level has been assumed equal to 10%, since this is the quantity of charge necessary to perform the longest trip, among the ones simulated in the area of study.

The optimization procedure has provided the optimum fleet dimension and the low critical and low buffer thresholds. The optimum fleet dimension is equal to 77 vehicles.

This fleet dimension seems reasonable, since it is in accordance with the outcomes from Barth and Todd’s research (1999). Barth and Todd found that, for all the various travel demand cases they analysed, the best number of vehicles ranged from 3 vehicles per 100 trips to 6 vehicles per 100 trips. We have 1644 trips per day therefore, according to these authors, the fleet dimension should range between 49 and 98 vehicles. The fleet has been assumed equally distributed among the stations at the beginning of the time period, as the different demand at the various stations is compensated through automatic relocation. The low critical thresholds were set to 2 and the low buffer thresholds to 3 vehicles for each station: these values have been determined again through optimization. The relocation technique used in the simulator is the shortest time.

The total value of the cost function is 485.61 €; the cost of users waiting time is 117.37 €, the cost of the fleet is 337.83 € and the cost of relocation is equal to 30.41 €.

The performance of the proposed car sharing system for the case study of Genoa has been assessed.

The trend of the cost function and its components with respect to: fleet dimension, low critical thresholds and low buffer thresholds, is represented in figures 2,3 and 4 respectively. The values reported are averaged over 30 simulator runs.

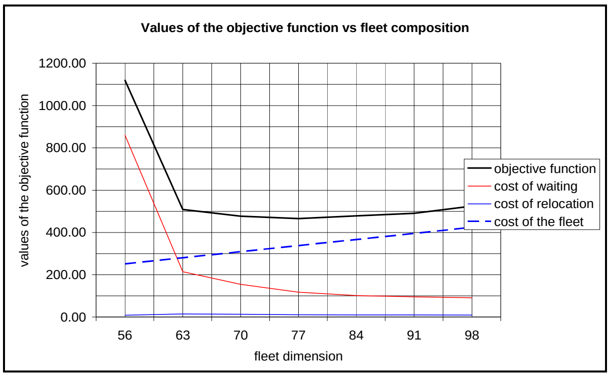

Figure 2: The trend of the cost function and its components (cost of waiting, cost of relocation and cost of the fleet) against the fleet dimension.

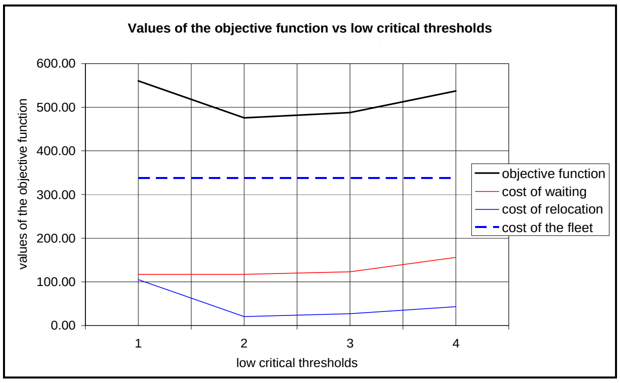

Figure 3: The trend of the cost function and its components (cost of waiting, cost of relocation and cost of the fleet) against the low critical thresholds.

In Figure 5 the number of PICAVs in each state is plotted against time. This figure refers to only one simulation run. The states taken into account are:

- available,
- occupied by users,
- required but not available because in charge,
- relocating,
- redirected because there is not free space in the destination station (FPT occurrences).

Time is expressed in hours, starting from 8 a.m. to midnight, when the last user returns the PICAV unit.

The diagram in Figure 5 shows that the selected charging technique (opportunity charging) is suitable for the case of study, since the vehicles' charge levels always remain above the minimum.

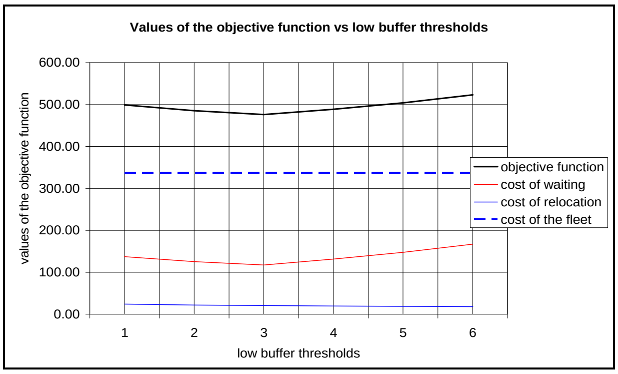

Figure 4: The trend of the cost function and its components (cost of waiting, cost of relocation and cost of the fleet) against the low buffer thresholds.

