On the Performance of a One-way Car Sharing System in Suburban Areas: A Real-world Use Case

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Abstract: In recent years, one-way car sharing systems have gained momentum across the world with their promise to encourage more sustainable urban mobility models. However, economic viability of car sharing is still uncertain due to high investment cost for station and fleet deployment, as well as high operation cost for fleet management and rebalancing. Furthermore, existing car sharing are typically confined to city centres with significant business and residential concentrations. In this study, we evaluate the performance of a novel one-way car sharing system that will be deployed in a suburban area of the city of Lyon using a detailed multi-agent and multi-modal transport simulation model. Data from a recent large-scale household travel survey is used to determine the travel demands on different transportation alternatives. We analyse the impact of different coverage constraints on the system capacity in terms of number of trips and vehicle availability. We also investigate the potential of user-based relocation strategies to increase the efficiency of the car sharing service. The model shows that: (i) the car sharing system is most sensitive to the infrastructure and fleet sizes, and (ii) user-based relocation does not have a significant impact on the total number of car sharing trips.

1 INTRODUCTION

Car sharing systems are innovative mobility services that are increasingly becoming popular in urban and sub-urban areas and have the potential to solve real-world problems of urban transports (Hampshire and Gaites, 2011). The principle of a car sharing system is that customers can rent for limited period of times a car from a fleet of shared vehicle operated by a company or a public organisation. Although car sharing services have been proposed in the early 1970s, they have emerged as a worldwide phenomenon only in the last decade. This is due to the deployment of one-way car sharing systems in which the customers are allowed to leave the rented car at a drop-off location different from the pickup location (Barth and Shaheen, 2002). This provides an increased flexibility for the users compared to two-way systems.

Typically, one-way car sharing systems suffer from unbalance distribution of available vehicles in the service area. Specifically, some locations can be more popular than others at different times of the day (e.g., residential areas at night-time as opposed to industrial and commercial areas at peak hours). This imbalance of demand easily results into situations in which vehicles accumulates in areas where there is a lower number of rental requests, while at the same time there is shortage of vehicles where they are more needed (Barth et al., 2004). When this happens, the operator can resort to rebalancing policies, i.e., redistributing vehicles from where they are not needed (taking into account the expected demand in the near future) with the objective of serving more effectively the travel demands. Clearly, this has a cost for the operator, thus redistribution should be performed only when economically viable.

However, before the operator resorts to rebalancing, he needs to know the optimal solution for infrastructure planning, giving the high investments costs and travel demand. In other words, he needs to determine the number, size and location of parking stations to deploy in the area where the car sharing system is supposed to operate in. In the literature, this problem is generally solved considering a spatial-temporal formulation of a MILP (de Almeida Correia and Antunes, 2012; Boyacı et al., 2015). In our previous work, we formulated a set-covering model coupled with queuing theory to guarantee certain level of service to customers (Boldrini et al., 2016).

Different approaches for vehicle relocation in car

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sharing systems exist (Weikl and Bogenberger, 2013). Operator-based solutions require the use of dedicated staff for executing the redistribution tasks. On the contrary, user-based solutions rely on users willing to relocate vehicles to locations where they are needed, usually on the basis of an economic incentive. However, both approaches can be costly. Furthermore, it is still uncertain whether users are willing to accept incentives for deviations from their destinations. Finally, the design of optimisation frameworks for the decision of which vehicles to relocate to which location can become intractable due to the extremely large number of relocation variables (Boyacı et al., 2015).

To cope with the aforementioned issues, in this paper we design a relocation algorithm that is inspired by physical arguments and leverages on an analogy between relocation tasks and thermal conduction. Specifically, the redistribution of vehicles from locations where they get accumulated to locations where there is a shortage of vehicles is modelled as a temperature gradient. Another key feature of the proposed relocation algorithm is that it is designed to operate with a new class of lightweight vehicles, called ESPRIT cars, which can be stacked, recharged and driven in a road train (ESPRIT, 2015). This is supposed caters for more efficient relocations since a single customer can relocated two vehicles at the same time.

