Effects of Noisy Occupancy Data on an Auction-based Intelligent Parking Assignment

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***Abstract*—Smartphones and cloud services can provide sophisticated parking assignment in modern intelligent cities. These solutions aim to guide drivers to vacant parking lots near their destination, reducing the necessary cruising for parking. Hence, they can smoothen the traffic flow and mitigate harmful emissions. Moreover, auction-based assignment can also dynamically optimize the actual parking prices, benefiting drivers, and parking lot operators.**

To operate such a system, we shall know the actual occupancy of the supervised parking lots. This data can come from various sources, e.g., crowdsourcing, parking lot operators, or third-party data providers. Sensing and fusing these records might lead to inaccurate input for the assignment method. In this paper, we analyze the impact of such noise on the performance of an auction-based parking lot assignment system. The results indicate that accurate information is crucial for perfect operation, but current state-of-the-art solutions provide sufficient input to benefit from the system.

***Index Terms*—auctions, noisy data, parking assignment**

I. Introduction

The advent of autonomous vehicles (AVs) could affect the appearance and use of future cities. Regardless of their ownership model, AVs will reduce parking demand; hence, nowadays parking facilities can be reconstructed into attractive areas, e.g., parks, playgrounds or community buildings [1]. However, recent financial processes negatively influenced the automotive industry, i.e., overall car production dropped to a decade-old level [2]. Consequently, car manufacturers have to decrease their investments in research and development, certainly postponing the introduction of AVs.

Moreover, traffic congestion is surprisingly expensive; for example, a single congestion event costs more than 50.000€ to the society [3], while a driver spent 110 extra hours in 2024 in Budapest, Hungary, according to TomTom's TrafficIndex[1] due to rush hours. In rush hours, many drivers cruise for parking [4], slowing down traffic and adding to congestion. Without AVs that minimize parking demand, we might be able to optimize parking usage to eliminate cruising and mitigate the harmful effects of traffic congestion.

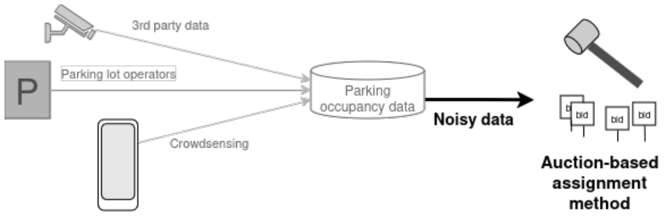

Fig. 1: System architecture of the assumed system.

A demand-based, market-priced curbside parking could effectively alleviate cruising for parking [4]. Therefore, we assume that a municipality deploys an intelligent parking assignment and pricing system based on auctions. However, this system requires constant monitoring of the available parking spaces. These monitoring data can come from various independent sources, including parking lot operators and video surveillance cameras. Moreover, drivers can also report the occupancy status of parking lots using a crowd-sourcing application; see Fig. 1. Naturally, combining these originally inaccurate observations leads to a noisy input for the auction-based assignment system, possibly impeding its performance. Thus, we will get two sets of free parking spaces. There is a set of *real* free parking spaces on the road, and there is another set of free parking spaces *represented* in the auction mechanism. If we had perfect information, the set of real and represented free parking lots would coincide. Considering a real-world free parking lot occupancy detector, there might be misclassifications; for example, it can mark an occupied parking lot free, or a free parking lot as occupied. Furthermore, the validity of the measurement data can also expire (someone occupies a parking lot or leaves it after the measurement); consequently, the set of free parking lots might not be identical. The problem addressed here is similar to an auction-based task allocation system in which we cannot know whether a task exists in the real world or whether all the real world tasks are represented on the actions. To our knowledge, no one has investigated yet how such noisy inputs affect an auction-based parking assignment system. In this paper, our aim is to fill this research gap. By microscopic traffic simulation of a central business district, we will assess how noisy observations

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[1]https://www.tomtom.com/traffic-index/budapest-traffic/ (accessed: 24/01/2025)

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reduce the traffic smoothing capabilities of such a parking assignment system. We will also check how successful parking reservations are when the assignment system does not receive perfect information. Finally, we also investigate how noisy observations influence the pricing mechanism and what the individual economic outcomes of operating such a system are.

