A Study to Promote Car-Sharing by Adopting a Reputation System in a Multi-Agent Context

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***Abstract*—In recent years the increasing rate of vehicular traffic due to private mobility caused congestion and environmental impacts in urban contexts all over the world. To face such problems an important contribution might be given by transit systems. However, transit systems are characterized by a discontinuous spatial and time coverage so that other forms of mobility, like car-sharing, can be an effective complement to it by providing the same flexibility and comfort of private cars. Several studies confirmed that car-sharing is almost as highly appreciated as private cars but having the advantage of lower costs. For such reasons, in recent years the car-sharing market increased continuously as it has been resulting more and more attractive for investors, although its market share remains limited. To encourage the car-sharing philosophy, from one hand traditional car-sharing companies are trying to reduce operational costs to offer lower fares and, from the other hand, several individual owners are starting to share their cars suitably supported by technology. To promote car-sharing activities, in this paper a multi-agent system able to monitor car-sharing users' driving habits is proposed. In particular, agents assist users in improving their driving, as well as in building their individual reputation measures over time. Such reputation scores can be used to allow the access to car-sharing services and personalized fares. Experiments on real and simulated data are encouraging and show the potentiality of this proposal.**

***Index Terms*—Car-Sharing, Multi-Agent System, Reputation System, Business Model.**

I. Introduction

The growing of urban traffic flows due to the increasing number of private cars, which represent the most part of the vehicles moving in urban areas, has worsened the citizens quality of life in terms of local environmental effects and traffic congestion [1]–[5]. To face such problems, several measures have been implemented by local authorities to reduce the use of private cars usually based on (*i*) restrictive rules and/or suitable monetary policies (for instance, by adopting road tolls, parking fees, limited traffic zones, interchange areas and so on) [6]–[12] and (*ii*) promotion of transit in urban areas, which represents the most suitable alternative to private mobility [13]–[15]. In this scenario, the main problem is that private cars are generally more appealing than transit in terms of comfort, privacy and flexibility [16]. Indeed, transit is characterized by discontinuity both in time and in space (it is available at a given time and at fixed stops). On the other hand, the ownership of a personal car requires an initial investment to buy it, some mandatory costs (e.g., insurance, taxes and so on) and some operational costs (e.g., gas, oil, service and so on). The *car-sharing system* (from hereafter only CS) is a solution able to give the same advantages of a personal car without the aforementioned disadvantages - mainly costs.

More in detail, CS follows a "*Car-As-A-Service*" paradigm [17], i.e. it is a membership based service mainly designed for both short time and distance trips, which is usually available on demand (or reservation) to all qualified drivers belonging to a community [18]. Three types of CSs are commonly identified, namely: (*i*) *Peer-to-Peer* (P2P): it takes place among private users offering their personal cars for money (it was the first type of CS and is receiving a new impulse from information technologies); (*ii*) *Business to Consumer* (B2C): it is made available by business companies with the obvious goal to obtain financial benefits; (*iii*) *Not-For-Profit* (NFP): in this case local communities or social organizations manage a CS service with the main aim to incentive a sustainable urban mobility.

The first CS initiatives were in Zurich (Switzerland) in 1948, Montpellier (France) in 1970 and Amsterdam (Netherlands) in 1971, but only after 1980 in Europe and in the USA the first of positive commercial results were achieved. Nowadays, many CSs (mainly B2C), similar for several aspects, are working all over the world almost exclusively in highly populated cities with significant congestion and parking problems, although there are some examples of CS implementations in medium size cities. Recently, CSs are receiving a strong impulse by improvements in information and communication technologies, which allow specialized companies to connect potential CS users and owners of private cars desiring to rent their personal vehicles when unused [19]–[21].

Given its increasing relevance, many studies have been addressed to explore the main issues characterizing CSs as (*i*) users' response and habits, for instance in terms of usage frequency and effects of information technology [22]–[24] (*ii*) environmental benefits, e.g. reduction of vehicle kilometers, accidents, emissions and fuel consumptions, increase in average speed [25], [26] and (*iii*) cost structure and system organization, including pricing schemes [27], [28] or the combined use of car sharing and public transport [29], [30].