To validate the performance of the proposed relocation strategy on a meaningful case we use the city of Lyon as case study. Specifically, we use a multi-agent simulation framework that we have previously designed (Laarabi and Bruno, 2016). It is based on MATSim, a popular open-source and agent-based traffic simulation platform, which supports dynamic traffic assignment, large scenarios and detailed modelling of transportation networks (Balmer et al., 2004). Then we set up a scenario using data from the 2015 Lyon conurbation household travel survey, which provides information about more than three million trips, and public data on the Lyon's public transit systems. Then, we analyse the impact of the infrastructure planning strategy (Boldrini et al., 2016) as well as the user-based relocation on the car sharing performance in terms of number of rental trips.

The remainder of this paper is organised as follows. Section 2 provides an overview of related literature on infrastructure planning, vehicle relocation and car sharing performance evaluation. Section 3 introduces the ESPRIT car sharing system and the user-based relocation in such a system. Section 4 describes the Lyon case scenario and travel demand. Section 5 discusses the simulation results. Finally, Section 6 draws final remarks and outlines future work.

2 RELATED WORK

There is vast body of research work on the design of optimal solutions for the planning and operation of car sharing systems. In the following, we overview previous works that are most related to this study.

2.1 Models for Infrastructure Planning

Infrastructure planning tries to determine the number, size and location of parking stations in a car sharing system in order to maximise some performance measure, such as demand coverage or profit. From a general point of view, this is an instance of the facility location problem, which is an optimisation problem extensively studied in the field of logistics and transportation planning (Farahani et al., 2012).

Existing planning frameworks typically rely on time-space optimisation approaches, which are models that assume a deterministic knowledge of the demand of vehicles at each time interval of the control period. For instance, A MILP formulation is used in (de Almeida Correia and Antunes, 2012) to maximise the profits of car-sharing system, which simultaneously optimises the location of parking stations and the fleet size under several trip fare schemes. The proposed model is then used to analyse a case study in Lisbon. A recent work (Boyacı et al., 2015) addresses the planning of an electric car-sharing system using a multi-objective MILP model that simultaneously determines the number, size and locations of stations, as well as the fleet size taking into account vehicle relocation and electric vehicle charging requirements. More recently, new modelling approaches (eg. queuing theory and fluid models) have been proposed to take into account that the demand process of customers is stochastic and exhibits seasonal effects. For instance, a closed queuing network modelling of a vehicle rental system is proposed in (George and Xia, 2011) to derive some basic principles for the design of system balancing methods. In our previous work (Boldrini et al., 2016), we formulated a set-covering model that minimises the cost of deployment (in terms of number of stations and their capacity) and leveraged on queuing theory to also guarantee a pre-defined level of service to the customers (in terms of probability of finding an available car/parking space).

2.2 Relocation Strategies

Vehicle relocation strategies can be classified into the following two broad categories: (i) user-based schemes, which incentive customers to participate in the relocation program, and (ii) operator-based schemes, which leverage on dedicated staff for relocation activities.

In (Kek et al., 2006) two operator-based strategies are simulated. The shortest time strategy relocates vehicles to minimise the travel times of staff members. The inventory balancing strategy moves vehicles from over-supplied stations to stations with vehicle shortage. In (Kek et al., 2009) an inter-programming model is developed to minimise the costs associated to staff-based relocation. A similar model is developed in (Jorge et al., 2014) to maximise the profit of the car sharing operator. In (Nair and Miller-Hooks, 2011) a stochastic MIP model is formulated to optimise vehicle relocations, which has the advantage of considering demand uncertainty. A multi-objective MILP model for planning one-way car-sharing systems is developed in (Boyacı et al., 2015) taking into account vehicle relocation, station deployment and electric vehicle charging requirements. The design of optimal rebalancing algorithms with autonomous, self-driving vehicles has been recently addressed in (Pavone et al., 2012) using a fluidic model, and (Zhang and Pavone, 2016) using a queueing-theoretical model. An alternative approach for operator-based relocation scheme consists in selecting trips so as to reduce vehicle imbalance, for instance by rejecting trips to stations with parking shortage (Uesugi et al., 2007; de Almeida Correia and Antunes, 2012).

