SUMO User Conference 2021
https://doi.org/10.52825/scp.v2i.93

Published: 29 Jun. 2022

Validating a parking lot assignment method by Eclipse SUMO

Levente Alekszejenkó[1] and Tadeusz Dobrowiecki[1]

Department of Measurement and Information Systems,
Budapest University of Technology and Economics,
Budapest, Hungary
alelevente@mit.bme.hu
dobrowiecki@mit.bme.hu

Abstract

The present paper shows how a novel autonomous vehicle (AV) algorithm can be tested and evaluated by multiple simulations with different levels of refinement.

As the first AVs will appear on our roads (possibly) within the upcoming decade, novel traffic problems, like parking lot assignment, will also emerge. Parking is that kind of activity that will fundamentally change. Today drivers attempt to find parking places close to the destinations to minimize the walking time. The autonomous vehicles will drop off passengers at their very destination, and then, on their own, will seek even a distant parking place. Such change will affect human activities, city traffic, and the parking infrastructure.

To investigate this problem we need an abstract city model, because an attempt to create a detailed model of the city traffic from the perspective of decades may be misleading and may lead to false emergent conclusions. We report on such an abstract model and the obtained conclusions in the paper.

A question remains how genuine is the introduced future city model. To validate it, we propose to confront it with a detailed microscopic traffic simulation on a road network borrowed from an existing city of corresponding layout and complexity. To this end, we use Eclipse SUMO simulating the traffic of an expansive Budapest district, and show that the results obtained with the simplified abstract mathematical model stay valid.

1 Introduction

The analysis of transportation in future cities is a challenging task. The principal difficulty is how to set up simulations of the future traffic when little if any may be known about it, besides futuristic assumptions and visions.

As the penetration rate of autonomous vehicles (AVs) is foreseen to reach a considerable level within the next 20-40 years, we aimed at this horizon in our research. The arising changes in vehicle ownership, technological advances, and changing habits made it hard to estimate the future traveling demands. The practical and important question was whether it is safe to use the existing microscopic traffic simulation platforms, set up for a detailed reproduction not of the future but of the existing traffic and city road networks. With such platforms, one consequently risks that the simulation results may become a mixture of emerging plausible and difficult to discern spurious phenomena.

Our research tackled, in particular, the parking problem of AVs based on their communication and assumed intelligent decision-making capabilities. To this end, and because of the above doubts, we created a semi microscopic but much more abstracted mathematical city model. Assuming that the basic city structure (including historical downtowns, buildings, utility infrastructures, etc.) will not change in the future, an abstract city model can describe future cities as well as cities of today. It can obscure the yet unknown details (like specific road networks), but it can provide sufficient information for qualitative comparisons. With such a city model we found interesting phenomena about the parking behavior of AVs. However, the most important question was whether such a model is acceptable. In an attempt to clarify these doubts, we deploy an analogy to the downward refinement consistency of [6]. More precisely, a phenomenon discovered on the abstract level shall also be observable in a more refined model when modeling the physical reality on different levels of abstraction. However, it might not be true the other way around.

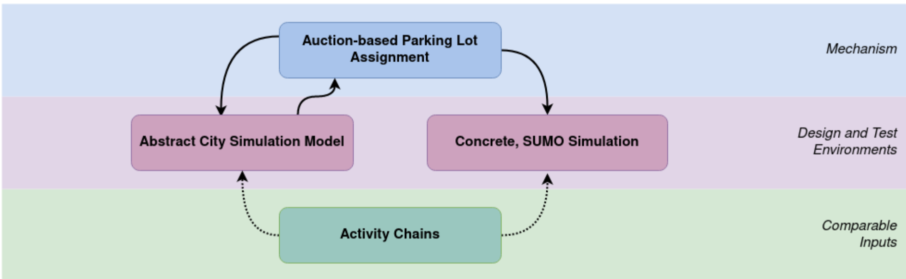

Figure 1: Overview of the validation process applied to the parking problem of AVs.

Thus, the point is that a more refined model permits the validation of a less detailed one. A feasible choice of such validating model of a city may be one of the available traffic simulation platforms. The open-source microscopic traffic simulation tool Eclipse SUMO [18] seems to be an efficient choice for lower-level validation tasks. To make both models comparable, the Eclipse SUMO model should describe a real city with dimensions and complexity similar to that of the abstract model. Figure 1 shows the interaction of the two models when applied to the same simulation task. In the following, in Section 2, we present why and how the AV parking problem might be discussed. After that, Section 3 contains a brief overview of the works already done in the topic of city modeling, then, in Section 4, we shortly review the auction-based parking assignment method used as a pilot problem. Then in Section 5 the composition and results obtained with the abstract mathematical model are presented. In Section 6 we set up the comparable SUMO simulation, and in Section 7 the results obtained with the two models are compared.