II. Related Works

As [4] concludes, parking pricing shall reflect market demand in a temporal-spatial way. For example, in San Francisco, USA, the *SFPark* project implements a demand-based pricing scheme. That project aims to keep the occupancy ratio in the 60-80% range. If the occupancy rate does not reach this level in particular parking spaces, the parking prices decrease and if they exceed 80%, the municipality increases the parking fee. In the *SFPark* project, price recalculation follows a strict rule; hence, it is a reactive system that requires many iterations to reach the target state [5].

Auction-based calculations can provide an optimal solution incomparably faster than *SFPark*. For example, a sealed bid Vickrey-Clarke-Groves mechanism only needs to compute the final results without testing the actual prices in the real world [6]. Unfortunately, this method is not budget-balanced, but with a restriction, it can avoid running with deficits [7]. However, participant drivers shall still report their valuation of the parking lots to a central agent. It might pose a privacy threat, as it reveals information about a driver's destination or financial status. To avoid sharing these pieces of information, instead of sealed bid auctions, one could implement an ascending auction mechanism for multiple items [8], as it only requires a single bit of information, whether or not a driver is willing to pay a particular price for a parking lot. The local greedy bidding (LGB) strategy, which means that each participant bids for items that maximize its utility function, can obtain, e.g., at most 1 item in simultaneously running independent ascending bid (online) auctions (SIA) [9]. Similarly to [10], we implemented an ascending bid auction system for parking assignment [11].

Hypothetically, individual parking operators can run the algorithms necessary for these independent auctions. In practice, even simpler intelligent parking solutions require tens of millions of dollars of infrastructural development [12]. Considering that municipalities cannot afford such investments, we assume that auctions run on remote servers. In addition to the bids of the drivers, the operation of this server requires the knowledge of the number of available parking lots. Recent studies have introduced various vision-based parking lot occupancy detectors. Some of these state-of-the-art solutions require a stationary surveillance camera on a high vantage point, facing a larger parking facility. A video-based solution, QuickSpot [13], can achieve 97.8-99.2% average detection accuracy, and a single-frame-based detection system can reach 89-95% accuracy [14]. Similarly to these results, a third stationary camera-based solution in [15] provides a detection rate of 96.43-100%.

Despite stationary surveillance cameras, parking occupancy detector solutions can also use images from dashcams in moving vehicles. The system described in [16] recognizes vacant parking spaces with 97% recall, and 86% classification accuracy. Besides individual recognition systems, a vision-based vehicular crowdsensing system of [17] provides a 83% average accuracy.

Crowdsensing systems usually run auction methods for orchestration [18], [19], or even to optimize the accuracy of the obtained data [20]. In this paper, we assume that the noise of the input data is independent of the auction mechanism; hence the system cannot enhance its accuracy. Moreover, there might be an uncertainty in the number of bidders, their valuation of the objects, the number of objects in auctions [21]–[23]. We note, that in our problem, the auction mechanism lacks these uncertainties as in our model the list of real free parking lots and the represented parking lots could be misaligned independently of the auction mechanism.

In the following, we will investigate how inaccurate parking occupancy detection influences the performance of an auction-based parking lot assignment system.

