Using Auction Mechanism for Assigning Parking Lots to Autonomous Vehicles

1st Levente Alekszejenkó
Department of Measurement and Information Systems
Budapest University of Technology and Economics
Budapest, Hungary
ale.levente@gmail.com

2nd Tadeusz Dobrowiecki
Department of Measurement and Information Systems
Budapest University of Technology and Economics
Budapest, Hungary
dobrowiecki@mit.bme.hu

***Abstract*—Considering that the Connected Autonomous Vehicles (CAVs) of the future can choose arbitrary parking lots when being idle, parking lot assignment for CAVs will be a challenging task. Auctions are computationally efficient and distributable assignment mechanisms, hence they may offer a suitable solution. In this paper, a single-unit demand, simultaneous independent auction is presented to solve the CAV parking lot assignment problem.**

The proposed method takes into account both the financial interests of the CAV operators and ecological or social interests of the community to favor closer alternatives instead of more distant ones.

***Index Terms*—CAV, simultaneous independent auction, single-unit demand auction, parking lot assignment**

I. Introduction

Replacing traditional parking lot searching methods might be possible as the mass usage of connected autonomous vehicles (CAVs) is emerging. Instead of the closest parking lots demanded by the drivers leaving their cars in the direct proximity of the destinations (to minimize the walking effort), CAVs can choose cheaper alternatives or a parking lots better positioned (e.g. not under direct sunlight). As [8] points out, cruising of (C)AVs, instead of parking, potentially doubles the traveled distances. Hence, it is beneficial to find parking places for privately owned CAVs. To make this possible, development of new parking lot choice strategies is inevitable.

Those methods naturally require distributed and efficient calculation. Moreover, they shall respect privacy as well, e.g. the origin and destination of the journey will be kept secret.

Besides, different CAVs can value the same parking lot differently. For example, for an expectedly short time parking, a closer parking place is more valuable than a distant one. Or, if returning to the garage is not a rational option, CAVs may value every parking lot more.

For these reasons, auctions might be a beneficial way for parking lot assignments as well. In this paper, we present a single-unit-demand, simultaneous-independent auction implementation, and its application to a parking lot assignment. The choice of this particular mechanism is dictated by the following assumptions: (1) the CAVs are (will be) privately owned, (2) the owner costs of using CAVs, and the community costs of providing infrastructure, are based on travel distance, energy costs, and community taxes, (3) the cooperation between an idle CAV and a parking lot is based on an auction, (4) a single CAV enters negotiations with multiple parking lots, rated according to its optimal interests.

The research has been supported by the European Union, co-financed by the European Social Fund (EFOP-3.6.2-16-2017-00013, Thematic Fundamental Research Collaborations Grounding Innovation in Informatics and Infocommunications).

II. Related Literature

Literature on auction mechanisms is abundant [1]. Now, we focus on multiple auctions, running simultaneously and in which we only have at most a single demand. It is trivially not a multi auction as defined in [2]. Weber [3] has mentioned simultaneous independent auctions, in which bidders must act simultaneously in multiple auctions, but the single-unit demand was not considered in that paper.

Menezes et al. [4] presents an overview of single-unit demand auctions, but simultaneous, independent auctions were not discussed yet. A general method for simultaneous independent auctions with n-unit demand was discussed in [5]. A concrete implementation of their method for a single-unit demand case is shown in this paper.

Polak et al. [6] summarizes the most common parking lot searching methods of human drivers. Unfortunately, none of these algorithms is guaranteed to secure a parking place for vehicles. Since parking lots are considered to be a limited resource also in the future, efficient transportation systems might ensure parking lot reservation for autonomous vehicles. As auctions provide the possibility of efficient and distributed calculation, no central agent is needed (and we can dispense with its negotiation complexity problems) [7]. Therefore, privacy of travel might be guaranteed as well, as no entity will know exactly the preferences or the destination of the parking lot seeking CAV.

Our solution assigns parking lots to CAVs using an auction method. Auction methods have been proposed already to solve some problems of CAVs, such as electric vehicle charging and discharging in microgrids [9], or for efficient distribution of parking lots and resources in a vehicular fog computing system [10]. The auction proposed in the latter paper considers the interest of both CAVs and fog node controllers. We assume, however, that monetary infrastructural interests are hidden from the CAVs. We believe that CAVs shall prefer closer parking places as it is more beneficial in ecological and social terms.