2 Autonomous Vehicles, Parking, and the Advantages of an Abstract City Model

One of the fundamental questions facing a private car owner is where to park. Traditionally most drivers attempt to minimalize the walking distance when looking for a suitable parking place. Therefore, spiraling around the destination with an increasing radius [17] might be an effective strategy. Unfortunately, it can also be quite time-consuming [20] as well. The AVs, by definition, will drive without any human supervision, so they may find a suitable place to park on their own after delivering passengers to their destinations. Here, an important issue regarding the ownership and the utilization of the future AVs pops up. It was supposed earlier that AVs would be shared as a Mobility as a Service (MaaS) solution. However, due to the experience of the pandemic, with social distancing and disinfection problems, moreover, due to other current trends [21], a significant part of the AVs is now expected to become private property, at least for a time. Hence, we assume in our research that the AVs will be either privately owned or shared among a socially closely related group of people. The parking problem of such AVs differs greatly from the MaaS solution. After dropping off the last passenger, a privately owned AV is not speeding to the location of the next order but seeks a place to wait for being resumed, somehow optimizing the actual and the future traffic exposure. Finding an optimal parking lot is thus a kind of intelligent decision that has to be studied profoundly. As a solution to this problem, an auction-based method was proposed in [3].

To obtain a clear picture of the efficacy of the proposed parking strategy, a simple but expressive mathematical city model is sufficient. The parking infrastructure, the traveling activities, and the destination geolocations are the most relevant aspects to be modeled. Any more details (e.g. modeling the traffic flow, the interaction of the vehicles, and specific road network-related effects) would only obscure the results.

The abstract model guarantees that statistically similar city models (e.g. with similar shape and dimensions, with alike parking facility placement) can be easily defined and generated, making the human activity patterns and the temporal parking lot usage comparable by analyzing statistical averages and variances.

3 Related Literature

There are plenty of reasons to model cities. According to the short but comprehensive summary of [8], one of the most important reasons is economic research, including housing costs and firm localization. City models are also necessary for numerous engineering principles, e.g. city planners use models to evaluate new development decisions. With the emergence of powerful computers, three dimensional (3D) models also got available. Usage of 3D models ranges from shadow-casting estimations through energy demand forecasting to analyzing radio-wave propagation [9].

The level of detail of such city models depends on applications and covers a wide range. For fundamental economic research, mathematical formulas may describe a city [5]; meanwhile, there are 3D models that cover a whole city and have *centimeter* precision [15]. The level of detail of microscopic traffic simulations, such as Eclipse SUMO [18], is in-between. They may not be mathematically formalized, yet they abstract many unnecessary details.

A recent trend in microscopic traffic simulation is to model drivers or AVs as intelligent agents, and traffic simulators were extended or coupled to suitable artificial intelligence (AI) system components (e.g. Eclipse SUMO [18] was coupled to JADE, a multi-agent experimental platform [22], furthermore as an open-source program, SUMO supports the integration of intelligent agent simulators, like e.g. in [4]). Such tools may require considerable computing power [16] and were used in the practical research usually limited to simple AV scenarios based on single road segments, ramps, or intersections, aiming at the local operational decision making, like car following, simple platooning, etc.

Evaluating decision making spanning the whole city and 24 hours of activities, including e.g. repeated looking for parking lots, demands more complex scenarios. In the paper, we use two models to evaluate an extensive auction-based parking assignment scenario. The first model is abstract, using only mathematical formulations to simulate a city. The second is a detailed model, a concrete SUMO scenario consistent with the first model. SUMO is involved in many studies (e.g. [10] or [14]) focusing on optimizing classical, human-driven vehicle parking. The `PyPML` toolkit [14] even makes SUMO more convenient to assess parking-related problems.

4 Auction-based Parking Lot Assignment

The pilot problem was to optimize parking decisions of the autonomous vehicles. As we assume, after delivering passengers, AVs will not be allowed to remain in the traffic circulation; therefore, AVs seek parking lots. However, the selected parking lot shall not be too far to guarantee in-time returning to the passengers. As [3] points out, coordinated parking lot assignment can be advantageous, as it reduces the number of required parking lots and shortens the time and the distance traveled until finding a suitable parking place.