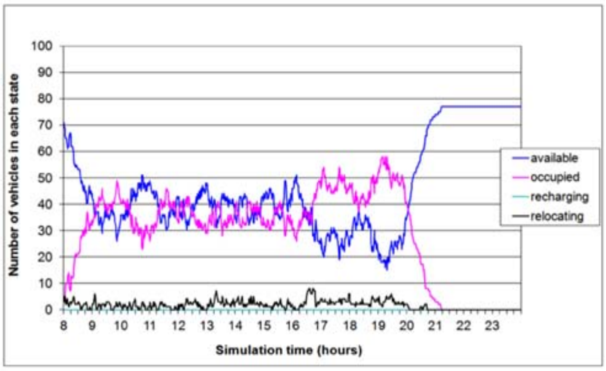

Figure 5: Number of vehicles in each state against time

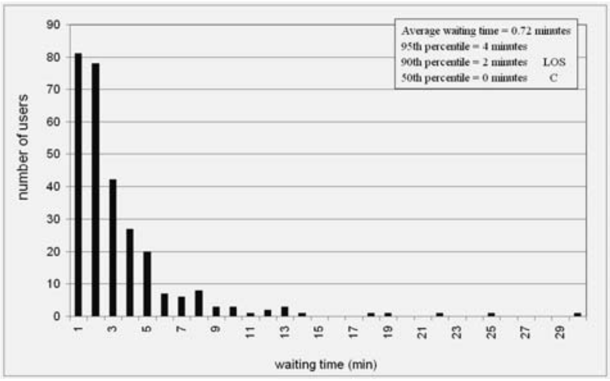

Figure 6: Distribution of users waiting time

If we consider the vehicles available to users which are occupied or available at stations, in the PICAV transport system, in the peak phase, about the 96% of the fleet results available to users and about 4% is therefore relocating. This means that the simulated relocation strategy works quite well for the case of study, since the number of vehicles subtracted to users for relocation is low.

The distribution of users waiting times is shown in figure 6. The reported values are averaged over 30 simulation runs. The average waiting time is equal to

0.72 minutes, and, according to the percentile values, the level of service is C.

6. CONCLUSIONS

The paper concerns a third generation car sharing system for urban areas. It is based on a fleet of intelligent vehicles which can be rented for short term periods (usually a couple of hours) and are shared through the day by different users. Vehicles can be accessed not only at stations, but also at any point of the intervention area. It is worth to underline that capillarity (i.e. the possibility that vehicles are available also along the roads) is a very good way to better satisfy user demand.

The car-sharing system has been planned and modelled in order to guarantee open ended reservation, instant access and one way trips. In the proposed system, a fully vehicle based relocation strategy is adopted, because the level of automation of PICAV vehicles allows them to move in an automatic way.

In order to plan such a vehicle sharing system for a given pedestrian area, an optimization procedure is presented in the paper which allows to assess the relocation strategy parameters that minimize the system cost, both in terms of level of service provided to users (that depends on waiting times) and the efficiency from the management point of view (that depends on relocation time and fleet dimension).

Since there is not an explicit expression for the cost function, the distribution of users waiting times and the total amount of time spent by vehicles in relocation, from which system cost depends, are assessed by microscopic simulation. The microscopic simulator follows an object oriented logic. The simulator follows each user and each vehicle within the simulation period, and gives the actual users waiting times and the relocation time.

As illustrative problem, the proposed transport system has been planned for the historical city centre of Genoa, Italy. The results of the simulation clearly show the effectiveness of the proposed car sharing system, because, with low staff costs, it allows users a high level of satisfaction. The model has been validated through a comparison of the simulation output data with those available in the body of knowledge.

Existing systems, such as Car2Go, DriveNow and Greenwheels, exploit the benefits of capillarity to avoid relocations. Actually, because of the widespread of vehicles, it is quite easy that the user finds an available vehicle quite close to his position. However, these systems do not work in cases of unbalanced demand and small cities. For example, if car sharing systems are used for trips to/from work, in the morning peak hour, it may happen that at a certain moment people who want to go to work cannot find anymore available vehicles. In this case, the only alternative is the automatic relocation.

As stated in Cepolina and Farina (2013b), the automatic relocation of PICAV vehicles still cannot be applied on the field because of legal problems in case of accident. To reduce the impact of automatically driven vehicles, also at legal level, it could be explored relocation by platooning. The operator drives the first vehicle of a platoon and the other vehicles follow the leader through automatic distancing. This relocation technique, however, increases the staff costs, as some operators to perform the relocation are needed. Moreover, because of the high level of capillarity, therefore vehicles should be redistributed all over the area, the relocation trips may be highly time consuming, therefore the staff needed is huge.

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