III. An Implementation of a Single-Unit-Demand, Simultaneous Independent Auction

A. Definitions and Assumptions

Considering that a CAV require at most one parking lot at a time, we focus now on a single-unit demand auction. Every free parking place can be bid at discrete points in time. Hence, the proposed algorithm is a single-unit demand simultaneous independent auction (SSIA).

Every single parking lot work as an auctioneer, trying to sell its free capacity. For efficient implementation, auctioneers ask every bidder whether it is willing to pay the current price or not (a cyclic auction).

Auctions are scheduled regularly, in our implementation in every three minutes. Every CAV which will arrive at its destination within this time frame shall participate in these scheduled auctions. Three minutes is roughly equivalent to traveling 1 kilometer in a city, therefore CAVs can estimate their arrival time accurately.

We assume that CAVs know (through V2I – Vehicle-to-Infrastructure communication) all parking lots in the area and can and will participate in auctions as bidders for a free parking place.

For convenience, let us call a bidder active in an auction if and only if it is currently bidding in that auction. A CAV can be active at most one auction at a time [1], otherwise, it might win more than one parking place, which is avoidable for an efficient parking lot assignment.

B. Greedy bidding

Every CAV has a monotonic preference list regarding the offered parking lots. Thus, a utility function must be defined to provide a monotonic ordering. This function naturally contains parking and traveling prices, moreover, a component which is proportional to the distance of the parking lot. Therefore, CAVs can opt for cheaper alternatives, meanwhile, the overload of the road network (and increased energy consumption, pollution or wearing out) is also avoidable.

As a b CAV sees it, the $u_{i,b}$ utility function of the ith parking lot is given by equation (1), where p_i stands for the sum of the parking price at the ith parking lot and the travel price to this parking facility. d_i is the distance to the parking lot (in meters) and c is a constant to scale distance values to the parking prices.[2] The $0.0 \leq \alpha \leq 1.0$ coefficient reflects how a CAV values parking prices over travel distances.[3] As a CAV has to travel $d_{i,b}$ distance two times, we shall represent this knowledge as a coefficient of 2 in the distance component.

$$u_{i,b} = \alpha \cdot p_i + 2 \cdot (1 - \alpha) \cdot c \cdot d_{i,b} \tag{1}$$

[1]Regardless the number of auctions at which the CAV is a participant.

[2]For Hungarian Forint (HUF), we simply use c=1.0

[3]In current paper, in favour of simplicity, we use an $\alpha = 0.5$ value.

As mentioned before, p_i has two components as well. One part of p_i is the c_p parking cost, and the other component is denoted as a $c_f(d_i)$ function. c_f represents a distance related fuel price (or some virtual form of fuel price as electronic vehicles might be more common in the future, and it seems unlikely that governments will waive fuel taxes) and additional amortization. Altogether, equation (2) shows the formula for calculating p_i.

$$p_i = c_p + 2 \cdot c_f(d_i) \tag{2}$$

By calculating u_i for all possible parking lots, CAVs will have a preference list covering them all. Let us assume, that auctions can run in an instant, therefore the only variable part of this formulation is the c_p parking price component. Thus, every CAV will have a currently favored parking lot to bid for. If possible, then a CAV will bid in the auction of this particular parking lot actively. To guarantee that a CAV will not win more than one parking lot, it shall be active in at most one auction. In the following, a detailed description of the auction mechanism is given.

C. Multiagent system and its negotiation algorithms

From a multiagent system point of view, auctioneers (the parking lots) and bidders (the CAVs) are two kinds of agents.

Auctioneers sell, in our particular case, free parking places. Given the $\mathcal{B}$ list of bidders and the starting price s_p, Algorithm 1 describes the task of an $a \in \mathcal{A}$ auctioneer agent. Auctioneers ask every $b \in \mathcal{B}$ participant cyclically whether they are willing to give the c_p current bid or not. When a bidder sends in the current bid, the auctioneer will raise it by a small $epsilon$ amount. An auction terminates when only one bidder entered the current bid ($n_w = 1$), or every participant left the auction ($|\mathcal{B}| = 0$). (The latter is possible if every bidder had already won in another auction, e.g. when the supply is higher than the demand for parking lots.) The only one bidder, who is willing to give the current bid, will be the b_w winner of the auction.

