# A City-aware Car Parks Marketplace for Smart Parking

Claudia Di Napoli[1][a] and Silvia Rossi[2][b]
[1]*Istituto Di Calcolo e Reti Ad Alte Prestazioni, C.N.R., Naples, Italy*
[2]*Department of Electrical Engineering and Information Technologies, University of Naples Federico II, Naples, Italy*

Keywords: Automated Negotiation, Multi-Agent Systems, Smart Parking, Resource Allocation, Social Welfare.

Abstract: Searching for a parking space in high populated urban areas is one of the major sources of traffic congestion, increased carbon emission, and wasted time for drivers. In this work, a multi-agent smart parking system is proposed to reserve parking spaces in response to parking requests. It is based on a distributed negotiation mechanism simulating a car park marketplace composed of parking space buyers and sellers. Negotiation is used to obtain parking allocations by taking into account different needs regarding parking location and price, an efficient distribution of parking spaces, and car circulation restrictions. In order to simulate a realistic marketplace, the distributed negotiation mechanism occurs among a set of drivers requesting parking spaces, and a set of parking vendors. The aim of the experimental evaluation is to determine the scalability of a distributed marketplace with respect to parking space re-sellers that share common city policy regulations, to allow for a smart distribution of allocations. The negotiation outcome is experimentally evaluated by considering the resulting social welfare of all the involved negotiators.

## 1 INTRODUCTION

Several studies highlighted how the problem of searching for a parking space in high populated urban areas is one of the major sources of traffic congestion, increased carbon emission and, not least, a very frustrating and time-consuming experience for drivers (Polycarpou et al., 2013). Commercial products have already been developed to equip urban areas with vehicle sensors, wireless communications, and data analytics systems in order to collect parking availability and location (Nakamura et al., 2000), so increasing the probability for drivers to find park spaces.

Nevertheless, these solutions leave the burden of making the parking decision on the drivers according to the available information on the destination area, but without limiting the competition for the available parking spaces. This forces to re-plan the search with consequences on the city life, and sometimes causing even more congestion in the monitored areas. Moreover, these solutions often do not support drivers in finding parking spaces that can be satisfying, since drivers unfamiliar with the location may not be aware of available alternatives that are not in the destination area, but are easily connected with it, for example by using public transportation (Di Martino and Rossi, 2016). In addition, the fragmentation of public and private parking owners, each one adopting their own technology to collect occupancy data and to advertise their availability, does not allow for a better utilisation of the parking spaces offered by a city as a whole. Indeed, smart parking applications should include benefits and revenues for the city itself. They should make it easier for drivers to find parking spaces, but also to take into account specific city needs that may change in time according to volatile events affecting car circulation at a specific time.

In this context, centralised agent negotiation mechanisms are proposed in our previous works to manage parking supply and demand. In (Barile et al., 2015; Di Napoli et al., 2014), negotiation occurs among software agents representing drivers searching for parking spaces, and one software agent representing a city authority in charge of administrating a set of parking spaces belonging to different car parks located in different city zones. The city authority is in charge of taking into account drivers preferences, parking vendors requirements, and social benefits for the city, so simulating a car parks marketplace where different and sometimes conflicting interests have to converge to a common solution, if any. Nevertheless,

[a] https://orcid.org/0000-0002-8626-5805
[b] https://orcid.org/0000-0002-3379-1756



Di Napoli, C. and Rossi, S.
A City-aware Car Parks Marketplace for Smart Parking.
DOI: 10.5220/0010227102420249
In *Proceedings of the 13th International Conference on Agents and Artificial Intelligence (ICAART 2021) - Volume 1*, pages 242-249
ISBN: 978-989-758-484-8

centralised negotiation models based on a single agent acting as parking re-seller are not suitable when the number of parking requests, and the number of managed parking spaces increases.

In the present work, differently from the previous centralised negotiation, a distributed negotiation mechanism is proposed occurring among a set of agents representing drivers, and a set of agents representing parking re-sellers, each one responsible for managing car park belonging to a specific city area. The car parks managed by the set of parking re-sellers are distributed in different city location, so covering wide city areas. Parking re-sellers negotiate in their own economic interests trying on the one hand to fill the less occupied car parks to increase their income, and on the other hand to meet user requirements regarding parking spaces. At the same time, they try to avoid the circulation and occupancy of city zones that are subject to certain limitations for circumstances that can occur in an unexpected and dynamic way (e.g., a strike, a protest, road works, and so on), or for specific city planning (e.g., pedestrian zones, resident-only zones, and so on), so preserving also city interested. To evaluate the benefits of the proposed mechanism, the outcomes of the negotiation are measured in terms of social welfare accounting for the different needs considered during negotiation.