Here we focus on the validation of an auction-based parking lot assignment method introduced in [3] and elaborated in [2]. We summarize it shortly in the following. For simplicity, we assume that every simulated vehicle is an AV, they are (as mentioned earlier) privately owned and each AV participates in the proposed parking assignment mechanism. An AV shall take part in the auction mechanism after it has delivered its passengers to their destinations.[1] An AV shall participate in *rational auctions*. An auction for a parking lot is *rational* if the bid parking lot is closer than the cheapest or cheaper than the closest alternative.

Every parking lot shall act as an auctioneer, selling its free places. Starting prices can be set by either the parking lot operators or the municipalities. At each auction round, the parking prices increase by a small amount. The auctioneers, the parking lots, are asking the participants, a set of AVs, in every auction round whether they bid or not. AVs calculate the u_i utility value for the ith parking lot, according to equation (1), to determine their answer.

$$u_i = c_{fp} \cdot p_i + 2 \cdot (1 - c_{fp}) \cdot d_i \tag{1}$$

An AV shall consider the d_i distance and the p_i monetary costs to park at the ith parking lot[2]. Here, p_i includes the (current) parking fee as well as the distance-related costs to get to this parking lot (fuel or energy prices, amortization, etc.). The free-cruising parameter c_{fp} is a weighing factor between the d_i and p_i components[3]. By adjusting the $c_{fp} \in [0..1]$ value, an AV-owner can decide whether the AV shall favor the cheaper parking alternatives or park closer to the owner. The latter has the theoretical advantage of a shorter waiting time when the AV is being recalled. It also implies a reduced impact on the traffic flow, as the AV uses a smaller portion of the road network.

By introducing precise rules, see [3], it is achievable that an AV may win at most one auction. If an AV is the winner at an auction, it occupies the won parking place. Otherwise, the AV shall return to its home garage, where an AV can park for free. At the auctions, a small, discrete parking price increment was applied. The maximal amount that an AV was allowed to spend on parking was 15000 Hungarian forint (HUF) per day.

5 Working with an Abstract City Model

To test the effectiveness of the mentioned auction-based assignment mechanism, an abstract mathematical simulation environment was created. This environment represents an abstract,

[1]In our experiments, we defined a three-minute look-ahead time. Hence, if an AV arrives at the destination of its passengers, within three minutes, it shall participate in the auction mechanism.

[2]Moreover, the auction mechanism (by modifying the utility function) can also take other factors (e.g. access to an electric charging station) into account when selecting a vacant parking place.

[3]In our research, we used Hungarian forint (HUF) as currency. The current rate of HUF makes the distance (measured in meters) comparable to monetary costs. For other currencies, a new coefficient might be introduced to make monetary costs and distances be in the same range.

circular city model with a radius of $R = 5$ km. If the parking lot assignment method is found to be effective in this environment, it is worth carrying out more detailed tests.

Using a traditional parking lot seeking algorithm[4] as a baseline, we consider a parking lot assignment mechanism effective if the following statements hold:

1. Average parking prices are not increased unacceptably (e.g. the increment is less than 20%).
2. Sufficient number of parking lots are still used (e.g. at least 30% of the original amount). Too low usage rate would indicate that an assignment method causes too much conflicts between the AVs. Therefore, instead of negotiating the sharing of the parking lots, AVs would prefer a conflict-free parking alternative, e.g. going to their home garage.
3. Average vehicle kilometers traveled is not increased by more than 50%.

As the defined test metrics are relative, it is enough to build a qualitative model[5]. In the following sections, we present a brief overview of the abstract simulation environment, together with the obtained results.

5.1 Derivation of the Abstract Model

To test a parking lot assignment method, the most fundamental components to simulate are the parking lots. We model two parking lot types: curbside parking lots and (park-and-ride, P+R) parking houses. The two types, along with parking charges, differ in capacities as well as in location distributions.

We also generate a synthetic population with simple, home-based trip chains. For simplicity, we assume that the simulated population uses solely AVs to travel. After carrying passengers to their destinations, the AVs will seek parking lots. As the empty cruising can generate significant traffic, we assume that municipalities will introduce an empty cruising distance regulation (d_r) to limit it.