III. The Auction Method

Following [9], we implemented[2] an SIA method for parking assignment. In this approach, dedicated auctions control the occupancy of every free parking space. Vehicles bid for a parking space in these auctions following the LGB strategy. Naturally, a driver aims to minimize the combination of required walking and parking fees. Hence, denoting $d_{i,j}$ the driving distance (which is an overestimate of the walking distance) from the original destination of vehicle j to parking lot i, let $d_{j,max} = \max_i d_{i,j}$, ρ_i the current hourly price of parking lot i and $\rho_{max} = \max_i \rho_i$, then the $c_{i,j}$ parking cost of vehicle j at parking i is calculated as:

$$c_{i,j} = 0.5 \cdot \frac{d_{i,j}}{d_{j,max}} + 0.5 \cdot \frac{\rho_i}{\rho_{max}}. \tag{1}$$

As $c_j \in [0.0, 1.0]$, and the vehicles aim to minimize parking costs, to maximize their utility, they shall maximize $1 - c_{i,j}$ over i. This yields, vehicle j shall prefer the $\mathcal{P}_j = \arg\max_i(1 - c_{i,j})$ auction.

To ensure that a vehicle gets assigned to at most one parking lot, it shall only bid on an auction if it is overbid in every other auction. In our experiments, bidders have a 2.43 €[3] upper bound of hourly parking price that they are willing to pay for a parking lot.

IV. Simulations

To test the described auction method with inaccurate input data, we created a simulation scenario of an abstract central business district (CBD). The road network of this CBD consists of 6×6 perpendicular road segments which are 100 m

[2]Source codes are available on Github: https://github.com/alelevente/bprof_mi_multiagent.

[3]2.43 €was equivalent to 1000 HUF (Hungarian Forint) at the writing of this paper, on 11th of November, 2024.

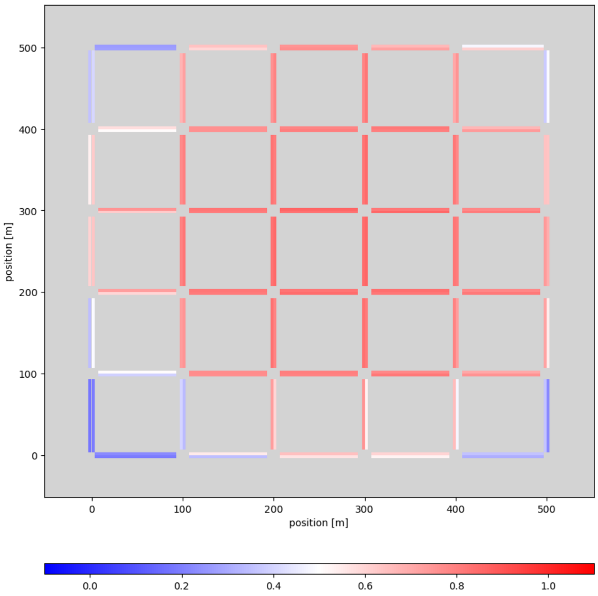

Fig. 2: Average parking lot occupancy rate in the uncoordinated (unc.) case. As turning right is generally easier in a right-hand side driving system, the top right corner of the road network is slightly more preferred than other corners of the road network.

long, see Figure 2. There are $t = 15$ parking spaces on the curb on both sides of each road.

We assume people come to the CBD, do their business there, and leave after a short stay (i.e., evenly distributed between 20 and 120 minutes). We assume that the demand for parking in the central part of the CBD is higher than in the outskirts. Therefore, we generated traffic for the simulation aiming at the central part of the grid 9 times more likely than the outer parts. Traffic demand decreases evenly as we move farther away from the center. We also assume that parking lot operators have already set parking pricing accordingly, i.e., central parking lots cost 1.1 €/h, while the most distant parking lots have a 0.12 €/h hourly price. The auction method uses these prices as starting prices.

We ran microscopic traffic simulations of this scenario in Eclipse SUMO [24]. In the simulation, we placed `ParkingLotRerouters` at the end of each road segment. These rerouters redirect vehicles to the nearest parking lots, ensuring that they find a vacant parking space. With induction loop-type traffic detectors placed at 60th m of each road segment, we measured the traffic flow in the simulation in vehicles/h ([veh/h]) unit. We also acquire the exact n_i number of each i free parking lot from Eclipse SUMO. We added different amounts of discrete noise δ to these values to achieve a predefined detection accuracy rate. To ensure experimenting with an expected target level of accuracy g, we sampled distortions from a uniform integer distribution $\mathcal{U}\big(0, 2(t - tg)\big)$. Hence, the $\tilde{n}_i$ distorted capacity of parking lot i will be:

$$\tilde{n}_i = n_i \pm \delta. \tag{2}$$

In this way, (2) defines an unbiased noise model with an expected accuracy of g.

