Evaluating the Social Benefit of a Negotiation–Based Parking Allocation

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Abstract. Smart parking systems usually support drivers to select parking spaces according to their preferences among competitive alternatives, which are well known in advance to the decision maker, but without considering also the needs of a city. In this paper a decision support system for selecting and reserving optimal parking spaces to drivers is presented, where the concept of optimality is related to the city social welfare including the level of satisfaction of both drivers and the city. It relies on an automated software agent negotiation to accommodate the different needs coming from the different actors involved in the parking allocation process. A simulator of such a system is evaluated with respect to a case of complete information sharing among agents, and a case of no shared information. Different metrics to evaluate the social benefit of the parking allocation in terms of both agents utilities, and allocation efficiency are considered.

Keywords: Social welfare · Agent negotiation · Resource allocation · Smart parking

1 Introduction

The problem of allocating parking spaces to drivers is becoming a challenge in big cities, and different solutions are being investigated to provide them with smart parking applications. Most of parking applications, proposed in the literature, are based on Parking Guidance and Information (PGI) systems that provide drivers with dynamic information on parking within controlled areas, and direct them to vacant parking spaces. Shortcomings of PGI systems are due to the competition for parking spaces leading to the possibility of not finding a vacant

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space, so forcing re–planning the search. In addition, these systems are designed to increase the probability of finding a parking space, but without considering the possibility to find a better solution. Finally, and more importantly, from a traffic city authority point of view, these systems do not allow for a better utilization of parking spaces, but sometimes they may cause even more congestion in the monitored areas.

In this context, our purpose is to design a decision support system helping drivers to select and reserve optimal parking spaces, where the concept of optimality is related to the city *social welfare*, intended as the overall satisfaction level of all the actors involved in a parking system that are: drivers, parking owners, authorities taking into account city needs coming from city regulations (in terms of permitted parking areas, traffic congestion, car emission limitations), or special events. The system is designed to find a parking space within car parks, and it uses an agent–based negotiation approach to accommodate the different needs that have to be fulfilled when selecting parking spaces. While in parking systems competitive alternatives are well–known in advance and shared by drivers, the proposed negotiation mechanism relies on the possibility to selectively show the information concerning the parking spaces to propose to the drivers. This allows to incentive the selection of parking spaces that represents a viable compromise for conflicting needs.

In the present work, a simulator of the decision support system is evaluated by considering a set parking requests to be served. We are interested in evaluating how an agent negotiation approach may be used to improve the well–being of a society as a whole, that is not attainable without negotiation. The evaluation carried out takes into account both agents' utilities, and an efficient allocation of parking spaces. To globally evaluate the social benefit of the overall allocation problem, different metrics are considered that evaluate the negotiation outcome not at the single agent level, as reported in [3], but at the global agent society level, as single negotiations may influence the overall global system behavior.

2 Accommodating Different Needs in Parking Allocation

Smart parking applications are designed to help drivers in finding a parking space that meets their requirements usually regarding cost, and location. Nevertheless, the problem of finding a vacant parking space in densely populated urban areas is a more challenging problem involving different entities: drivers who want to find a vacant parking space that meets their requirements; car parks owners, both public and private, who want to maximize their economic income by selling as many parking spaces as possible; city managers who want to avoid car circulation in specific areas of the city and to have a fair distribution of parking spaces among requesting drivers to limit traffic congestion in the proximity of car parks.

In this context, the problem of finding a parking space is not merely a selection problem, but rather the possibility to find an agreement accommodating the different needs coming from drivers, parking owners, a city manager aware of city needs. For this reason, an automated negotiation mechanism is a viable approach to drive the selection of a parking space. In fact, negotiation allows to find an agreement that satisfies different and sometimes conflicting needs of the entities involved in the selection process, and to manage the dynamic nature of these needs depending on changeable conditions affecting the decision mechanism of both drivers and city managers.

In order to find an agreement among the different entities involved when selecting a parking space in urban car parks, we propose to model the decision support system of a smart parking application as a multi–agent system. The selection of a parking space upon a driver's request is modeled as the result of an agent automated negotiation process occurring among a set of Driver Agents (DAs), each one acting on behalf of a driver looking for a parking space, and a Parking Manager Agent (PMA) responsible for assigning parking spaces. The model extends the one presented in [3], where automated software agent negotiation was used to support users to find a parking space, preventing them to park in specific areas of a city, but without evaluating the overall parking allocation for a set of drivers.