The evaluation of the distributed negotiation mechanism shows that when more parking re-sellers are involved sharing the same city policies other than to their own profit, the global social welfare has the same trend. Furthermore, the proposed approach has the benefit to manage, and hence allocate, more parking spaces with respect to the centralised negotiation.

## 2 A CAR PARK MARKETPLACE

From an open market point of view, the problem of finding and booking a vacant parking space in densely populated urban areas involves drivers (i.e., buyers) who want to find a vacant parking space that meets their requirements, but also parking spaces suppliers (i.e., vendors) who want to maximize their economic incomes by selling as many parking spaces as possible. Their interaction can be modeled as a demand and supply market mechanism regulating the parking space allocation. Nevertheless, in a smart city, in order to limit the negative impact on the city caused by looking for a parking space, also the city needs concerning car circulation should be taken into account. This is to avoid car circulation in specific areas of the city, to have a fair distribution of parking spaces among drivers, and to limit traffic congestion in the proximity of car parks. In this context, finding a parking space is not merely a selection problem in a sequence of alternatives, but rather the possibility to find an agreement accommodating different needs coming from drivers, parking owners, and city managers aware of city needs regarding car circulation.

In this context, the proposed Car Park Marketplace is an infrastructure aimed at helping drivers to reserve parking spaces by serving their requests through negotiation. Negotiation takes place among a set of Driver Agents (DAs), each one acting on behalf of a driver that wants to reserve a parking space for a required time in order to reach a specific destination, and a set of Parking Managers (PMs) that supply/resell parking spaces. Utility functions, mapping the DAs and PMs evaluation criteria on the negotiation outcome, lead to a partial ordering of outcomes, so providing a measure of the satisfaction level of that outcome for the respective agents (Barbuceanu and Lo, 2001). The allocation of a parking space occurs if an agreement can be found as the result of the automated negotiation process.

In order to consider both the PMs incomes and city needs when allocating parking spaces distributed among the available car parks, a business model is associated to PMs modelling the economic needs of car parks suppliers/re-sellers. The model is based on the assumption that PMs try to fill their car parks as much as possible to improve their profit, and, at the same time, they act to meet the same city needs consisting in limiting traffic congestion due to the concentration of cars in specific and/or more requested city areas.

The DA model is based on the assumptions that drivers have preferences on the cost and the location of a parking space, and that they are unaware of parking spaces that could be available for their needs, so they do not have enough information to make counterproposals. For this reason, each DA decides whether to accept or not a parking space allocation by considering only its own utility value. The utility is compared with a value, called *threshold value*, associated to each DA, that characterizes its attitude to reach a compromise determining the acceptance of an offered parking space.

### 2.1 Negotiating for Parking Allocations

For each DA's request, a negotiation process consists in $m$ one-to-many iterative sub-negotiations, each one occurring between a DA and one of the $m$ PMs that received the request. Only PMs make an offer by proposing a parking space, at each negotiation iteration. On the contrary, a DA does not issue a counterproposal, and it can only accept or reject a received offer. A single sub-negotiation with a PM can proceed until there are available parking spaces (corresponding to different off-street parking places with different attribute values) to offer, so the maximum number of iterations, known as the *negotiation deadline*, is different for each sub-negotiation and it is set by each PM as the number of available car parks it is in charge of. The deadline is not known to the DA that can keep on negotiating until at least one PM has an available parking proposal. The negotiation occurs in an incomplete information configuration from the DA side, since the information on all the available car parks is known only to the PMs, even though each PM only knows the car parks it is responsible for. The incomplete information setting leads to the possibility of accepting a sub-optimal agreement.

A negotiation starts with a DA that sends a parking request, `cfp`, to all the available PMs. If there are not available offers, the negotiation ends with a failure. Otherwise, the DA collects the offers received by each PM (within a fixed deadline), it evaluates them according to its utility function, and it selects the one with the greater utility (best bid $B$). In case the selected parking space satisfies the driver's requirements to some extent (i.e., the utility values for the DA is greater that the threshold value $v_{DA}(B) > DA_{att}$), it accepts the offer, otherwise a new negotiation iteration is started with all available PMs. Once an offer is accepted, the corresponding DA waits for a booking confirmation by the PM that issued the offer.