User-based relocation policies are typically considered more convenient for the car sharing operator as they do not require the use of a staff. However, it is still uncertain whether users would be willing to participate in a rebalancing program by accepting an alternative destination or a more distant vehicle (Herrmann et al., 2014). For this reason, most of the studies in this field focus on designing pricing incentive policies for encouraging users to relocate the vehicles themselves (Febbraro et al., 2012; Clemente et al., 2013). Clearly, the effectiveness of these schemes highly depends on users' participation and their willingness to accept changes of their travel behaviours.

2.3 Simulation of Car Sharing Systems

In general, evaluating the performance of a car sharing system is a difficult task due to the complex and time-variant interplay between the demand and supply processes. Specifically, the availability of vehicles in a car sharing system is intrinsically dependent on trips that are demanded by the customers and vice-versa. In addition, there are several operational conditions that add uncertainties to the system about the future location of vehicles, such as the impact of pricing schemes impact on the decisions of individual users. Therefore, a simulation approach can be very useful to cope with operation complexities and to quickly evaluate the effectiveness of different planning and operation models.

Studies of micro-simulation for performance evaluation of carsharing system has been investigated as early as 1982 (Bonsall, 1982). During that period, there was not yet the large panel of traffic simulation tools that are existing nowadays. Thus, the critics held by the author in (Bonsall, 1982) regarding the computational complexity and availability of data should be taken in moderation. In 1999, a queuing-based transport simulation has been proposed by (Barth and Todd, 1999) for the assessment of the performance of a shared one-way vehicle system. Different measures of efficiency were determined, such availability of vehicles, their distribution and energy consumption, while some relocation strategies were tested. However, the simulation model is exactly predictive and does not capture the inherent uncertainty of real world systems. A more detailed car sharing simulation model and open source was introduced by (Ciari et al., 2013), where it is based on multi-modal agent-based traffic simulator, such that each agent seeks to fulfils its daily plan as a set of activities connected by legs. In our previous work, we designed a similar but more sophisticated car sharing simulator (Laarabi and Bruno, 2016), in such a way to separate the carsharing mobility simulation model from the operational and demand model. The purpose is to allow users test different operational models and strategies using the same tool. We have, therefore, used this simulation model to study the performance of a new car sharing system deployed in a suburban area of Lyon.

3 ESPRIT: RELOCATION CASE

The underlying design principles of cars are rapidly evolving and the design of innovative lightweight vehicles is coming to the fore of current academic and industrial research programs. The long-term vision is to reinvent urban mobility systems by leveraging on vehicles specifically designed for city use with significant smaller spatial use and carbon footprints, as well as considerably less expensive to own and operate (Mitchell et al., 2010). For instance, several concept prototypes of stackable, and foldable two-seat urban electric cars are currently under development, such as the MIT BitCar (Vairani, 2009), or EO Smart (Birnschein et al., 2012). A step forward is take by the ESPRIT European Project that is designed and prototyping a new vehicle that is stackable with mechanical and electrical coupling, and it can be driven in road trains as shown in Figure 1.

Figure 1: The architecture of an ESPRIT-based car-sharing system (ESPRIT, 2015).

ESPRIT vehicles have the potential to facilitate the deployment of one-way car sharing by also supporting more efficient operational procedures. In particular, redistribution is made easier because the vehicles can be driven in a road train. As a consequence, a single staff can drive a road train of up to eight vehicles, or users may drive a road train of two vehicles with a conventional driving license. As discussed in the previous section, one of the main hurdles for user-based relocation strategies is to encourage the users to change their destination to perform a relocation task.

With ESPRIT, we can afford a different way of user-based relocation, where operator can take advantage of actual trips and augmenting their relocation efficiency by delivering two vehicles instead of just one. However, this strategy has been proven, in the following paper, to have a low impact on the total number of car sharing trips.