5.1.1 Modeling Distances

The distance plays a crucial role in the evaluation of costs and many metrics describing the traffic. Using the d_E Euclidean or the d_M Manhattan distance between two points of a city would be a simplistic approach. Unfortunately, road networks are seldom that simple. No left turns, curved streets, one-way roads, and col-du-sacs modify the actual d_d driving distances. Hence, we introduce an s (see equation (2)) parameter, which describes how regularly a city is shaped. In our experiment, we draw s values from a Gaussian-distribution $s \sim \mathcal{N}(1.3, 1.8)$. The parameters of that distribution were calibrated by driving distances measured between various points on the map of Budapest, Hungary, see equation (2) (these values are also compatible with similar findings summarized in [19]). After the reformulation of equation (2), we obtain formula (3) for driving distances between two points of the simulated abstract city. Formula (3)

[4]The parking lot searching method begins after arriving at the destination. To this end, the parking lots are listed by the order of their distance. (It is analogous to spiraling around the destination with an increasing radius.) During the search, the AV visits each parking lot in the order of their distances until it can find a free spot.

[5]Quantitative models would require more involved knowledge, more detailed data, and numerous surveys. However, precise quantitative models might be useful in industrial development and in engineering work, a qualitative model is sufficient for current research purposes.

also ensures that no driving distance between two points can be shorter than their Euclidean distance.

$$s = \frac{d_d - d_E}{d_M - d_E} \tag{2}$$

$$d_d = \max\{d_E, d_E + s(d_M - d_E)\} \tag{3}$$

5.1.2 Modeling Parking Lots

Nowadays, there are two fundamentally different types of paid parking lots. The first type is the curbside parking lots. They are close to the destination of the travelers and usually have an hourly price. (With AVs, the billing can have finer granularity, e.g. billing per seconds instead of billing per minutes or hours.) We can observe that curbside parking lots have a decaying density as we move farther from the city center. Hence, we model curbside parking lots with Gaussian distributions, described in Table 1. As streets can have various lengths and layouts, curbside parking lot capacities are modeled with a uniform distribution; for details, see Table 1.

The other parking lot type is the parking house. In the last decades, (park-and-ride, P+R) parking houses are often built at the perimeter of the cities to support efficient modal change. Table 1 describes their modeled locations[6] as an annulus around the city center with randomized radius and width. Their capacity is more frequently predetermined than that of curbside parking lots; therefore, we use constant capacity values for each parking house.

Relatively high parking charges and nearby parking places make curbside parking feasible for shorter activities, e.g. for daily shopping. We expect that AVs will prefer to park in cheaper but more distant parking houses during the more prolonged activities of their passengers.

We model parking charges for the baseline evaluation, according to Table 1. At the beginning of the auctions, those parking fees act as starting prices as well. Curbside parking is considered more expensive, if the d_c distance of the parking lot from the city center is smaller. Hence, a decaying function is used to approximate the parking fees. An example of a generated city model can be seen in Figure 2.

Moreover, many shops and working places provide free parking lots for their customers and workers. The usage of such alternatives is subject to special conditions; hence, they are out of scope of this research.

	Curbside	**Parking Houses**
Location coordinates (R is the city radius)	$x \sim \mathcal{N}(0, R)$ $y \sim \mathcal{N}(0, R)$	$r \sim \mathcal{N}(0, 0.6R) + 2R$ $\theta \sim \mathcal{U}(0, 2\pi)$
Capacity per facility [vehicles]	$\mathcal{U}(1, 10)$	const. 300
Parking fees [HUF] for t_p seconds of parking	$\max\{140, 400 \cdot e^{-.00009 \cdot d_c}$ $+ \mathcal{N}(0, 70)\} \cdot \lceil \frac{t_p}{60 \cdot 60} \rceil$	$\mathcal{N}(1200, 600) \cdot \lceil \frac{t_p}{24 \cdot 60 \cdot 60} \rceil$

Table 1: Parameters of the simulated parking lots in the abstract city model

[6] For parking houses, it is more expressive to use polar coordinates instead of Cartesians.