The DA requests are processed concurrently by the PMs hence, from the PM point of view, a negotiation process consists of multiple single negotiations taking place between the PM and each DA that sent a request. Once a `cfp` is received, each PM retrieves a set of possible alternatives to be offered to the DA with respect to the received query location, and it evaluates the corresponding utility according to its utility function, ranking the parking spaces in descendant order. Offers are sent one by one to the DA at each iteration according to this order. If an agreement is reached with the offer sent at iteration $t$, the PM checks the status of the corresponding car park, and it updates the utility value of the accepted offer, since it may have changed during negotiation because of parking space allocations occurred in other negotiations. If such value did not change or it changed within an acceptable range for the PM, then the parking space is allocated, and the park space occupancy is updated. Otherwise, the offer is discharged, an `inform` of failure is sent, and the negotiation proceeds. A parking space offered at round $t$ is not considered available at round $t+1$ for the same DA to model the possibility to assign a rejected parking space to another driver. In case there are not proposals available satisfying the DA request, a `failure` message is sent to the DA and the negotiation ends.

## 2.2 Agents Utility Functions

Both the PM and the DA have their own private multi–dimensional utility functions (Barbuceanu and Lo, 2001), allowing them to evaluate the offers in terms of their own preferences, where each dimension relates to an attribute of a parking space. These utility functions are based on static attributes of a parking space, such as its default hourly price, its location in the city, the capacity of the car park it belongs to, and on dynamic attributes, such as its distance from a required location, the current occupancy, or its current price, whose values are calculated at the time a parking request is processed. The agreement on the outcome is reached if the values of parameters, used by the PMs and the DAs to evaluate their utility values, are in their respective agreement spaces (Di Napoli et al., 2013). Even though the object of negotiation is a parking space, the attributes, used by the PM and the DA to evaluate it, are different because they have different preferences regarding a parking solution. Of course, an agreement between them is possible if their respective acceptable regions have a non-empty intersection, i.e. a parking space with attribute values acceptable for both of them.

Upon receiving a DA request for parking a PM selects the set of car parks located in the city sectors it is responsible for, within a given radius (named *tolerance*) from the user request. In order to incentivize a DA to park outside a red zone and in less occupied car parks, the PM adopts a dynamic parking pricing scheme that applies a discount to the default parking hourly price depending on the car park occupancy and location, i.e., the farther away the parking space is from a red zone, the higher the discount factor is, and the higher the occupancy percentage is, the lower the discount factor is. The PM evaluates each selected car park according to its private utility function, and it orders them in a descending order of their utility values. The strategy adopted by the PM to issue a counter-proposal, i.e. a new offer, is to concede in its utility by offering one parking space at a time in the same descending evaluation order, so applying a monotonic concession strategy. The utility function is the weighted sum, normalised in $[0,1]$, of the car park availability ($q_{1,j}$), i.e., the number of free parking spaces at the time the request is processed, and the car park distance from the nearest red area ($q_{2,j}$).

$$U_{PM}(p_j) = \sum_{k=1}^{2} (\alpha_k * \frac{q_{k,j} - \min(q_{k,j})}{\max(q_{k,j}) - \min(q_{k,j})}) \quad j \in \{1,\ldots,n\} \tag{1}$$

where, $\alpha_k$ are weights associated with each parameter (with $\sum \alpha_k = 1$), and $n$ is the number of car parks selected for the request. Both terms of the summation are normalized w.r.t. the minimum ($\min(q_{k,j})$), and the maximum ($\max(q_{k,j})$) values of each parameter among all the selected car parks. Weights model the possibility for the PM to privilege one parameter or the other, according to the specific city needs at the moment the request is processed, i.e., by increasing parking occupancy or pushing drivers towards more distant car park.

The DA evaluates each offer according to its utility function given by the weighted sum of the parking space hourly cost ($p_{1,j}$), and its travel distance from the required destination ($p_{2,j}$):

$$U_{DA}(x_j) = 1 - \sum_{k=1}^{2} \beta_k * \frac{p_{k,j} - c_k}{h_k - c_k} \tag{2}$$

where, $\beta_k$ are weights associated to each parameter (with $\sum \beta_k = 1$), $c_k$ is the DA preferred value over the k-th parameter, $h_k$ are constant values introduced for normalising each term of the formula into the set $[0,1]$. Such weights can be used to model different decision models of drivers.