Typically, current relocation systems are based on complex integer programming models that do not scale to the size of real-world car sharing systems. In this study we adopt an alternative approach that is inspired by the physical laws that describe heat conduction. Specifically, we assume that car sharing stations behave as heat source in the field, while relocated vehicles behave as particles that conduct heat from the stations to each other. Then, the difference in vehicle availability at each station is assume to be equivalent to temperature difference in a field. More formally, let us denote the temperature $T_i(t)$ of a station s_i during time interval $[t, t+\tau]$ as follows

$$T_i(t) = T_i^0(t) + \lambda_i(t) - \mu_i(t) \tag{1}$$

where $T_i^0(t)$ is defined as the number of vehicles that are parked at station s_i at the beginning of the time interval $[t, t+\tau]$. According to formula 1, a station s_i is an hot spot if vehicles accumulate at the station, while is a cold spot if vehicles disappear from the station during the time interval $[t, t+\tau]$. Then, vehicle rebalance would require to move heat from hot spots to cold spots.

However, a vehicle relocation task has a cost for the operator because the customer must be incentive to participate in the rebalancing program. Thus, it is reasonable to assume that relocation opportunities are limited. Thus, rebalancing activities should be prioritized by given precedence to relocations between stations with the maximum temperature difference (i.e., the maximum unbalance of vehicle availability). More formally, let $R_h(t)$ be a ranked list of the hot spots, in which the stations are sorted in descending order of temperature (i.e., the top ranked station is the one with the highest vehicle surplus). Similarly, let $R_c(t)$ the ranked list of the cold spots, in which the stations are sorted in ascending order of temperature (i.e., the top ranked station is the one with the highest vehicle shortage). Then, relocation trips are only allowed between the m top-ranked stations in the two lists. This policy ensures that relocation trips are performed only to stations that have a potentially high number of blocked customers, and that vehicles are taken only from stations with a large vehicle surplus. Note that necessary conditions for the feasibility of a relocation trip between station s_i and destination s_j are: i) $T_i(t) \geq 0 \geq T_j(t)$; and ii) $p_{ij} > 0$. Clearly, the closer m is to n, the larger is the number of feasible relocation trips that are actually performed. The relocation model could be further complicated by assuming that customer k interested in travelling from station s_i to station s_j is willing to accept to relocate a second vehicle by receiving an economic incentive e_{ij} with a probability:

$$g_{ij}^k(e_{ij}) : R_{\geq 0} \longrightarrow [0, 1]. \tag{2}$$

It is reasonable to assume that a relocation between station s_i and station s_j is more effective if the difference $\Delta T_{ij}(t) = T_i(t) - T_j(t)$ is high. Thus, the economic incentive could be determined in such a way that the probability of accepting a relocation task is proportional to $\Delta T_{ij}(t)$. Finally, our rebalancing algorithm can be briefly summarised as follows:

1. At time $t' \in [t, t+\tau]$ a customer k generates a request for a rental vehicle from location O to location D;

2. The central controller of the car sharing system determine the station s_i that is the closest to location O with an available vehicle, and the station s_j that is the closest to location D with an available parking space;

3. The central controller checks if $\Delta T_{ij}(t) > 0$ and if both station s_i and station s_j are ranked in the first m top positions of ranking $R_h(t)$ and $R_c(t)$, respectively. If yes, a relocation task is decided;

4. The central controller offers to customer k an economic incentive to ensure that the customer accept the relocation task with a probability that is proportional to $\Delta T_{ij}(t)$.

For the sake of simplicity, in the following evaluation we assume that $g^k_{ij}(e_{ij}) = 1$, i.e. a customer is always willing to participate to the relocation activities. The incorporation of the users choice models in the rebalancing design is left as future work.

4 SCENARIO AND TRAVEL DEMAND DATA

Our simulation model is applied to a case study in the city of Lyon. The operating area of the simulated car sharing system is shown in Figure 2, and corresponds to three suburban district of the city of Lyon. The road network is constructed from OpenStreetMap data. Regarding the public transit systems, we use data publicly available from Grand Lyon Data platform[1] to define transit routes and modes (buses, tram, underground), transit stops, as well as schedules and vehicles capacities.