Even though in recent years CS has been growing in popularity among consumers and, consequently, among investors, its market share is limited with respect to other transport modalities so that its impact on the overall urban mobility is essentially marginal. Therefore, to increase demand for and offer of CS services, they should be more attractive for users and investors. To this purpose, different policies can be implemented and combined to support changes in users' habits [31] as, for instance, discouraging the use of private cars in specific urban areas, increasing the number of cars available for rent [32], enlarging the urban areas covered by CS services [33], improving the financial appeal for all the CS actors by making CS services more affordable for customers and, at the same time, by increasing economical benefits for investors.

The implementation of suitable actions addressed to act on the financial aspects of the CS market is then crucial. To analyze the context, the cost of a CS service depends on several factors which can be grouped in *Marketing*, *Organization* and *Production* costs (see below), where the last group also depends on customers' behaviors in using the CS services.

Even though the effects of the driving features are not completely characterized, a general consensus exists on the fact that an "aggressive" driving (e.g. speeding up, hard braking and so on) has more than one negative effect [34]. In particular, it has direct impacts on costs for service, and affects indirectly CS productivity because vehicles should be stopped for maintenance. By promoting good driving habits, some CS costs could be reduced in order to (*i*) offer lower fares to users [34] by making CS more appealing with respect to private cars and/or (*ii*) increase the financial profits for CS activities by supporting existing companies in their initiatives as well as by attracting new investors and new actors in the CS business.

To support this, a possible approach widely exploited in different contexts involving real and virtual communities is represented by the adoption of a reputation system, often combined with agent technologies [35]. Indeed, intelligent software agents can both monitor CS consumers when they are using CS services and compute their individual reputation score. These scores can be used for different aims as, for instance, to select users admitted to CS services, which is particularly useful to encourage more individual owners to share their personal cars, or to determine personalized fares awarding the better customers. At the same time, agents monitoring CS users' driving activities can support them in improving their habits.

In this scenario, the main difficulty is the monitoring of CS customers. However, progresses made in different fields as computer science, electronic, control systems, signal processing and communications make it not a very complex task. The adoption of intelligent software agent technology can help in monitoring users [36], simulating, controlling and managing transportation networks at different levels of detail by providing intelligent decision-making frameworks [35] as well as managing trust and reputation systems [37].

In this paper, we investigate on the opportunity to support CS customers by adopting a distributed reputation scheme within a multiagent system in order to promote CS activities.

In the following, Section II provides an overview of the considered CS scenario and Section III presents the proposed multi-agent architecture, while Section IV describes in detail the activities carried out by the car-agents. The reputation system is described in Section V and the results of the simulated experiments are presented in Section VI. Finally, in Section VII some conclusions are presented.

II. The Proposed Scenario

Commonly, the industrial costs ($\mathcal{C}$) of a CS activity are represented as:

$$\mathcal{C} = C_M + C_O + C_P$$

where:

- C_M is the *Marketing cost* derived by advertising, promotional events and whichever activity addressed to promote the CS use;
- C_O is the *Organizational cost*, which mainly involves costs for employees, buildings, parking areas and similar features;
- C_P is the *Production cost* due to management and use of the fleet.

The relevance of each component is strictly related to the CS business modality, i.e. P2P, B2C or NFP.

Generally, the entries having the greater impact on the *Production costs* are those for buying or renting the fleet, the vehicle insurance, taxes and finally the costs for the fleet maintenance and cleaning. Costs due to the adoption of information and communication technologies are less significant. As previously introduced, some of such costs are related to the habits adopted in using the CS vehicles. Reckless or inappropriate driving habits can lead to accidents or abnormal consumptions of both mechanical parts and consumables and this implies higher costs due to the service and lower profits for the stopped time of those vehicles. Furthermore, in the case of P2P-CS, inappropriate driving behaviors can also force individual owners to avoid sharing their own cars.