In addition to simulating the traditional *uncoordinated* (unc.) parking search method, we also experimented with auction-based parking assignment. In the latter case, every 15th seconds of the simulation, we run auctions for the parking spaces. Vehicles that have departed since the last auction runs shall participate in these auctions to reserve a parking space. Then, we instruct Eclipse SUMO to reroute the cars to their assigned parking lots. However, some vehicles (approximately 1.5%) complete their route faster than 15 s; consequently, we cannot reroute them according to the reservation mechanism. In addition, inaccurate parking lot occupancy data can lead to overreserved parking lots. In this case, if the demand for a parking lot exceeds its capacity, excess vehicles shall find another vacant parking space via the traditional cruising method as a fall-back algorithm. To ensure that users of the auction-based parking lot assignment mechanism do not lose money, they shall only pay the auctioned parking fees if the parking reservation is successful. Otherwise, they will pay the original price of the parking space they managed to occupy. To handle stochasticity, we repeated each simulation for 10 times.

V. Results of the Inaccurate Parking Occupany

In the following, we analyze the results obtained from the simulations. Firstly, we check how the auction method influences macroscopic traffic and whether it can mitigate congestion by improving the flow of traffic. Secondly, we present what an individual driver would experience using the auction-based parking assignment method. Finally, we check how inaccurate data influences the auction method.

A. *Impact on Macroscopic Traffic*

The auction-based intelligent parking assignment system improves traffic flow; see Fig. 3. The traditional, uncoordinated (unc.) system provides the lowest average traffic flow, and the perfect information achieves the highest. However, the amount of non-zero noise in the parking occupancy data has a negligible effect on macroscopic traffic flow.

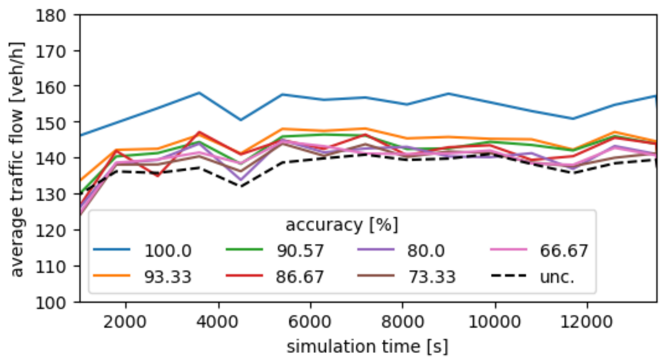

Fig. 3: Traffic flow with different accuracy levels.

On the other hand, parking habits change significantly due to the auction method. Previously, drivers solely preferred to park close to their destination, resulting in a high occupancy rate in the central part of the simulated road network; see Fig. 2. In addition to traditional walking distance, auction-based assignment also optimizes parking costs using the (1) cost function when bidding with the LGB strategy. That leads vehicles to cheaper, farther away parking spaces. Fig. 4 groups parking lots by their Euclidean distance from the center of the road network. While the traditional uncoordinated (unc.) system provides a larger demand in the center of the road network, the novel system fills the more distant parking lots instead. When parking lot occupancy data are less accurate, more and more drivers must revert to the traditional parking cruising method by deviating from new parking habits.