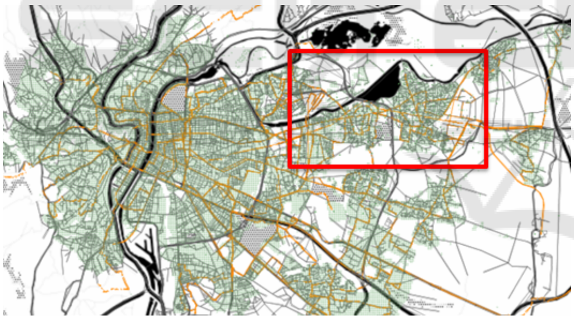
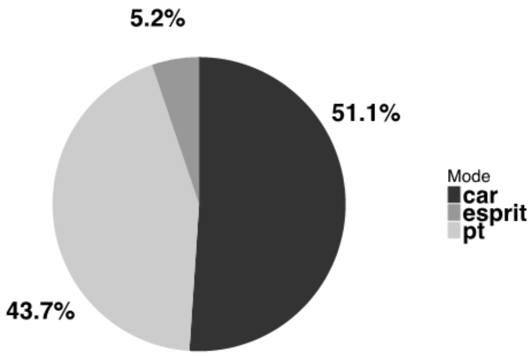


Figure 2: Lyon map on Via traffic visualizer, showing the road network (gray lines), the public transit network (orange lines), the facilities (green dots), and the study area marked with the rectangular frame.

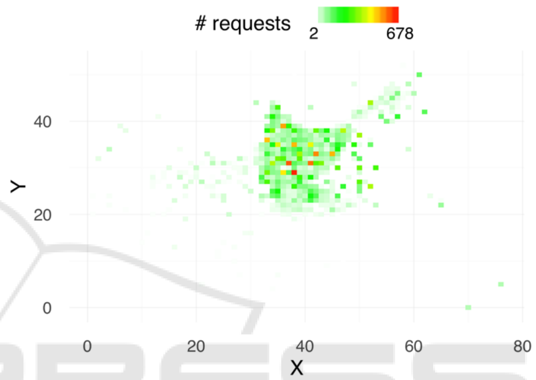
One of the most important modelling task is to construct the travel demand for different transportation modes. Traditionally, travel demand data is organised as trip origin/destination (O/D) matrices, which simply contain the number of trips that are taken from an origin node to a destination node in a specific period of time.

However, since we use a multi-agent modelling approach, the travel demands are constructed as individual daily plan dairies, which contain sequence of activities and the preferred transportation mode for trips between activities. Then, we use data from the

[1] http://data.grandlyon.com/.



(a) The modal share: private cars, ESPRIT car sharing, and public transport



(b) Estimated spatial distribution of the demand by number of requests

Figure 3: The simulated demand of the Lyon Scenario.

2015 Lyon Travel Survey to synthesise the population of travellers and their travel demands. More precisely, the traffic demand is provided in terms of travel modes and travel purposes of 20,244 households distributed across the area. Census data is used to expand the travelling population of the survey to 133,981 travellers. Four types of travel purposes are considered: work, shopping, leisure, and school. Activities are performed in related facilities, which are randomly placed within the area based on travellers' densities. Note that our travel demand includes only trips that have an origin/destination in the case-study area or that go through the study area (thus, contributing to traffic congestion).

The constructed demand is depicted by both the modal share in Figure 3(a) and the spatial distribution in Figure 3(b). On one hand, 5.2% of the trips are car sharing trips. To put it in numbers: the people who would like to use ESPRIT in Lyon study area are 8345 out of 133981, while the car sharing trips represents 18952 out of 363502. On the other hand, there are surrounding areas with very low number of potential car sharing requests. This led us to wonder whether it is worthwhile to provide a car sharing service in those areas!