The DA strategy is to accept an offer if its utility value is above a *threshold value* ($DA_{att}$) representing a measure of its attitude to be flexible on its preferred values for the considered parking space attributes. Since the utility function is normalised, its values may range in the interval $[0,1]$. It should be noted that the DA utility varies according to the received offer, so it is not monotonic as the PM one. This means that keeping on negotiating does not guarantee the DA to find a better parking space in terms of its utility. Moreover, as already discussed, the DA can evaluate an offer only with respect to its own utility since previously proposed parking spaces are not available anymore. In addition, the DA is not aware of the available car parks, so it could end up without reserving any parking space if it keeps on negotiating.

# 3 EVALUATING THE BENEFITS OF PARKING ALLOCATIONS

In order to evaluate the *social welfare* of the interaction (one DA and multiple PMs), we considered only the utility of the DA and the PM pair whose negotiation reached an agreement on a parking space assignment ($x_{agr}$). Note that, it cannot be the case that more than one PM has a positive utility value as a result of a single request. A set of parking space requests are considered as a request block, each one processed through a negotiation process. The problem can be assimilated to a distributed indivisible resource allocation case, where the selection of resources to be allocated for a specific request is carried out through a bilateral negotiation without considering the other requests. In our case, given a set of available resources $\mathcal{R}$ (i.e., parking spaces), and a set of driver agents $\mathcal{DA}$, the overall process is to assign a single resource to each request (if available), in order to best match the DA request and, at the same time, to fulfill as many requests as possible. In resource allocation problems the social welfare is also used as a metric to evaluate the efficient allocation of resources (Endriss et al., 2006). Hence, social welfare, computed for all requests, including the not fulfilled ones, can be used also as a metric to evaluate an efficient allocation of parking spaces.

Given a set $\mathcal{DA}$ of agents requesting a parking space, an optimal allocation of available spaces is the one that maximizes the social welfare. Here, we consider a social welfare ($SW_+$) obtained as the sum of DA and PM utilities.

$$SW_+ = [\sum_{i \in \mathcal{DA}} ((U_i(x_{agr}) + U_{PM}(x_{agr}))/2)]/|\mathcal{DA}| \tag{3}$$

This definition does not account for imbalanced distribution of utilities among agents, so the Nash Social Welfare definition ($SW_*$) (Ramezani and Endriss, 2010), is also used.

$$SW_* = [\sum_{i \in \mathcal{DA}} (U_i(x_{agr}) \cdot U_{PM}(x_{agr}))]/|\mathcal{DA}| \tag{4}$$

The prototype for the experimental evaluation is implemented as a client/server application within the JADE framework (Bellifemine et al., 2008). A negotiation session occurring among a set of DAs and a set of PMs is a multi-threaded process, where each thread manages a negotiation of one PM and one DA. A storage module is responsible for maintaining information on the available car parks, their capacity and their occupancy that is updated every time a parking request is fulfilled. In addition, PMs collect information from external services: Google Maps (Pan et al., 2007) to compute the arrival time from a car park to the destination specified by a driver, OpenStreetMap (Haklay and Weber, 2008) to collect information on car park locations, a city planning service to collect information regarding the red zones.

Our reference scenario consists of a large number of drivers all choosing a destination in the red zone