The PMA acts on behalf of the entity responsible for re–selling a set of parking spaces located in different car parks of a city. It takes into account the economic needs of car parks owners that try to fill their car parks as much as possible to improve their profit, and, at the same time, the social needs of a city manager that tries to limit traffic congestion mainly in city centers, and to distribute drivers in different car parks to limit the concentrations of cars in specific or more required city areas. The Driver Agent is the entity acting on behalf of a driver that wants to reserve a parking space located in a specific city destination for a required time, and not exceeding a given cost. The allocation of a required parking space occurs if an agreement between the PMA and the DA can be found as the result of an automated negotiation process.

3 The Negotiation Process

The adopted negotiation protocol is an iterated contract–net interaction protocol [5] occurring between the PMA and a set of DAs issuing parking space requests. The PMA manages a set of available parking spaces and it has the goal to allocate them trying to satisfy all the different requests.

A request (`park_req`) is characterized by a geographical location, representing the required destination for the driver, located in an urban area, an hourly cost the driver would prefer to pay for the space, and a time interval the parking space is required for. The urban area is split in concentric rings (named *city sectors*) starting from the city center that are used to localize the considered car parks with respect to the city center.

A car park is characterized by static and dynamic attributes. A static attribute is its location within a ring, i.e. with respect to the city center, while a dynamic attribute is the number of available parking spaces at the time a parking space request is issued. The hourly static price for a parking space is assigned according to the criteria that car parks far from city centers are cheaper, so the adopted metric is to discount the price of a factor depending on the quadratic car park distance from the city center. In fact, it is assumed that car parks located in city centers are more expensive since they are located in the most requested and hence most densely populated city areas.

A negotiation process consists of all negotiations taking place between the PMA and each DA that issued a request over a set time window. Requests are collected and processed by the PMA, one by one according to their arrival order.

At the first negotiation iteration, a DA sends a `park_req` to the PMA that replies with an offer (x_j), if any, or with a `decline` message.

An offer has the form $x_j =< j, p_{1,j}, p_{2,j} >$, where j is a selected car park, $p_{1,j}$ is the static hourly cost (`static_price`) of the corresponding parking space, $p_{2,j}$ is the travel distance (`travel_dist`) between the car park location and the destination specified in the request. The travel distance is evaluated in terms of the time necessary to reach the destination from the car park location either by walking, for distances within 500m, or by public or other alternative means of transportation for longer distances.

It should be noted that that the PMA uses a Google Map service to compute the travel distance, but it is assumed that additional city services providing information on specific events that may influence the time necessary to cover such a distance, are made available from a city administration.

The DA replies to an offer with either an `accept` or a `reject` message according to its evaluation of the offer, i.e. if the selected parking space satisfies the driver's requirements. If an agreement is reached with the offer sent at iteration t, the negotiation ends successfully at that iteration, otherwise the offer is rejected and, if $t + 1 \leq t_{MAX}$, the negotiation continues with the PMA proposing another offer until the negotiation deadline t_{MAX} is reached (where t_{MAX} is the number of allowed iterations in the negotiation). The maximum number of iterations is the same as the number of car parks selected by the PMA, and it is not known to the DA. Note that a parking place offered at round t is not considered available at round $t + 1$ to model the possibility to assign a rejected parking space to another driver. So, the negotiation occurs in an incomplete information configuration from the driver agent side, since the information on all the available car parks is known only to the PMA agent. In fact, car parks attribute values may vary in time, so their sharing would require computationally expensive updates. The incomplete information setting leads to the possibility of accepting a sub–optimal agreement.

3.1 Agents Utility Functions

In automated agent negotiation, agents are assumed to have preferences, which represent (partial) orderings on outcomes. Agent preferences can be mapped into values of utility, using an utility function that is simply a mapping from a space of outcomes onto utility values, so providing a measure of the satisfaction level associated to a given offer for the agent.

Both the PMA and the DA have their own private multi–dimensional utility functions, allowing them to evaluate the offers in terms of their own preferences, where each dimension relates to an attribute of the specific parking space.