Algorithm 1 Algorithm of an auctioneer

$c_p \leftarrow s_p$
repeat
  $n_w \leftarrow 0$ ▷ No one has bid in the current cycle yet
  for $b \in \mathcal{B}$ **do**
    answer ← ASK(b, a, c_p)
    if answer = "bid" **then**
      $c_p \leftarrow c_p + \epsilon$ ▷ Increasing the current price
      $n_w \leftarrow n_w + 1$ ▷ One more bidder gives c_p
      $b_w \leftarrow b$ ▷ Current winner can be b
    end if
  end for
until $|\mathcal{B}| > 0 \land n_w > 1$ ▷ There are bidders, no one won
if $n_w \neq 1$ **then** $b_w \leftarrow \varnothing$ ▷ No one had bid, no one won
end if
return b_w

For a b bidder, the most important function is *ASK* and is presented as Algorithm 2. This function, given an auctioneer a and a current price c_p determines the *answer* whether to enter or not with the current bid. A bidder leaves an auction, if its current price exceeds the m_p maximal price of a bidder. If the auctioneer (the caller of the *ASK* function) is the preferred one ($a = a_p$), and the b bidder has already overbid ($c_p > c_g$, where c_g is the last bid of b), then a bidder might choose another preferred auction (a_p) to bid in. If this preference is unchanged, then the bidder will enter the current price, otherwise it will not, moreover it will note that it cannot win any auctions currently, as it did not place a winning bid.

Algorithm 2 Algorithm of a bidder

> **function** ASK(b, a, c_p)
>   answer $\leftarrow$ "do not bid"
>   **if** $c_p > m_p$ **then**
>   LEAVE_AUCTION(a, b)
>   **end if**
>   **if** $a = a_p$ **then** ▷ Caller is the preferred auction
>   **if** $c_p > c_g$ **then** ▷ Have we been overbid?
> $a_p \leftarrow \arg\min_i u_{i,b}$, where $i \in [0..|\mathcal{A}| - 1]$
>   **end if**
>   **if** $a = a_p$ **then** ▷ Has our preference changed?
>   answer $\leftarrow$ "bid"
> $c_g \leftarrow c_p$ ▷ Last bid is the current bid
>   **else** $c_g \leftarrow 0$ ▷ No bid has been entered
>   **end if**
>   **end if**
>   **return** answer
> **end function**

D. Computational efficiency of SSIA

When every bidder is willing to give the m_p, maximal price for an object in a specific auction, then it requires $\lceil \frac{m_p - s_p}{\epsilon} \rceil$ steps for the auctioneers. Supposing $n = |\mathcal{B}|$, n further steps are also necessary to ask every bidder once again (when none of them will accept the current price). Altogether, this case requires at most $k = \lceil \frac{m_p - s_p}{\epsilon} \rceil + n$ steps. The auctioneer has to maintain a list of its bidders, besides some technical information (eg. current price, bid step). Hence, the algorithm of an auctioneer runs in $\mathcal{O}(n)$ time with $\mathcal{O}(n)$ memory demand in the n number of its bidders.

For the bidders, the most steps are required when the bidders have exactly the same preference lists in every auction cycles. Supposing that a bidder participates in m auctions, the auctioneers make at most $k - n$ steps without any of the bidders winning in an auction. In the last cycle, however, the bidders might win the m auctions one-by-one. Therefore, at most $l = m(k - n) + m$ steps are required. As actual bids or some additional technical data of the auctions shall be maintained, arrays of m-length might be required. Thus, the algorithm of a bidder also runs in $\mathcal{O}(m)$ time and with $\mathcal{O}(m)$ memory demand, in the m number of auctions.

IV. SSIA SIMULATION EXPERIMENTS

Considering that we cannot anticipate the ways future cities are expected to adapt to the future needs and behavior of their citizens yet, detailed simulations do not necessarily yield assessable results of the future traffic. Therefore, we shall use a more abstract simulation framework, like the one described in details in [11].