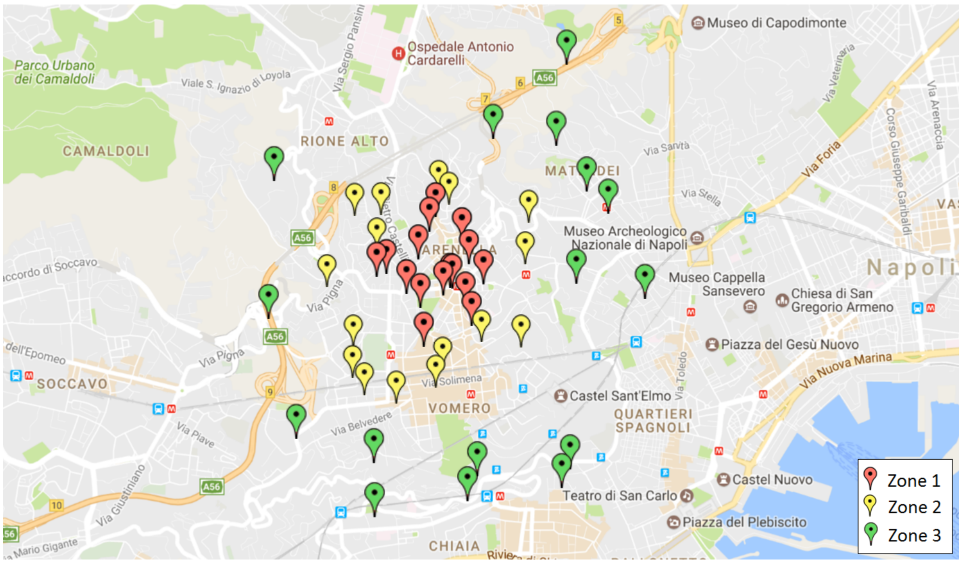


Figure 1: Parking distribution w.r.t the nearness of city zones to the red zone.

and for the same time window to evaluate both the allocation of parking spaces in terms of the social welfare of the whole multi-agent system, and the distribution of allocated parking spaces among the considered zones. In this set of experiments, we also evaluated the impact of having more than one PM on the social welfare of the system. Hence, we considered four different settings, respectively with 1, 2, 4 or 8 PMs. Our hypothesis is that the case of only one PM would result in a better application of the smart city policy (and so a greater PM utility). For each setting, we considered the cases of 50, 100, 400, 1200 simultaneous requests in the red zone. Each test is repeated 50 times. The total number of available parking spaces was set to 960 and equally distributed among the considered 48 car parks. Moreover, each PM will have the same distribution of parking spaces among the areas. In Figure 1, the parking distribution for the considered zones in the city of Naples is shown, with each zone identified by a different colour. The considered drivers have the same preferences regarding the parking space attributes and the same attitute to come to an agreement $\beta_1 = 0.4$, $\beta_2 = 0.6$, and $DA_{att} = 0.5$.

In Figure 2, the average utilities of the DAs and the PMs are plotted for each setting. As we expected, by increasing the number of available PMs, the average utility of the PMs decreases (see Figure 2 (right)). However, this trend is shown only for the cases of 50 and 100 requests. Indeed, by increasing the number of requests, the average utility of the PMs is constant. In these two cases (50 and 100 requests), the number of parking requests is smaller than the number of available places. This, in the case of more available PMs, will produce a competition among PMs and so a smaller average utility (see Figure 2 (right)). Reasonably, in the case of few requests and more PMs, there are more available and better choices for the DA, so the average DAs utility increases in the case of 50 and 100 requests and an increased number of PMs. A greater number of requests, on the contrary, will allow each PM to allocate more parking spaces, leading to an average PMs and DAs constant utilities for all considered cases.

Finally, by increasing the number of requests, the average utility of the PMs decreases. Of course, with few requests, only the parking spaces with the highest PMs utilities are allocated, while by increasing the number of requests also spaces with lower PMs utility values are selected by the DAs. Notice that a constant PMs utility is obtained also in the case of 400 requests (with respect to 960 available parking spaces). The lower line reports the 1200 requests case. The opposite trend happens in the case of DAs utilities. By increasing the number of simultaneous requests leads to longer negotiations (see Figure 4 (left)), so, potentially, parking spaces that are better for the DAs and worse for the PMs are gradually disclosed. However, also for the DAs, the case of 1200 requests is the one with the lowest value since the number of requests is greater than the number of available parking spaces, so the average utility considering all the requests (including failures) decreases.

In Fig. 3, the average values for $SW_+$ and $SW_*$ are plotted for the cases of 100 and 400 requests. Following the trend in Figure 2, the social welfare average values $SW_+$, that is obtained by considering the sum of the PMs utilities (with positive values) and the DAs utilities, does not change varying the number of PMs.