In general, the utility of an offer x_j at round t is evaluated as follows:

$$U_i(x_j) = \begin{cases} 0 & if\ t = t_{MAX} \text{ and not } (\mathbf{agr}) \\ v_i(x_j) & if \quad t \leq t_{MAX} \text{ and } (\mathbf{agr}) \end{cases} \quad (1)$$

where, $v_i(x_j)$ is the agent's evaluation function. The evaluation function is a weighted sum of the parking attributes (normalized in the range $[0, 1]$), assuming the independence of each attribute. The attributes for the PMA and the DA are different, since they have different preferences regarding a parking solution. Of course, an agreement between them is possible if their respective acceptable regions have a not–empty intersection, i.e. a parking space with attribute values acceptable for both of them.

In the proposed negotiation approach, only the PMA may actually negotiate the values of these parameters, since it may propose a new offer, i.e. a new parking space with different attribute values, at each negotiation iteration. On the contrary, the DA does not issue a counterproposal, since it can only accept or reject the received offer.

Upon receiving a DA request, the PMA selects the set of car parks located in the city sectors within a given radius (named *tolerance*) and centered in the driver's specified location. The tolerance value is private to the PMA, and it can be dynamically set by the PMA according to both the location specified by the driver, and the city needs. In fact, if the destination is very close to the city center, or to an area that for the time specified by the driver should be avoided, the considered radius value may increase to allow for more car parks to be selected, so having more alternatives to provide to the driver. The PMA evaluates each selected car parks according to its own private evaluation function, and it orders them in a descending order of their utility values. The PMA strategy to issue a counterproposal, i.e. a new offer, is to concede in its utility at each negotiation iteration, by offering one parking space at each iteration, in the same descending evaluation order, so applying a monotonic concession strategy.

The adopted evaluation function models the main objectives of the PMA that are: to incentivize drivers to park outside the city center, in order to limit car circulation in most crowded city areas, and to fill the less occupied car parks to allow for a better distribution of the traffic, and profit.

Hence, the evaluation function is the weighted sum of terms modeling the PMA preferences that are: 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 city center ($q_{2,j}$), calculated as distance of two GPS–located points.

$$v_{PMA}(x_j) = \sum_{k=1}^{2} \left(\alpha_k * \frac{q_{k,j} - \min(q_{k,j})}{\max(q_{k,j}) - \min(q_{k,j})}\right) \qquad j \in \{1, \ldots, n\} \quad (2)$$

where, α_k are weights associated to each parameter (with $\sum_{k=1}^{2} \alpha_k = 1$), 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. The weights are used to take into account the possibility for the PMA to privilege one parameter or the other in its evaluation according to the specific city needs at the moment the request is processed.

An offer includes attributes of a parking space that are relevant for the DA, i.e. its hourly cost ($p_{1,j}$), and its travel distance from the destination specified by the user ($p_{2,j}$). Upon receiving an offer, the DA evaluates it according to its own parameters using an evaluation function given by the weighted sum of these parameters as follows:

$$v_{DA}(x_j) = 1 - \sum_{k=1}^{2} \beta_k * \frac{p_{k,j} - c_k}{h_k - c_k} \tag{3}$$

where, β_k are weights associated to each parameter (with $\sum_{i=1}^{2} \beta_k = 1$), c_k is the DA preferred value over the k–th parameter, h_k are constant values introduced for normalizing each term of the formula into the set $[0, 1]$.

The weights are used to model different type of drivers:

- **business**, i.e. drivers that consider very important the location of the parking space w.r.t. the location they need to reach, also being available to spend more money to get it ($\beta_1 < \beta_2$),
- **tourist**, i.e. drivers that are available to choose a parking space not so close to their preferred destination, provided that they can save money ($\beta_1 > \beta_2$).

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 normalized, its values may range in the interval $[0, 1]$. It should be noted that at each negotiation iteration, the DA utility varies according to the received offer, so it is not monotonic as the PMA one. This means that by keeping on negotiating does not guarantee the DA to find a better parking space in terms of its utility. In addition, the DA is not aware of the car parks available, so it could end up without reserving any parking space if he keeps on negotiating.

Currently, two DA profiles are considered:

- **strict**, i.e. drivers who are quite strict on their preferences, i.e. they are characterized by a high threshold value,
- **flexible**, i.e. drivers who are more flexible on their preferences, i.e. they are characterized by a low threshold value.