Figure 2: Locations and parking charges of different parking lot types in a generated abstract city model with radius $R = 5$ km

5.1.3 Modeling Trip Chains

In the previous sections, we described the structural aspects of the abstract city model. Now, we will focus on the dynamic components of the simulation, i.e. on the activities of the inhabitants of the abstract model. These activities form *activity chains*. We model the most frequent activity chains according to [7]. As numerous activities are undistinguishable at the abstract level, some simplification was applied:

- **Working and education:** Working and education activities are similar in various ways (e.g. both last for longer periods, normally neither requires transportation during the activity); consequently, we created a joint *working* (`w`) category.
- **Shopping and leisure:** Moreover, shopping and leisure can be similar as well, as they are likely to last for a shorter time. Hence, a common *shopping* (`s`) activity type represents them in our simulations.

With these simplifications, the most frequent activity chains and their distribution is given in Table 2. [1] surveyed shopping habits in Switzerland and summarized that most commonly, shopping time ranges from 20 to 120 minutes. We can model it with a properly scaled beta distribution, as shown in Table 3. We assume that two types of working activities exist. The first is the usual working activity that has an average duration of 8 hours per day. However, this working time is uncommon among e.g. businessmen or tradesmen. Hence, we model interrupted working activities that consist of two shorter, averagely 4 hours activity. Working times are modeled with Gaussian distributions, with these expected values, together with some random variance, as Table 3 describes them.

The trip chains of the simulated persons begin and terminate at home locations, evenly distributed in the city, see Table 4. People are likely to start their activity chains in the

Activity chain	w	s	ws	ss	wws	sss
Probability	38.60%	44.15%	3.70%	7.64%	5.70%	0.21%

Table 2: Activity chains and their probability

Activity	Length in hour (h)
Shopping	$\mathcal{N}(0.5\text{ h}, 0.22\text{ h}) + \beta(3,7) \cdot 2\text{ h}$
Working (interrupted)	$\mathcal{N}(4\text{ h}, 0.28\text{ h})$
Working (usual)	$\mathcal{N}(8\text{ h}, 0.28\text{ h})$

Table 3: Activity lengths

morning, as shown in Table 4. The AVs transport passengers to their destinations, and after that, they shall always look for a suitable parking place. For example, to serve the activity chain of `ws` (going to work, then doing some shopping) an AV will have to take the following actions:

1. *Leave home* in the morning.
2. *Transport passenger* to work.
3. *Seek for parking.*
4. *Stay there* for about 8 hours.
5. *Return and pick up passenger* at work.
6. *Transport passenger* to a shop.
7. *Seek for parking.*
8. *Stay there* for about 1 hour.
9. *Return and pick up passenger* at the shop.
10. *Transport passenger* to home.

In abstract simulation, we did not intend to experiment with traffic flows. Hence, we applied time offsets between each activity in an activity chain to represent traveling times.

5.2 Simulation Results

When experimenting with a new mechanism, we needed answers to some crucial questions. The most important is whether the proposed algorithm is capable of fulfilling its task. If the method seems promising, we shall check how the free parameters can influence the obtained results. And finally, we may try to fine-tune these parameters to optimize our goal functions.

The described abstract, mathematical city model is intended to answer the first two questions. In Section 5.2.1 and Section 5.2.2 we present a brief overview of the results. However, parameter fine-tuning requires more detailed simulations. For that reason, we applied Eclipse SUMO, see Section 6 for details.

Parameter	Distribution
Time of leaving home	$\mathcal{N}(7{:}30 \text{ am}, 0.54 \text{ h})$
Travel time offset	$\mathcal{N}(0.17 \text{ h}, 0.1 \text{ h})$
Home locations (in the function of R city radius)	$x \sim \mathcal{U}(-2R, 2R)$ $y \sim \mathcal{U}(-2R, 2R)$
Activity locations (in the function of R city radius)	$x \sim \mathcal{N}(0, R)$ $y \sim \mathcal{N}(0, R)$

Table 4: Miscellaneous stochastic values for simulating trip chains

5.2.1 Comparison Between the Traditional Parking Lot Seeking and the Auction-based Parking Lot Assignment Mechanism

The proposed parking lot assignment mechanism was compared to the traditional method with a simple simulation. At the beginning of every simulation run, we draw random values from the previously described distributions to create a new abstract city representation. It includes recreating parking lot locations and capacities, together with generating new trip chains. Each run simulates the trip chains of a whole (working) day by 180 s time steps. We ran 10 simulations for both parking strategies.