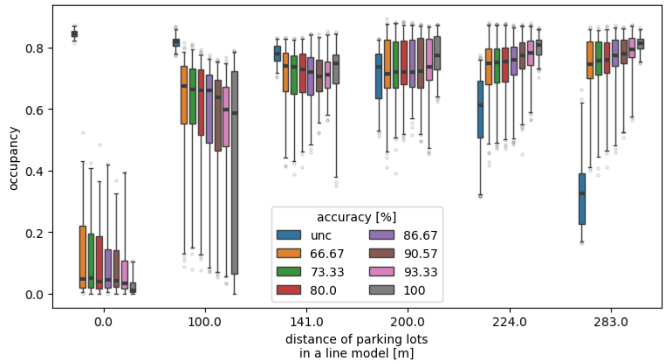

Fig. 4: Parking occupancy rates at different distances from the center with different accuracy levels. Uncoordinated (unc.) case shows a completely different parking habit compared to the auction-based parking assignment system.

B. Impact on Microscopic Traffic

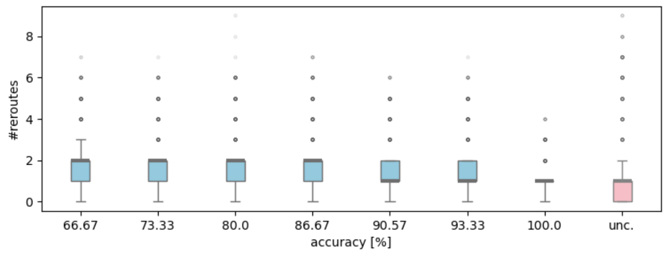

Fig. 5: Number of reroutes in Eclipse SUMO with different accuracy levels. Medians significantly decrease at ≈90% accuracy.

The assignment system influences drivers in two ways. We call the first *number of reroutes*. There are two reasons to experience a rerouting event. Firstly, when a vehicle gets an assigned parking lot from the system, it changes its target to that parking space, similar to a route recalculation of a modern navigation system. Secondly, if the vehicle cannot park in a parking lot, it keeps cruising and looking for a vacant

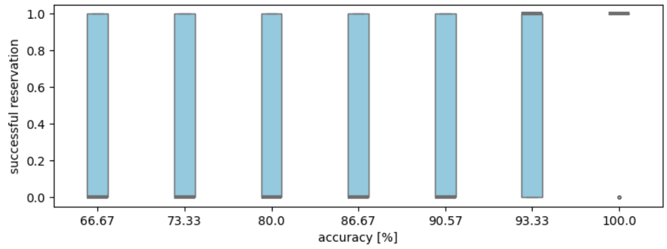

Fig. 6: Rate of successfully occupied parking lots offered by the auction method. Medians significantly increase at ≈93% accuracy.

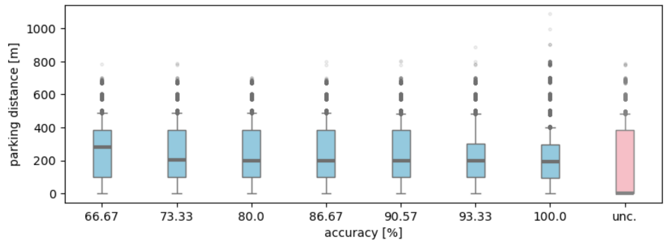

Fig. 7: Driving distance between the occupied parking lot and a driver's original destination.

parking space. It also triggers a reroute event if a car passes an intersection during this cruising. Fig. 5 shows the number of reroutes. The traditional uncoordinated (unc.) system can even force vehicles to cruise on up to 9 streets until finding a free parking space. If the auction system has perfect input data, it naturally needs one (recalculating route-type) reroute. Outliers are due to the mechanism mentioned in section IV. With decreasing accuracy, the number of reroutes increases. Its reason is that the noisier input data of the assignment system reduces the success rate of occupying the assigned parking lot; see Fig. 6. Consequently, most vehicles cannot occupy the parking space reserved by the auction method below ≈93% of accuracy.