An important opportunity for promoting CS activities is to encourage suitable individual driving modalities. Potentially saved money could be used to reduced maintenance costs and also for awarding, with personalized lower fares, those consumers having appropriate behaviors. Therefore, as a hoped result, such behaviors will permit financial benefits for all the CS actors.

The question is "How is it possible to realize this?" Progresses made in computer science, electronic, control systems, signal processing and communications help us to answer the question above. Indeed, vehicles can be currently equipped with at least 120 different types of sensors and their number is increasing quickly (also including those equipments allowing the new form of CS-P2P [19]–[21]). Data gathered by sensors plugged into cars can also be used to analyze drivers' behavior. For instance, some insurance companies make available sensor-based equipments to be placed into cars and offer lower insurance fees because of the possibility to examine in a semi-automatic way the insured driving behavior in case of accident. In this study, we associate each vehicle with an intelligent software agent (hereafter simply agent) that analyzes automatically data collected by the vehicle sensors, classifies each driver based on his/her behavior and assists him/her in improving his/her driving.

Such a classification will be used to compute the drivers' reputation, which can be defined as: "*what is generally said or believed about a person's or thing's character or standing*" [38]–[40]. In other words, within a community the reputation has the meaning of a collective indirect measure of trustworthiness deriving by referrals or ratings provided by the other community members on the basis of their past interactions.

The computed reputation scores will be used for both allowing/avoiding the access to the CS service and determining personalized CS fares, e.g. a greater or a lower discount on the baseline price

III. The Car-Sharing Multi-agent Architecture

In this Section, we provide a short overview about the proposed multi-agent platform, which fits all the types of CS (i.e., P2P, B2C and NFP). The components of this platform are (*i*) a community of agents, named *car-agents* (CA), each one associated with a car, and (*ii*) their *Agency*.

More in detail, for each driving session carried out on the associated car, each car-agent provides to:

- analyze some data coming from sensors plugged on board in order to classify the driving habits of the current CS user;
- support the CS user in improving his/her driving style;
- compute a score (i.e., feedback) on the basis of its monitoring activity, which will be sent to its Agency.

In a complementary way, the Agency provides to:

- collect the feedbacks computed locally by the car-agents to update the reputation score[1] of each user exploiting the CS service the Agency is managing;
- apply specific policies on the basis of the computed drivers' reputation measures (e.g., the Agency allows or denies the access to the CS service, determines personalized fares for the CS service and so on);
- make available some common services to all the CAs associated with it (e.g., the agent white pages).

IV. The Car-Agent Activity

This section describes the car-agent activities introduced in the previous section.

Each car-agent accesses all the data coming from the sensors plugged on board of its associated vehicle that are useful for its goals. Note that almost all the new cars are provided with a significant number of sensors and processors to analyze sensors data. The number of on board sensors (i.e., information sources) is expected to grow significantly, similarly to those on vehicles that currently are equipped to test autonomous driving. In such a context, some future scenarios foresee that within few decades, mainly for safety reasons, only autonomous driving vehicles will be legal [41] and, as a consequence, CS and other forms of mobility, for instance taxi services, will be different from those that we know nowadays. However, the current equipment is already suitable for car-agent activities to be carried out[2].

To realize the agent tasks described in Section III, a given CA analyzes the sensor data collected in real time and exploits them to: (*i*) address the driving habits of the CS users on the basis of its data analysis; (*ii*) compute an overall score for evaluating the driving style of the current CS session.

As for the first task, we note that some dashboards already provide information to the driver mainly to optimize the gasoline usage. In our proposal, we suppose that the CA is able to give driver information useful to optimize the use of the vehicle under a more general point of view (e.g., gasoline, brakes and so on) or, in other words, to optimize his/her driving habits. The second task of the CA is addressed to compute a feedback, identified as F, exploited by the Agency to update the value of the driver's reputation measure as specified in Section V.