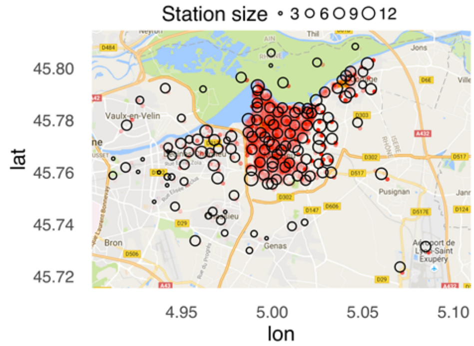
5 RESULTS AND DISCUSSION

Our car sharing model is implemented in MATSim, a popular open-source and agent-based traffic simulation platform, which supports dynamic traffic assignment, large scenarios and detailed modelling of transportation networks (Laarabi and Bruno, 2016; Balmer et al., 2004). We evaluate the performance of the proposed rebalancing algorithm from the perspective of the car sharing provider. Specifically, the car sharing operator is interested in maximizing its net profit. Clearly, a key contribution to the operators profit is due to revenues from the rental services provided to the customers. Note that users are charged for the distance they travel, or the time they reserved the car, or both. Thus, the first metric of interest is the total number of rental trips. However, the potential increase in the transportation demand or a rebalanced system comes at cost of additional trips due to vehicle relocations. Thus, the next metrics of interest are the number of relocation trips and the average length of relocation trips. The latter metric is important because relocation trips consume energy and vehicle battery have to be recharged before a rental trip.

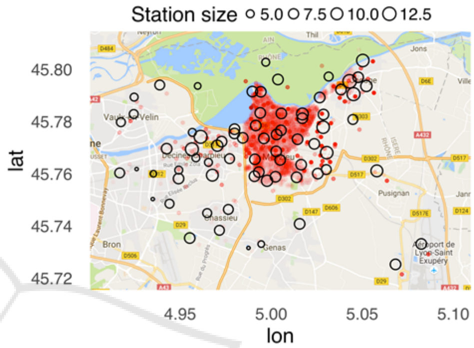
Before assessing relocation performance, we set up two scenarios such as each one of them correspond to a different infrastructure planning, using the our approach previously discussed in (Boldrini et al., 2016). The objective is to compare the two scenarios on the basis of the first metric, that is the number of trips. We refer to the first deployment with *Coverage 1*, as in Figure 5(a), such that there are 135 stations with 1023 parking space and 409 car sharing vehicles, while each station is assumed to have a coverage radius of 380 meters. Figure 5(b) shows the second deployment, called *Coverage 2*, which sets 72 stations with 549 parking space and 220 car sharing vehicles and a coverage radius of 635 meters. Note that the fleet size represents 40% of the total parking space, a percentage considered as a rule of thumb, as it is the case for Autolib in Paris.

Results are depicted by Figure 5 that refers to the availability of cars and parking spaces in stations in the case of both coverages, and Figures 6-7, which refers to the number of trips and distances covered by each trip.

We observe then that our deployment strategy is, on one hand, very effective in ensuring parking availability, while car availability is much more difficult to ensure. Since deploying large stations in a dense

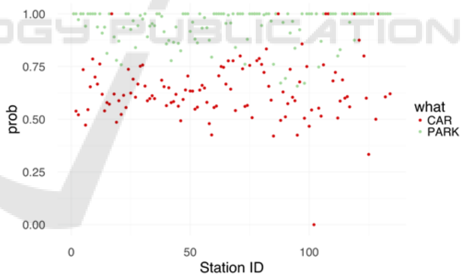


(a) Coverage 1: 135 stations with a radius of 380m

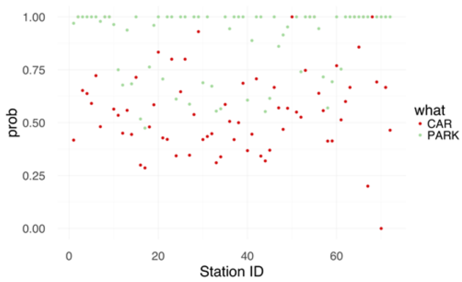


(b) Coverage 2: 72 stations with a radius of 635m

Figure 4: Station deployment such that cost of station is equivalent to cost of parking spaces.