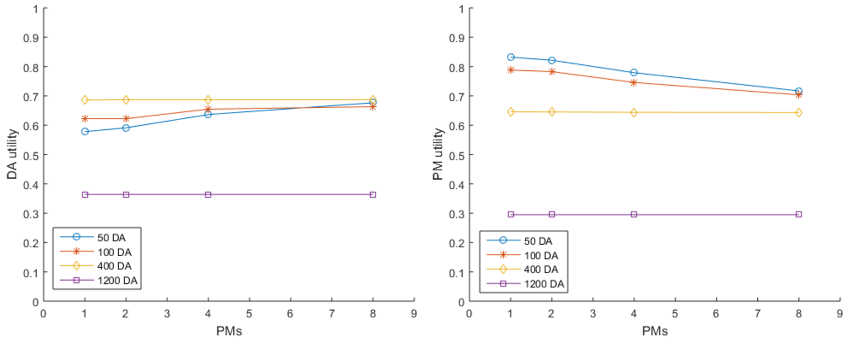


Figure 2: DAs (left) and PMs (right) average utilities varying the number of PMs.

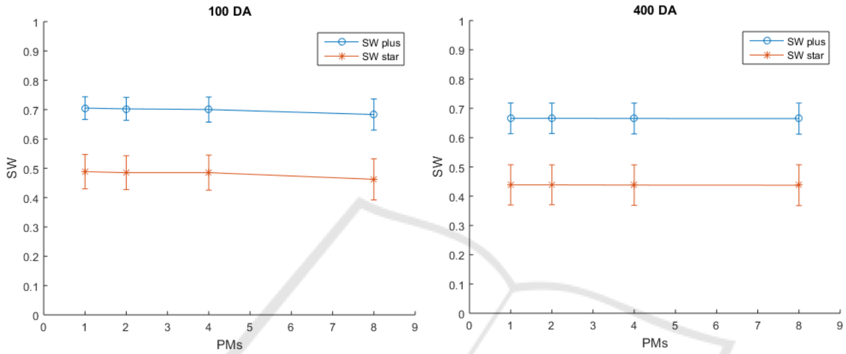


Figure 3: $SW_+$ and $SW_*$ average values varying PMs for 100 and 400 requests.

This is because the slight decrease in the PMs utility is compensated by an increase in the DAs one. However, the calculation of the social welfare takes into account also the total number of requests (thus including also the unsuccessful negotiations). The average social welfare is slightly smaller in the case of 8 PMs and 100 requests, but such difference is not significant. Trends of 50 and 1200 requests are similar, and so they are not reported here. The trends of $SW_*$ also show a constant behavior by varying the number of PMs and the number of requests. Contrarily to what expected, including more than one PM does not produce a negative impact on the global social welfare.

In Figure 4 (left), the trend of the average number of negotiation rounds with respect to the number of queries and the number of available PMs is plotted. The plots show that, by increasing the number of available PMs, and so the number of possible parking choices at each iteration, the average number of rounds, considering only the cases of successful negotiations, decreases. This is to say that, while from one hand having more than one PM will produce an increase in the communication (since more messages are needed), from the other hand this is compensated by a decrease in the number of required rounds. As we expected, increasing the number of considered requests produces an increase in the average number of rounds. However, while in the case of a single PM, there is a variation of 8 rounds between the cases of 1200 and 50 considered requests, the increase of the number of PMs reduces this variation only to 2 rounds. So, a market with more PMs leads to a more stable negotiation behavior.

In Figure 4 (right), a plot reporting the ratio benefit/cost of the negotiation is shown, and it is evaluated as the obtained average social welfare ($SW_+$) with respect to the number of rounds. This plot shows that, when considering a fixed set of requests, the case with more PMs will always produce a better benefit/cost value. Moreover, the reported values for the case of 50 and 100 queries are very similar, while they decrease when considering a larger set of queries.

To conclude, in Figure 5, the percentage of the distribution of the parking allocations in each zone for 100 and 400 queries, by varying the number of PMs is plotted. Remember that, Zone 1 is the destination zone of the considered set of requests (that is indeed a red zone). As we already discussed, the increase in the number of considered requests has an impact on the zones selected for the allocations, since also parking spaces with lower PMs values are disclosed, and so selected by the DAs. In particular, in the case of few requests (50 or 100), most of the selected car parks were mainly in Zone 3 or eventually in Zone 2.

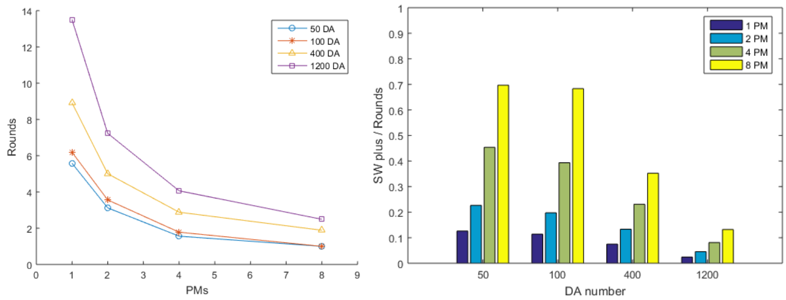


Figure 4: Average number of rounds varying the number of PMs (left), and benefit/cost plot w.r.t. different requests sets.