To compute the value of F [3], let CA_i be the car-agent associated with the vehicle i and let u_j be a user exploiting that CS service. Moreover, let $F^S_{i,j}$ be the feedback computed by the agent CA_i for the user u_j with respect to the service S into the domain $[0,1] \subset \mathbb{R}$, where 0 means the minimum appreciation for the u_i's driving habits and 1 denotes the maximum one. Based on the information $s^S_{i,1}, \cdots, s^S_{i,n}$ given by the n sensors on the vehicle i, the car-agent CA_i calculates the feedback $F^S_{i,j}$. Different strategies and algorithms can be used for computing such a feedback and, therefore, we describe it as the result of a function $\mathcal{F}(\ )$ depending on the parameters $s^S_{i,1}, \cdots, s^S_{i,n}$ in the form:

$$F^S_{i,j} = \mathcal{F}(s^S_{i,1}, \cdots, s^S_{i,n}) \tag{1}$$

Note that Eq. 1 is the kernel of the system and its correct definition could represent a very complex problem. For a low number of parameters also a simple *if-then-else* approach could be applied; differently, for a high number of parameters other computational techniques, among which fuzzy-logic or artificial neural networks, appear more suitable candidates for implementing F.

V. The Reputation System

In order to compute the drivers' reputation scores, we designed a specific reputation system, realized by the Agency, which satisfies the following three properties, summarized in [42]:

[1]Note that some corrective actions on the reputation scores could be adopted in presence of events that cannot be gathered in an automatic way as, for instance, car body damages, interior cleaning and so on (see Section V).

[2]Similar services are already make available by some fleet management softwares in a centralized way.

[3]Note that the function $\mathcal{F}(\ )$ could not be the same for all the car-agents managed by Ag so that the score evaluations can not be uniform along all the multiagent system.

- each involved entity is time persistent, so that for each interaction an expectation of future interactions always exists;
- reputation ratings about current interactions are captured and spread within the involved community;
- reputation ratings about past interactions are used to guide decisional processes about current interactions.

More in detail, let CA_i be the car-agent associated with the vehicle i belonging to a CS company managed by the Agency and let u_j be the user of the CS service S on i. When the CS service ends, the car-agent associated with the shared vehicle sends to its Agency the feedback $F^S_{i,j}$ for u_j, computed based on the information gathered by the vehicle sensors during S. The Agency will exploit $F^S_{i,j}$ to update the reputation score of u_j.

More formally, let $R_j \in [0,1] \subset \mathbb{R}$ be the reputation of the user u_j. After the car-agent CA_i has sent to the Agency the feedback $F^S_{i,j}$ for the service S consumed by u_j, then the reputation of u_j is updated as follows:

$$R_j^{new} = (\alpha \cdot \sigma^S_{i,j} + (1-\alpha) \cdot R_j^{old}) \cdot P^S_j \qquad (2)$$

where:

- α is a system parameter ranging in $[0,1] \subset \mathbb{R}$ and ruling the behavior of the reputation system. More in detail, it weights the relevance of the parameter $\sigma^S_{i,j}$ (see below), which takes into account the feedback $F^S_{i,j}$, in updating the reputation of u_j (i.e., R_j). In other words, the higher its value, the lower the sensitivity of the reputation at quick changes and vice versa.
- $\sigma^S_{i,j}$ is the contribution to the reputation due to S, which also takes into account the feedback $F^S_{i,j}$. More formally, $\sigma^S_{i,j}$ is computed as:

  $$\sigma^S_{i,j} = F^S_{i,j} \cdot V^S_{i,j} \cdot \xi_i \qquad (3)$$

  where:
  - $F^S_{i,j}$ is the feedback computed and sent by CA_i to the Agency.
  - $V^S_{i,j}$ is a parameter belonging to $[0,1] \subset \mathbb{R}$ and referred to the monetary cost $C(S)$ of the service S (Eq. 4) computed as:

    $$V^S_{i,j} = \begin{cases} 1 & \textit{if } \; C^S_{i,j} = C_{Max} \\ \dfrac{C^S_{i,j}}{C_{Max}} & \textit{otherwise} \end{cases} \qquad (4)$$

    where $C_{Max}(S)$ is a system threshold representing the maximum cost for a CS service after which $V^S_{i,j}$ is considered satured. Therefore, the lower the cost, the lower the effect on the value of the feedback given by the service S. This is a countermeasure introduced to reduce the weight of positive reputation for marginal CS services and then avoid misleading behavior addressed to consume such reputation for expensive CS services. For NFP-CS it is worthless and, therefore, in this case the value of V is set to 1.
  - ξ_j is a system parameter ranging in $[0,1] \subset \mathbb{R}$ intended to give the reputation system a uniform metric by taking into account those characteristics of the CS services not intrinsically considered by the parameter $C^S_{i,j}$ and mainly due to the adoption of different policies by the CS companies.
- P^S_j is a penalization coefficient for u_j ranging in $[0,1] \subset \mathbb{R}$ used in the case of behaviors/effects not automatically detectable/verifiable by the car-agents[4]. For default P^S_j is set to 1, i.e. absence of penalization for u_j.

On the basis of the reputation score the Agency can adopt different fare policies and even deny the possibility of using a CS service to a customer having a very low reputation score.

VI. Experiments

In this section we present the results of two experiments addressed to verify the effectiveness of the approach previously discussed.

The first experiment is addressed to verify if the system can compute a reasonable feedback. To this purpose, the OpenXC repository [43] was exploited. It consists of a number of anonymous tuple, i.e. the data do not permit their association with drivers, referred to different scenarios and driving habits. More in detail, each tupla is made as {"name":"string", "value":integer, "timestamp":time}, where the first pair identifies the type of information, the second pair gives its value and the last pair returns a progressive time. As an example, see the tupla above:

{ "name":"accelerator_pedal_position",
"value":2,
"timestamp":1361454211.483000 }

To solve the problem given by the anonymity of the OpenXC data, we generated 100 driver' profiles belonging to five driver styles (respectively named *very soft*, *soft*, *neutral*, *aggressive* and *very aggressive*). Then for each simulated driver, 10 driving tracks have been built by suitably assembling the OpenXC data for a global number of 1000 driving tracks.

More in detail, each driving category has 20 simulated drivers. Each category is characterized by a different driving habit in terms of aggressive driving data (e.g., hard acceleration, hard braking and so on) included into the tracks data (see Table I) and randomly assigned to each simulated driver. Therefore, for a specific simulated driver the associated driving tracks consist of suitable sequences[5] of homogeneous (e.g., "aggressive" or "not aggressive") OpenXC tuple matching the assigned profile. Finally, given the adopted method

[4]Note that the evaluation of damages as accidents, damages, interior cleaning, penalties and so on, currently have to be necessarily processed by humans.

[5]Each sequence consists of 8 tuple and each driving track is different for number of tuple, i.e. time length.

Driving Category	aggressive/non aggressive ratio
$very\ soft$	1:0 (i.e., only not aggressive actions)
$soft$	from 4:1 to 2:1
$neutral$	1:1
$aggresive$	from 1:4 to 1:2
$very\ aggresive$	0:1 (i.e., only aggressive actions)

TABLE I
THE ADOPTED AGGRESSIVE/NON AGGRESSIVE DRIVING ACTIONS RATIO

to assemble the driving tracks, a timestamps harmonization procedure needed. However, this procedure did not affect the experimental results in any way.