The size of the simulated population was 3000. To supply the parking demand, 350 curbside parking lots and 5 parking houses were placed in the model.[7] We have two free parameters for the auction mechanism. The first one is the free cruising parameter c_{fp}. We set $c_{fp} = 0.5$ in this phase of the study, implying that monetary costs and vehicle distance traveled are valued evenly. The other free parameter is the municipal empty cruising distance limitation d_r. The role of this parameter is to limit empty cruising of the vehicles; therefore, limit their adverse effect on the city traffic. We used $d_r = 2R = 10$ km, as it statistically makes 95% of parking lots reachable, due to the empirical law. We applied a 50 $\frac{\text{HUF}}{\text{hour}}$ bid increment during the auctions.

For the comparison of the two parking strategies, we evaluate the following metrics:

- *Total parking prices:* cumulated parking prices that AVs spent on parking.
- *Parking lot occupancy rate:* Portion of parking lots that was occupied during a day.
- *Empty cruising distances:* cumulated distance that AVs traveled to and from parking places.

We have already concluded [3] that the auction-based parking lot assignment mechanism has many advantages compared to the traditional parking lot searching method. According to Figure 3, parking lot assignment significantly reduces the empty cruising distances as the AVs know precisely where to find a free parking place.

There are periods when the applied auction mechanism reaches even higher parking lot occupancy rates than the traditional method, see Figure 4. Meanwhile, the highest mean occupancy rate difference is about 50% (with the traditional method, AVs occupy approximately 32% of the parking lots; and with the auction-based mechanism it is around 16%).

Total parking prices are also reduced due to the lower occupancy rate, as it is shown in Figure 5. So, if we double the total parking prices for the auction-based case, we will get a fair

[7] 350 curbside parking lots have the expected capacity of $350 \cdot 5.5 = 1925$ vehicles. 5 parking houses provides parking for $5 \cdot 300 = 1500$ vehicles. Hence, the expected parking lot capacity is 3425 vehicles in this case.

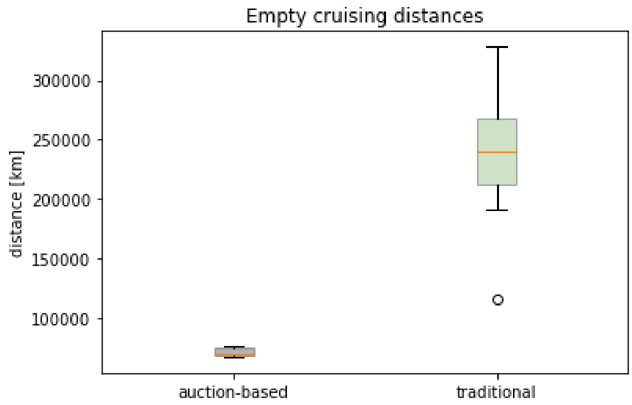

Figure 3: Comparing cumulated empty cruising distances between the case of an auction-based parking lot assignment and the traditional method

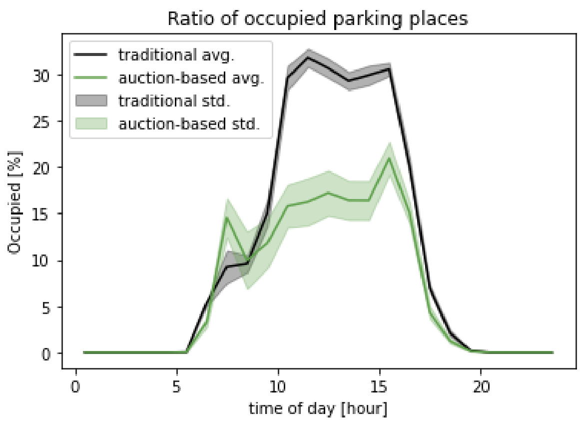

Figure 4: Comparing parking lot occupancy rates during a day between the auction-based parking lot assignment and the traditional method

upper estimate for the parking prices. It means an average total parking price of $7 \cdot 10^6$ HUF for the auction-based mechanism. Compared to the traditional method ($6 \cdot 10^6$ HUF), it is a 16.7% increment.

As an initial result, we conclude that the proposed auction-based mechanism is capable of effectively assigning parking lots to AVs. Therefore, we shall carry out further tests.

5.2.2 Testing Sensitivity to the Settings of the Free Parameters

As the second question, we studied the auction-based assignment mechanism sensitivity to the settings of its free parameters. We increased the size of the simulated population to 10000. The auction bid increment step was decreased to 10 $\frac{\text{HUF}}{\text{hour}}$.