Now, we simulate the activity-chains of 3000 people in a city with an area of 10000 m × 10000 m with residential surrounding of 20000 m × 20000 m. These human activities might be going to work or going to shopping and every movement involves using a CAV which ultimately will be left to itself awaiting to be recalled at the end of the activity. At least one and at most three specific activities make every activity chain, which start with a departure from a home position and ends with an arrival at this home position. Home positions are distributed evenly ($X_h, Y_h \sim \mathcal{U}(-10000, 10000)$) in the city.

Between every human activity in a chain, the CAVs shall find a suitable parking place. We model two types of parking lots: curb-side parkings and parking houses. 350 curb-side parking lots are concentrated in the city center according to the Gaussian distribution ($X_c, Y_c \sim \mathcal{N}(0, 5000)$) with capacities $N_c \sim \mathcal{U}(1, 10)$, i.e. from a single place up to 10 parking places, while 5 parking houses are distributed in an annulus around the city (with their distance from the city center, distributed circularly with Gaussian radius and uniform angle: $R_p \sim \mathcal{N}(0, 3000) + 10000$, $\Phi \sim \mathcal{N}(0, 2\pi)$). They have a capacity of $N_p = 300$.

To realistically represent the d driving distance between two points of the city, the $d = E + s(M - E)$ formula is used, where E stands for the Euclidean, and M stands for the Manhattan (or taxi-cab) distance of the two points. The s is a probabilistic coefficient ($s \sim \max(0, \mathcal{N}(1.3, 1.8))$), estimated from measurement of real-world driving distances in Budapest.

A. Parking lot seeking methods

In the described simulation framework, we compared a traditional parking lot searching strategy to an SSIA based one. The traditional strategy was to *spiral away* from the last destination (similar to Strategy VI of [6]). In the simulation, this method requires listing parking lots based on their distance from the place of the human activities. To check whether these parking lots are free or not, a CAV shall travel from one parking lot to another following the order of the distance list, which ensures spiraling away and around the destination, instead of a greedy depth first search.

The SSIA method was used to licit for a parking fee calculated on a per second basis. The starting prices are the same as they were when the parking lots were generated, see [11]. We used $\epsilon = \frac{5}{60 \cdot 60}$ $[\frac{HUF}{s}]$ increment and $m_p = \frac{5000}{8 \cdot 60 \cdot 06}$ $[\frac{HUF}{s}]$ maximal price, representing an increment of 5 HUF/hour and a maximum of 5000 HUF for a parking of eight hours.

As travelling further than the cheapest alternative or paying more than at the closest alternative are irrational parking lot choices, CAVs will not participate in such irrational auctions. In our simulation, going home is always an option, hence if a CAV cannot win any auction, it shall return to its home position. (There is a possibility, that CAVs will find the first free parking lot at their own home position in the traditional method as well.)

B. Compared values

The simulations of both parking lot searching methods were run for 10 times, each time with a newly generated city model. To compare the possible benefits of SIAA over the traditional method, the following values were measured.

Unloaded distances: The commulated distance the CAVs travel without carrying passengers or cargo. (In this particular case, it is the distance traveled to and from parking places to the destination of the passengers of the CAVs.) *Total parking prices:* The total amount of money spent on parking. *Ratio of occupied parking places:* The ratio between the occupied and the total parking places in the simulation by hours of a day.

C. Measurement results

The SSIA method is capable of directly assigning parking places to CAVs, hence no unnecessary traveling is needed to find a free parking place. As it can be seen in Fig. 1, SSIA can reduce unloaded distances even by 90% compared to the traditional method.

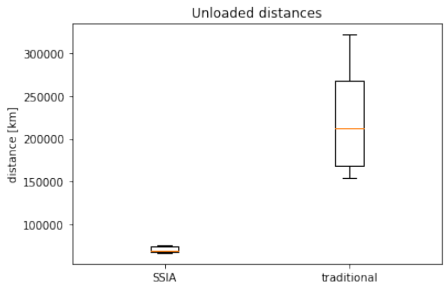

Fig. 1. Cumulated unloaded distances traveled by 3000 CAVs to and from parking places.

According to Fig. 2, parking prices are also reduced by SSIA, however, we shall check Fig. 3 as well for parking lot occupancy. As approximately two times more parking lots are occupied with the traditional method, we can conclude that SSIA slightly increases the paid parking costs. We would like to add, that as SSIA results more free parking lots (with significantly lower parking lot searching traffic demand), hence these unoccupied parking lots can be recultivated as e.g. sidewalks, terraces of cafés or bike lanes, etc.