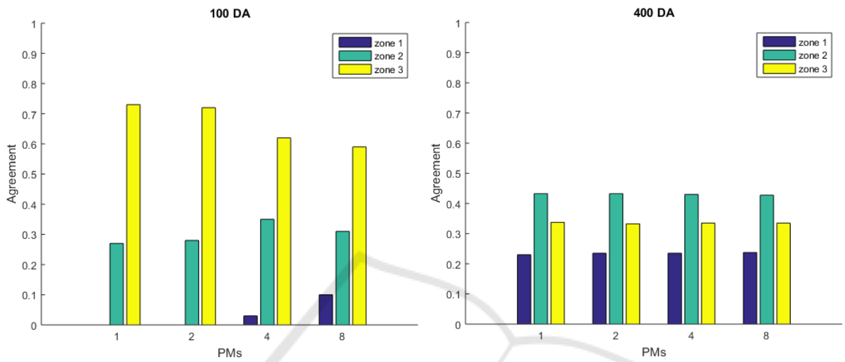


Figure 5: Distribution of the parking allocations in each zone in percentage.

Only a low percentage of selections were made in the Zone 1, for the case of 8 PMs (and also 4 PMs for 100 DAs). Cases with 400 and 1200 requests showed a uniform distribution of allocations among the considered zones, leading to the case of 1200 queries where the percentage of allocations in the Zone 1 is the same as the allocation in Zone 2 (with lesser allocations in Zone 3). Note that the case of 1200 requests does not correspond to a complete allocation of the 960 parking spaces (namely 646 in the average), since there are still failures, and so there is not an equal distribution of allocations among zones.

## 4 CONCLUSIONS

Reservation-based parking systems have been proposed in the literature developing optimal park allocation strategies. For example, (Geng and Cassandras, 2013) proposed an efficient and optimal allocation strategy obtained by solving a sequence of Mixed-Integer Linear Programming problems, which are guaranteed to have a feasible solution and to satisfy some fairness constraints. Optimality is obtained by making allocations for all the considered users, and users who have already reserved a resource may be assigned to a different one in a successive decision point until they physically reach the resource and occupy it. Here, we do not consider the possibility to modify the resource allocation after an assignment, so all requests are independent from each other. The optimal allocation of car parking spaces was also studied in (Mejri et al., 2013), where a semi-centralised approach for optimising the parking space allocation is proposed, improving the fairness among parking zones by balancing their occupancy-load. This approach considers all the drivers' requests over a time window and it assigns a free parking space to each one simultaneously. Parking coordinators are used for distributing the optimisation allocation problem that is not manageable in a centralised way. Here we do not consider collaboration among parking sellers because in a marketplace sellers negotiate for their own interests, but sharing a common city policy.

Multi-agent negotiation has already been used for parking allocations in Intelligent Transportation System applications. In (Chou et al., 2008), negotiation on parking price is used to find better and cheaper parking spaces from the driver point of view. Each parking manager announces the parking spaces and waits for bids from drivers, so parking price changes according to the level of drivers competition. In (Adler and Blue, 2002), cooperative agent negotiation is used to optimise traffic management relying on shared knowledge between drivers and network operators about routing preferences. Here, the negotiation items are the parking spaces to be assigned with dynamical characteristics (i.e.; the price) that may change from one request to another, but they are fixed during a single negotiation process.