The second effect of the auction-based parking assignment system is the distance between the parking lot and the driver's original destination, called *parking distance*. As walking distance is less than equal to the driving distance (obtainable from the Eclipse SUMO simulation), it gives an upper estimate of the walking distance. Fig. 7 shows a decreasing trend in the parking distance as accuracy increases. At higher accuracy levels, the deviation of the parking distance distribution also decreases. Fig. 5 can explain these observations, as more accurate input data decrease the number of reroutes, the length of cruising for parking, and, according to Fig. 6, help drivers occupy their assigned parking lot. Naturally, as the uncoordinated mechanism has a different goal function that only minimizes the parking distance, it mainly achieves shorter parking distances than the auction mechanism.

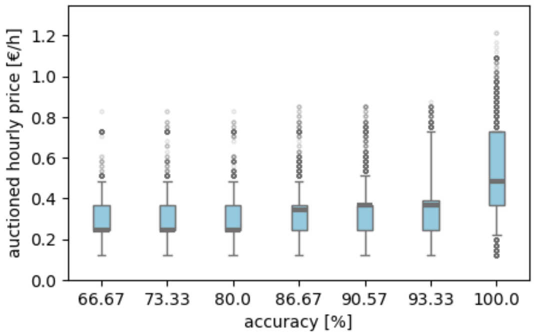

Fig. 8: Hourly parking prices provided by the auction-based assignment method.

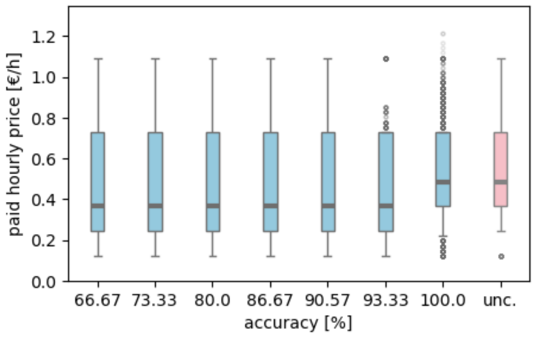

Fig. 9: Actually paid hourly parking prices.

C. Impact on Auction Method

Finally, we analyze how imperfect data affects the auction method itself. To this end, we check the resulting auctioned prices (determined by the number of bids) that reflect the competition between vehicles for parking spaces. According to Fig. 8, prices increase as the accuracy of the input data increases. It indicates that the competition decreases if the number of free parking spots is overestimated due to the (implied) larger supply. On the other hand, competition also decreases if we underestimate the number of free parking spots because vehicles would choose other parking alternatives rather than competing. Consequently, exact knowledge improves the competition, resulting in higher auctioned hourly parking pricing, converging to the market value of the curbside parking pricing.

As drivers are only required to pay the auctioned parking price if they can occupy the reserved parking space, the actually paid hourly prices can differ from the auctioned prices. Fig. 9 summarizes the actual hourly prices. Due to the changed parking habits, the auction mechanism reduces the users' parking costs compared to the uncoordinated case. We can also see that, below the accuracy of ≈93%, any further inaccuracy has no significant effect on the paid prices.

VI. Conclusion

In this paper, we analyzed how inaccurate parking lot occupancy data can affect an SIA auction-based intelligent parking lot assignment method. Simulation results indicate that the system provides most of its merits with perfect information. However, approximately 93% accuracy is enough to experience the positive effects of the auction-based parking assignment system. According to our literature overview, state-of-the-art camera-based parking occupancy detectors can provide the expected data accuracy to operate such an intelligent parking coordination system. With further investment in infrastructure, as in the case of the SFPark project [12], more precise data would be available to enjoy all the benefits such a system can provide.

Furthermore, following the analogy of section I, the presented problem is a concrete case of an auction-based task assignment mechanism without exact knowledge of the existence of tasks and without any guarantee of the completeness of the task list. In other similar scenarios, typically in search and rescue missions, an imperfect list of tasks might also hinder the system performance. Therefore, further research is needed to exploit all the merits of auction-based multi-agent systems.

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