(a) Coverage 1

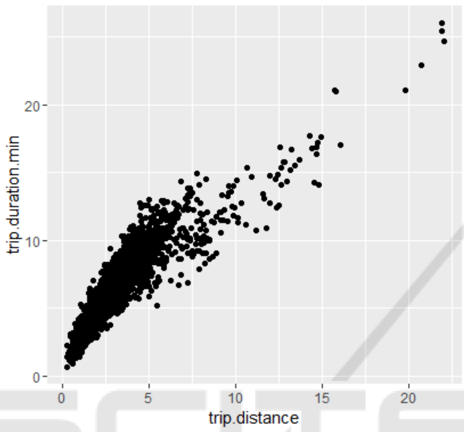


(b) Coverage 2

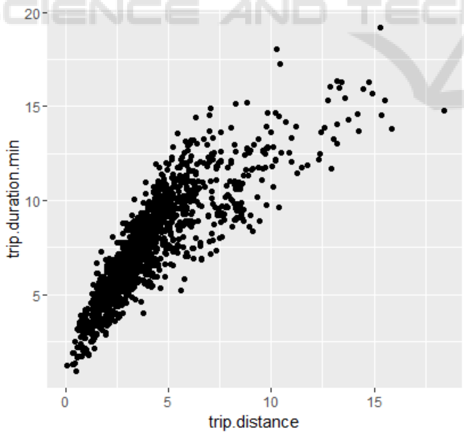
Figure 5: Car & Park availability.

manner is not sufficient, because fleet size remains an important factor. On the other hand, with less deployed station parking availability becomes more critical, which requires improving the strategy to better capture availabilities in sparse networks.

From the figures related to the first and second metric, we remark longer trips duration and less number of trips (rotations) per vehicle for *Coverage 1*. While with *Coverage 2* the results show shorter trips and wider difference between trips distance and travel time, as well as more rotations per vehicle. It is worthwhile to mention that the high number of rotations per vehicle is due to the small size of the suburban area where the car sharing system is deployed.



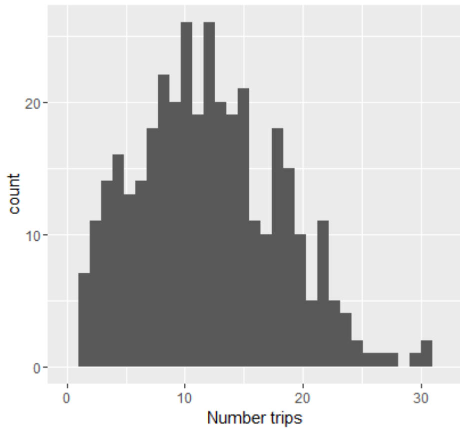
(a) Total number of trips is 10760 (56.7% of the total demand), with R=380m, S=135, K=1023, V=409



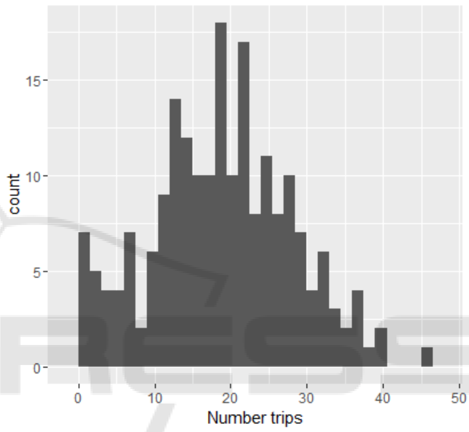
(b) Total number of trips is 6552 (34,5% of the total demand), with R=635m, S=72, K=549, V=220

Figure 6: The proportion trip distance per travel time.

When applying user-based relocation strategy to both deployment, the improvement (new trips) was only 0.04%. Figure 8 shows that there are many stations that seem to have a good potential for relocation, such as red triangles refer to high temperature stations i.e. many more drop-offs than pick-ups, while blue



(a) R=380m, S=135, K=1023, V=409



(b) R=635m, S=72, K=549, V=220

Figure 7: The proportion trip distance per travel time.

triangles refer to low temperature stations i.e. many more pick-ups than drop-offs. However, due to the fact that the model is constrained by real trips, which happens to not be going from hot stations to cold station, user-based relocation cannot take advantage of the unbalance in the system unless we encourage customers to change their destination, such as trips coming from hot station would be directed to cold stations. Besides, some stations with hot temperature might not be that hot as there are many high pick-ups/drop-offs events during a short period of time, and any decision of relocation from such stations might disturb the original car sharing traffic flow.