In this work, a multi-agent smart parking marketplace is proposed relying on a distributed negotiation mechanism. Negotiation allows parking managers and drivers to evaluate parking spaces according to their own private preferences, and to come to a solution that can be acceptable by both parties. A dynamic pricing scheme is used to incentivize drivers to select parking spaces that lead to both a better car park utilisation, and to limit traffic circulation in specific city areas. Differently from a centralised negotiation approach previously proposed, a distributed solution is more realistic and more suitable to deal with the complexity of modern transportation systems. The benefit of the negotiation was evaluated in terms of a Social Welfare metrics measuring the degree of satisfaction of all involved parties. Results showed that, in the case of the number of parking requests smaller than the number of available parking spaces, the increasing number of Parking Managers leads to a competition among them, and consequently to a smaller average utility for the Parking Managers. Of course, since there are more and better choices for the Driver Agents, their average utility increases. On the contrary, a greater number of requests allows each Parking Manager to allocate more parking spaces, so leading to an average Parking Managers and Driver Agents constant utilities. In addition, by increasing the number of Parking Managers and the number of queries, the social welfare remain constant, so a decentralised negotiation approach does not have a negative impact on the overall level of satisfaction of the involved negotiators. Finally, by increasing the number of available Parking Managers, and so the number of possible parking choices, the average number of rounds necessary for successful negotiations decreases. So, while from one hand having more than one PM causes an increased communication cost due to an increased number of exchanged messages, it is compensated by a decreased number of rounds to reach an agreement.

## REFERENCES

Adler, J. L. and Blue, V. J. (2002). A cooperative multi-agent transportation management and route guidance system. *Transportation Research Part C: Emerging Technologies*, 10(5–6):433 – 454.

Barbuceanu, M. and Lo, W.-K. (2001). Multi-attribute utility theoretic negotiation for electronic commerce. In *Agent-Mediated Electronic Commerce III, Current Issues in Agent-Based Electronic Commerce Systems*, pages 15–30. Springer-Verlag.

Barile, F., Di Napoli, C., Di Nocera, D., and Rossi, S. (2015). Evaluating the social benefit of a negotiation–based parking allocation. In *Advances in Practical Applications of Agents, Multi-Agent Systems, and Sustainability: The PAAMS Collection*, volume 9086 of *LNCS*, pages 15–26.

Bellifemine, F., Caire, G., Poggi, A., and Rimassa, G. (2008). Jade: A software framework for developing multi-agent applications. lessons learned. *Inf. Softw. Technol.*, 50(1-2):10–21.

Chou, S.-Y., Lin, S.-W., and Li, C.-C. (2008). Dynamic parking negotiation and guidance using an agent-based platform. *Expert Systems with Applications*, 35(3):805–817.

Di Martino, S. and Rossi, S. (2016). An architecture for a mobility recommender system in smart cities. *Procedia Computer Science*, 98:425 – 430.

Di Napoli, C., Di Nocera, D., and Rossi, S. (2014). Agent negotiation for different needs in smart parking allocation. In *Advances in Practical Applications of Heterogeneous Multi-Agent Systems. The PAAMS Collection*, volume 8473 of *LNCS*, pages 98–109.

Di Napoli, C., Pisa, P., and Rossi, S. (2013). Towards a dynamic negotiation mechanism for qos-aware service markets. In *Trends in Practical Applications of Agents and Multiagent Systems*, volume 221 of *AISC*, pages 9–16. Springer.

Endriss, U., Maudet, N., Sadri, F., and Toni, F. (2006). Negotiating socially optimal allocations of resources. *J. Artif. Intell. Res. (JAIR)*, 25:315–348.

Geng, Y. and Cassandras, C. (2013). New smart parking system based on resource allocation and reservations. *IEEE Transactions on Intelligent Transportation Systems*, 14(3):1129–1139.

Haklay, M. and Weber, P. (2008). Openstreetmap: User-generated street maps. *Pervasive Computing, IEEE*, 7(4):12–18.

Mejri, N., Ayari, M., and Kamoun, F. (2013). An efficient cooperative parking slot assignment solution. In *The Seventh International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies*, pages 119–125. IARIA.

Nakamura, K., Hondo, I., Hataoka, N., and Horii, S. (2000). Car information systems for its. *Hitachi Review*, 49(3):102–106.

Pan, B., Crotts, J. C., and Muller, B. (2007). Developing web-based tourist information tools using google map. In Sigala, M., Mich, L., and Murphy, J., editors, *Information and Communication Technologies in Tourism 2007*, pages 503–512. Springer Vienna.

Polycarpou, E., Lambrinos, L., and Protopapadakis, E. (2013). Smart parking solutions for urban areas. In *IEEE 14th International Symposium on World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, pages 1–6. IEEE.

Ramezani, S. and Endriss, U. (2010). Nash social welfare in multiagent resource allocation. In *Agent-Mediated Electronic Commerce. Designing Trading Strategies and Mechanisms for Electronic Markets*, volume 59 of *LNBIP*, pages 117–131. Springer.