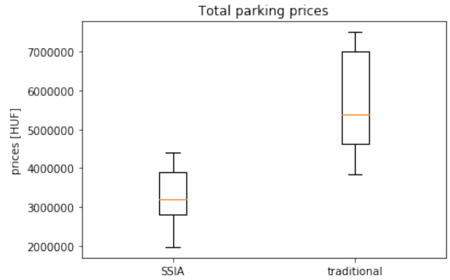

Fig. 2. Cumulated parking fees payed by 3000 CAVs.

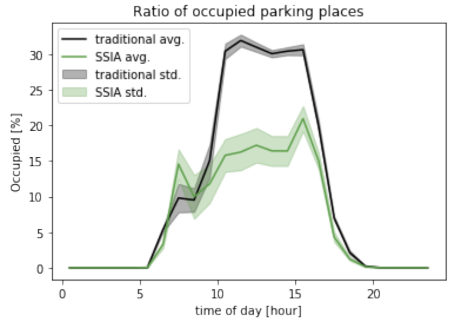

Fig. 3. Occupation of parking lots during a simulated day.

V. Conclusion

In this paper, a single-unit demand, simultaneous independent auction (SSIA) method is proposed for assigning parking lots to connected autonomous vehicles (CAVs). Simulations with an abstract, qualitative city model were carried out, which prove that, however, the SSIA increases the parking costs, it efficiently reduces the distance traveled unloadedly while looking for free parking lots, and it may also reduce the number of required parking lots as well.

References

[1] J. Cassady R., *Auctions and Auctioneering*. Berkeley: University of California Press, 1967.

[2] W. Vickrey, "Counterspeculation, Auctions, and Competitive Sealed Tenders," *The Journal of Finance*, vol. 16, no. 1, pp. 8–37, Mar. 1961.

[3] R. J. Weber, "Multiple-object Auctions." J.L. Kellogg Graduate School of Management Northwestern University, Evanston, Illinois, Aug. 1981. [Online]. Available: https://www.kellogg.northwestern.edu/research/math/papers/496.pdf

[4] F. Menezes, "Auctions of Identical Objects With Singleunit Demands: a Survey," *Brazilian Review of Econometrics*, vol. 18, no. 2, pp. 309–340, Nov. 1998. [Online]. Available: http://bibliotecadigital.fgv.br/ojs/index.php/bre/article/view/2839

[5] V. Bansal and R. Garg, "Simultaneous Independent Online Auctions with Discrete Bid Increments," *Electronic Commerce Research*, vol. 5, no. 2, pp. 181–201, Apr. 2005. [Online]. Available: https://doi.org/10.1007/s10660-005-6156-1

[6] J. Polak and K. Axhausen, "Parking Search Behaviour: A Review of Current Research and Future Prospects," *University of Oxford, Transport Studies Unit (1. Jan. 1990)*.

[7] S.-Y. Chou, S.-W. Lin, and C.-C. Li, "Dynamic parking negotiation and guidance using an agent-based platform," *Expert Systems with Applications*, no. 35, pp. 805–817, 2008.

[8] J. Bischoff, M. Maciejewski, T. Schlenther, and K. Nagel, "Autonomous Vehicles and their Impact on Parking Search," *IEEE Intelligent Transportation Systems Magazine*, vol. 11, no. 4, pp. 19–27, 2019.

[9] D. Li, Q. Yang, D. An, W. Yu, X. Yang, and X. Fu, "On Location Privacy-Preserving Online Double Auction for Electric Vehicles in Microgrids," *IEEE Internet of Things Journal*, vol. 6, no. 4, pp. 5902–5915, Aug. 2019.

[10] Y. Zhang, C. Wang, and H. Wei, "Parking Reservation Auction for Parked Vehicle Assistance in Vehicular Fog Computing," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 4, pp. 3126–3139, Apr. 2019.

[11] L. Alekszejenkó, "Connected autonomous vehicle (cav) and the urban parking problems," Master's thesis, Budapest, Hungary, 2021, in Hungarian. [Online]. Available: https://diplomaterv.vik.bme.hu/en/Theses/Kommunikalo-onvezeto-auto-CAV-es-a/Attachment/50899