Finally, the availability of vehicles is significantly high during the day as shown by Figure 9. This is due to the fact that very few trips are connecting hot stations with cold stations, as mentioned before hand, and therefore inviting a customer to take a second vehicle with him/her cannot solve the situation. Therefore, an operator-based relocation would clearly address this issue with more flexibility, which leaves the door open for a possible theoretical hybrid approach

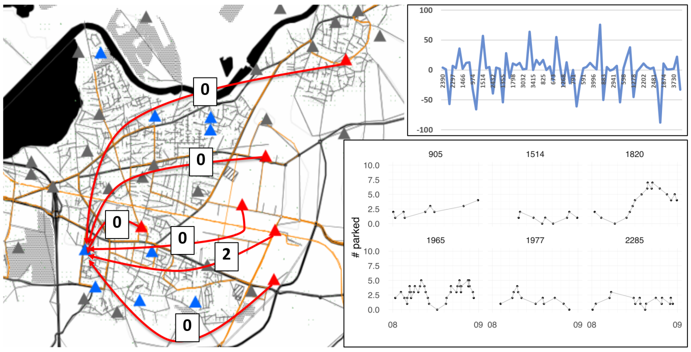
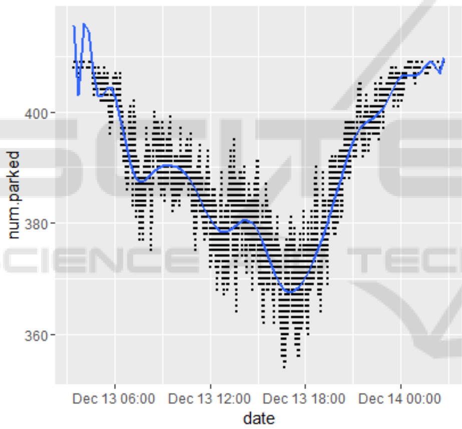
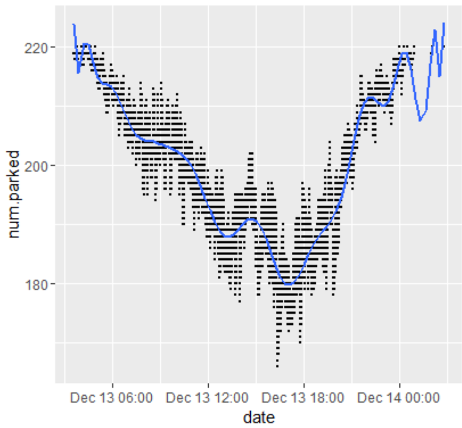


Figure 8: On the left: Study area map between 8:00AM and 8:30 AM on which blue triangle refers to very cold stations, while red triangles refers to very hot stations. Numbers in boxes refer to number of trips going from hot stations to cold stations during same period. On the top right, temperature graphs of stations between 8:00AM and 8:30 AM, while bottom right, temperature of individual stations during same period.

where both operator and user relocation co-exists to solve the unbalancing problem while minimizing the operational costs.



(a) R=380m, S=135, K=1023, V=409



(b) R=635m, S=72, K=549, V=220

Figure 9: Vehicle availability during the whole simulated day.

6 CONCLUSION

The objective of the paper is to evaluate the performance of a one-way car sharing system in a suburban area of Lyon, France. Two different deployments have been generated then tested with the car sharing simulation framework. While we have obtained clear distinction in the number rotations per vehicle and trips distances between the two deployments, we have deduced also that user-based relocation does not have a significant impact on the total number of car sharing trips. For this reason, as an ongoing work, we intend to focus on the operator-based relocation as it offers better guarantee for solving the unbalancing problem and significantly increase of the number of total trips.

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