4 Computing the Social Benefit of a Parking Allocation

Both the DA and the PMA try to maximize their individual utility when negotiating with each other. The designed negotiation mechanism, proposed in [3], aims at finding an agreement between the conflicting needs of a DA and the PMA, leading to an outcome that is a viable compromise.

Here, a set of parking space requests to be globally processed are considered, each one processed through a negotiation process. The problem can be assimilated to a distributed indivisible resource allocation problem, 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 used as a metric to evaluate the efficient allocation of resources [4]. 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 as follows.

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 of the driver agents, given by the sum of the individual outcomes (i.e. utilities) for all requests, fulfilled or not. So, $SW_{DA} = \sum_{i \in \mathcal{DA}} U_i(x_{agr})$, where U_i depends only on the agent i and on the selected parking space (agr). Hence, the overall utility of a set $\mathcal{DA}$ correspond to the sum of the individual utilities. In order to get a global utility value that does not depend on the cardinality of $\mathcal{DA}$, a normalized version of the social welfare is used:

$$SW_{DA} = \frac{\sum_{i \in \mathcal{DA}} U_i(x_{agr})}{|\mathcal{DA}|} \tag{4}$$

Equation 4 accounts for the social welfare of driver agents and for the allocation problem in the sense that an high number of fulfilled requests with an high average utility will result in a high SW_{DA} value. However, in order to evaluate the social benefit of a global parking space allocation, the social welfare should include also the utility of the PMA. In fact, there could be two parking spaces that have the same utility for the DA, but one is more beneficial for the city welfare, i.e., it has a greater utility for the PMA, so being a Pareto optimal solution with respect to the other one. For this reason, a global social welfare (SW_+) should include also the PMA utility, so it is obtained, for each negotiation, as the sum of DA and PMA utilities, normalized in $[0, 1]$.

$$SW_+ = \frac{\sum_{i \in \mathcal{DA}} (U_i(x_{agr}) + U_{PMA}(x_{agr}))/2}{|\mathcal{DA}|} \tag{5}$$

A fair outcome of the negotiation is an agreement that maximizes the global social welfare.

While in multi–agent literature the definition of SW is taken for granted, the economic literature provides different definitions and interpretations.

The adopted definition of social welfare does not account for situations with an imbalanced distribution of utilities among agents. In order to detect these situations the Nash Social Welfare definition [10] can be used, defined as follows:

$$SW_* = \frac{\sum_{i \in \mathcal{DA}} (U_i(x_{agr}) \cdot U_{PMA}(x_{agr}))}{|\mathcal{DA}|} \tag{6}$$

Equations 4, 5, and 6 are used to evaluate the outcome of negotiation for the parking spaces allocation problem.

5 Negotiation Simulations

In order to assess if the proposed negotiation mechanism is able to push drivers to select a parking space that is beneficial for the different involved entities, an experimentation was carried out simulating a set of drivers' requests sequentially processed in a time window. The experiments are aimed to evaluate the percentage of the allocated parking spaces with respect to the number of processed requests, the available car parks, and the corresponding PMA and DAs utilities, when negotiation is used.

The evaluation is carried out against two baseline cases without negotiation, named *DA-Best* and *PMA-Best*. In the first case, the availability and locations of all parking spaces are known to the DA (i.e., there is a complete knowledge), and the DA selects the parking space (x_i) with the highest utility ($x_i = argmax(U_{DA}(x_j)), \forall j$), and it reserves it if this utility is above its threshold ($U_{DA}(x_i) > DA_{att}$). In the second case, the PMA selects the parking space with the highest utility ($x_i = argmax(U_{PMA}(x_j)), \forall j$) to offer, and the DA accepts it if its own utility for that offer is above the threshold ($U_{DA}(x_i) > DA_{att}$), otherwise it rejects the offer.

All requests specify a random destination in a city center that is located in the first city sector with a radius of $500m$. The considered car parks are located in city sectors ranging within a radius of $5km$ from the city center and none located in the first sector that is assumed to be a pedestrian area.

The requests are issued by four different types of users as follows:

- **Flexible business**: $DA_{att} = 0.5$, $\beta_1 = 0.3$, and $\beta_2 = 0.7$;
- **Strict business**: $DA_{att} = 0.7$, $\beta_1 = 0.3$, and $\beta_2 = 0.7$;
- **Flexible tourist**: $DA_{att} = 0.5$, $\beta_1 = 0.7$, and $\beta_2 = 0.3$;
- **Strict tourist**: $DA_{att} = 0.7$, $\beta_1 = 0.7$, and $\beta_2 = 0.3$.