The computation of the feedback F for a driving track (i.e., a driver) is computed on the basis of the ratio between the driving time (in seconds) and the overall number of aggressive actions in that time. In order to identify an aggressive action an Artificial Neural Network (ANN) [44] has been adopted, a tool able to deal with problems denoted by uncertainty and frequently used in trasportation research [45], [46] The ANN has been set up after preliminary tests that identified the optimal pattern structure and the ANN architecture, topology and learning strategy. More in detail, for the ANN training set we used the data coming from the 30% of the generated driving tracks arranged in patterns. Each pattern contains as input 9 data deriving by three tuple [6] and a unique real value ranging in $[0, 1]$ as output data, where 0/1 means minimum/maximum aggressiveness degree. In particular, each tupla consists of an integer number coding the attribute "name", the associated value and the time interval occurring with the previous tupla [7].

The ANN model and learning algorithm we identified as the most profitable solutions, are a three-layer ANN trained by a back-propagation (BP) algorithm [44], having 9, 120 and 1 nodes for the input, hidden and output layers and hyperbolic and sigmoid activation functions for the neurones of the hidden and output layers. The above described trained ANN recognized *aggressive* driver actions on the remaining driving tracks with an accuracy of over 79%, which can be considered a satisfactory preliminary result given the nature of the exploited dataset.

The second experiment is addressed to test the effectiveness of the proposed reputation system. To this purpose, 1000 simulated drivers have randomly associated with the driver typologies presented in Table I. Two different scenarios were considered: the first scenario (named A) assumes a uniform drivers' behavior along all the simulation, while the second one (named B) is addressed to test the robustness of the reputation system as regards to oscillatory behaviors by assuming that aggressive drivers try to build a positive reputation on cheap CS services for consuming it on expensive CS services (25% of the CS services was assumed to be expensive). In the simulations, the reputation system parameters α, ξ and P were respectively set to 0.15, 1 and 1, while the feedback F and the parameter V were randomly generated coherently with the drivers' nature and the involved scenario. When the simulation starts, all the drivers receive an initial reputation score of 0.5 and for each *epoch* only 20% of the overall number of drivers is randomly selected. Clearly, the higher is the percentage of drivers correctly identified, the higher is the accuracy of the proposed reputation system.

Both scenarios provided satisfactory results (depicted in Figure 1). In particular, line A shows that 90% of the drivers nature is correctly recognized after less than 80 epochs. Note that initially all the *normal* drivers are recognized and, although it is due to the assigned initial reputation score of 0.5, this result does not change along all the simulation. Some tests carried out by adopting a different initial reputation score (e.g., 0.75) led to a similar result. The proposed reputation system works well also in presence of drivers' oscillatory behavior and 90% of the *aggressive* drivers have been recognized (line B) after less than 140 epochs also under these particular conditions.

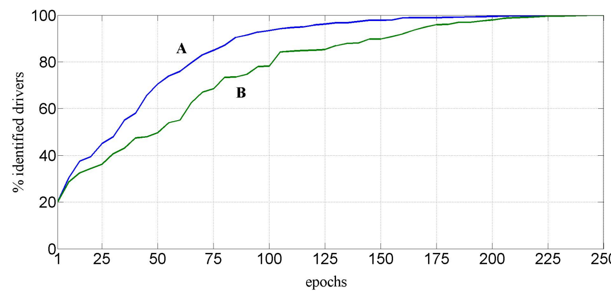

Fig. 1. Percentage of drivers correctly identified. Scenarios A and B.

VII. CONCLUSIONS

CS can play an important role to support public and private mobility and contribute to reduce traffic and environmental problems affecting urban contexts. To this purpose, in this paper we investigated about the possibility of improving convenience and profits for CS users and CS suppliers, respectively.

To address these issues we propose the adoption of a reputation system implemented by intelligent software agents and tested by performing some experiments based on real and simulated data. The aim is to identify good driving behaviors to reduce CS fees, and vice versa, thus making the system more attractive for both CS users and CS suppliers. The first experiment exploited real vehicular sensor data to identify the driving users' habits; the second one, based on simulated data, verified the effectiveness of the proposed reputation system for two scenarios. The results of these preliminary experiments encourage future researches for further developments of this proposal.

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[6]The target tupla and those referred to the previous and following actions.
[7]Note as the first tupla of each driving track is not considered.

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