The PMA instead has the same preferences on the attributes included in its utility function, i.e. $\alpha_1 = \alpha_2 = 0.5$ Two sets respectively of 50 and 100 requests are considered, and the number of total available parking spaces is 100 equally distributed over 20 car parks. The requests are processed one by one, and if a request is satisfied the corresponding assigned parking space is reserved and it is not available for the other requests. If a request is not satisfied it is discarded and not processed anymore. We recall that the deadline of a negotiation (t_{MAX}) may vary for each requests according to the number car parks with available places for that request.

5.1 Experimental Results

The overall DAs and PMA utility values (U_{DA} and U_{PMA}), and the percentage of successful allocations ($\%all.$), normalized w.r.t. the number of requests, obtained by simulating 50 and 100 requests, are reported in Table 1. Such utilities are evaluated for the negotiation case (Negotiation), and for the two baseline cases without negotiation, i.e., when the best parking space respectively for the DA (DA–best), and the PMA (PMA–best) are selected.

Table 1. DAs and PMA utilities in different settings

	50 req./100 spaces			100 req./100 spaces		
	U_{DA}	U_{PMA}	$\%all.$	U_{DA}	U_{PMA}	$\%all.$
Negotiation	0.68	0.64	94%	0.67	0.55	91%
DA–best	0.66	0.38	86%	0.60	0.38	79%
PMA–best	0.31	0.37	46%	0.32	0.39	48%

The results show that with negotiation a better parking space allocation is obtained (94% and 91%), with an increased overall utility for the DAs (0.68 and 0.67). Furthermore, the results confirm that with negotiation also the PMA utility increases, so potentially finding an allocation that is more beneficial for the city as well (0.64 and 0.55). As expected, when privileging only the PMA needs (PMA–best) the PMA utility does not increases, compared to the negotiation case, because of the high number of failures in the allocation process for both 50 and 100 requests, that is respectively 44% and 42%, i.e. the complement to the percentage of success.

Table 2. SW_{DA}, SW_+, and SW_* values for 50 and 100 requests

50 Req./100 spaces

	SW_{DA}	$max(SW_{DA})$	SW_+	$max(SW_+)$	SW_*	$max(SW_*)$
Negotiation	0.68	0.76	0.67	0.73	0.44	0.53
DA–best	0.66	0.66	0.52	0.71	0.29	0.57
PMA–best	0.31	0.36	0.34	0.35	0.25	0.26

100 Req./100 spaces

	SW_{DA}	$max(SW_{DA})$	SW_+	$max(SW_+)$	SW_*	$max(SW_*)$
Negotiation	0.67	0.72	0.64	0.69	0.40	0.47
DA best	0.60	0.60	0.49	0.65	0.29	0.51
PMA best	0.32	0.38	0.36	0.37	0.27	0.28

In Table 2 the social welfare values (SW_{DA}, SW_+, and SW_*), evaluated respectively with Equation 4, 5, and 6, are reported along with their corresponding maximum values ($max(SW_{DA})$, $max(SW_+)$, and $max(SW_*)$) for the cases of 50 and 100 requests. It should be noted that the definition of Equation 4 is exactly the overall DAs utility ($SW_{DA} = U_{DA}$).

As already highlighted in Table 1, a better overall utility for the DAs is obtained with negotiation, also compared with the DA–best baseline case. This unexpected result is due to the fact that negotiation leads to an increased percentage of parking spaces allocation, and hence, while the average value of the utilities is sub–optimal (i.e., it is less than $max(SW_{DA})$, $0.68 < 0.76$ and $0.67 < 0.72$), it is greater than the optimal value achieved in the case DA–best ($0.68 > 0.66$ and $0.67 > 0.60$). So, even though this negotiation simulation does not lead to an optimal social welfare, it still improves the social welfare with respect to the case of shared information.

When including the PMA utility in the social welfare (SW_+), the values obtained with the negotiation are greater than both baseline cases. In addition, these values are now closer to their respective optimal values ($max(SW_+)$), i.e., the negotiation leads to near optimal global outcomes.

Finally, negotiation allows for a better balancing of utilities among the involved agents, as showed by the values reported for SW_* ($0.44 > 0.29$ and $0.40 > 0.29$). Nevertheless, the values of $max(SW_*)$ with and without negotiation represent an opposite behavior, apparently showing that utilities could be more balanced without negotiation. But this is not the case, since the values of $max(SW_*)$ are not comparable with each other. In fact, the maximum values are considered only at local level for each selection step, but they do not represent the global maximum values for the overall selection process, that should instead be evaluated for all the possible permutations of allocations.

6 Related Works

Multi-agent negotiation has already been used in Intelligent Transportation System applications. In [2] negotiation is used to find better and cheaper parking spaces from the driver point of view, while in [1] cooperative agent negotiation is used to optimize traffic management relying on shared knowledge between drivers and network operators about routing preferences.

In [11] the authors presented, as in our case, a smart parking application that tries to find a trade–off between benefits of both drivers and parking providers. To balance the needs of involved parties, they use a dynamic parking price mechanism as an incentive, as also used in [7], for the drivers to balance the convenience and cost in terms of parking price and the convenience in terms of parking distance from the user's destination. Differently from our approach, in [11] all the information is available and the parking selection is obtained as a maximization of drivers' utilities. In our approach, we showed that a negotiation process is more effective, in terms of social welfare maximization, than a one–sided utility maximization. Dynamic price mechanisms were also explored in [8], where the objective was to set up prices for available parking spaces in a such a way to propose the most efficient parking allocation, in terms of social welfare, intended as the total utility value of all agents for which a parking space is allocated. The social welfare in our approach is a result of a mediation of the conflicting needs of drivers and the city management.

The optimal allocation of cars in car parks was also studied in [9], where the authors propose a semi–centralized approach for optimizing the parking space allocation, and improving the fairness among parking zones by balancing their occupancy–load. In this approach, parking coordinators are used to distribute the optimization allocation problem that is not manageable in a centralized way. In [6] the parking space allocation strategy, is also implemented as a global optimization problem, through the use of a Mixed Integer Linear Program. It is based on a user's objective function that combines proximity to destination and parking cost, while ensuring that the overall parking capacity is efficiently utilized. A set of requests are collected in a given time window, and they are processed by a software module producing an overall allocation that tries to optimize ad hoc function describing both driver–specific requirements, and system–wide objectives. In our case, the use of negotiation allows to model the parking space allocation problem not as a global optimization problem, but as the possibility to find a feasible compromise accommodating different needs.

7 Conclusions

Smart parking applications provide drivers with dynamic information on parking availability within controlled areas and direct them to vacant parking spaces by taking into account their preferences that, as reported in literature, mainly regard parking cost and location. These applications do not take into account that the problem of finding a parking space is not only a user–driven selection problem, but it may impact the well–being of the city causing traffic congestion, and an overbooking of specific and better located car parks. In this context, the parking allocation problem cannot depend only on drivers' needs, but also on needs coming from parking owners, trying to maximizing their profit, and city managers trying to consider the global benefits for the city limiting traffic congestion, or car circulation in specific city areas (e.g., pedestrian areas, or areas car prohibited for special events).

So, we model the parking allocation as a multi–agent negotiation process to find an agreement among different and sometimes conflicting needs. Negotiation occurs among Driver Agents acting on behalf of drivers requesting to reserve a parking space that satisfies their own criteria, and a Parking Manager Agent acting on behalf of a city authority that tries to allocate parking spaces by accommodating city needs.

We already showed in a previous work [3] that negotiation is a viable approach to push drivers to select parking spaces that are also beneficial from a city point of view, in the case of a single parking request. In the present work, we show that also when considering the global parking allocation problem for a set of requests, negotiation leads to better utilities for both the DAs and the PMA, and it allows to improve percentage of fulfilled parking requests with respect to the cases without negotiation.

In order to provide a measure of the social benefit of an allocation that takes into account different needs, the negotiation was evaluated in terms of the obtained social welfare of the global outcome of all negotiations occurring for the received parking requests. Different types of social welfare were evaluated by taking into account: the distribution of parking spaces with respect to only drivers needs, the same distribution with respect to both drivers and city manager needs, and finally the same distribution with respect to how the drivers and city needs are balanced. The results of the experiments carried out confirm that negotiation leads in average to better allocations and utilities for all the adopted measures when compared to experiments carried out without negotiation.

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