Holistic tests were performed by adjusting the cfp $\in \{0.0, 0.2, 0.4, 0.6, 0.8, 1.0\}$ free cruising parameter and the dr $\in \{500\text{ m}, 2500\text{ m}, 4500\text{ m}, 6500\text{ m}, 8500\text{ m}\}$ municipal empty cruising

Figure 5: Comparing total parking prices between the auction-based parking lot assignment and the traditional method

distance regulation. 5 simulation runs were conducted with each $(c_{fp} \times d_r)$ parameter pair. At the beginning of the simulation runs, as discussed earlier, a new abstract city representation was generated. We focus on the total parking prices and empty cruising distances again.

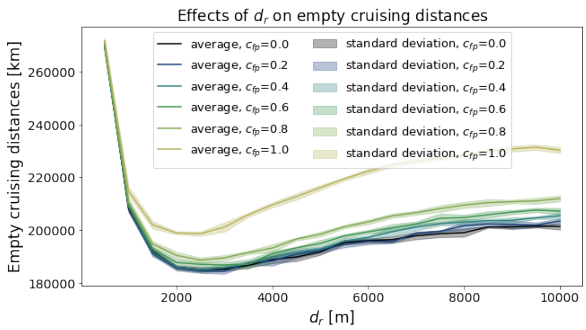

Figure 6: Cumulated empty cruising distances at different c_{fp} and d_r levels measured in abstract simulations

As we can see in Figure 6, empty cruising distances have a local minimum between 2500—3500 m of d_r. Hence, to minimize the additional load of the road network, the municipality shall select the d_r empty cruising regulation value from this range. At lower levels of d_r, many AVs are unable to find a suitable parking place; hence, they have to return to their home garages. Returning trips were not prohibited in our simulations, and in these cases, they resulted in higher empty cruising distances. At higher levels of d_r, more and more parking lots get into range. Therefore, AVs can choose cheaper alternatives instead of closer ones. Moreover, as expected, the c_{fp} free cruising parameter has a moderate positive correlation with the empty cruising distances. We may presume, it worth keeping $c_{fp} \in [0.0, 0.8)$ interval to prevent reaching too high empty cruising rates. Around $c_{fp} = 1.0$ only the (continuously changing) parking charges count when determining which parking lot is suitable, see equation (1). It may lead to unstable parking lot preference lists, causing more unsuccessful auctions. Consequently,

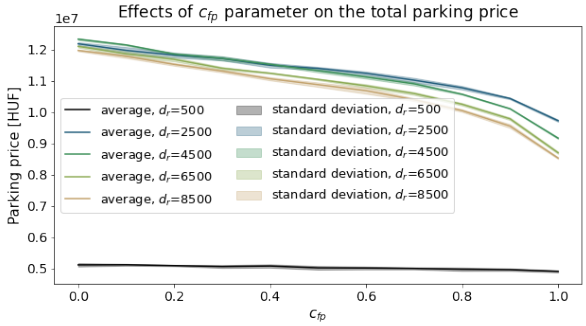

Figure 7: Total parking prices at different c_{fp} and d_r levels measured in abstract simulations

fewer parking lots are occupied, and AVs will have to cruise farther. As expected, a higher c_{fp} free cruising parameter will reduce the total parking prices for the same d_r empty cruising regulation level, see Figure 7.

6 Detailed Simulations with Eclipse SUMO

The presented abstract model intendedly lacks many details. For example, traffic flow is not represented at all. To validate the results and to verify their efficacy we will now conduct measurements with a more detailed model, involving a concrete road network and microscopic traffic simulation. To this end, to make additional tests, we will use Eclipse SUMO.

6.1 Creating a Proper Scenario

Recently, many complex scenarios have appeared for SUMO. We were looking for a proper scenario that is comparable with the abstract model. Hence, the selected scenario shall have approximately 10 km × 10 km dimensions.

We checked some publicly available scenarios for SUMO[8]. Unfortunately, Monaco [12] has many individual features. As it is located on the coast, it significantly differs from the presented abstract, circular city model. Luxembourg [11] would have both appropriate size and shape. However, this scenario does not include parking lots.

As these scenarios were not appropriate for our research, we created a new scenario. We extracted the road network of Budapest 11$^{\text{th}}$ district from OpenStreetMap (OSM). It resulted in a rectangular network with a diameter of approximately 10 km. There are numerous P+R parking facilities in the perimeter of this district, see Figure 8. As they were marked in OSM, `netconvert` tool of SUMO was able to recognize them as `parking areas` with higher capacities. The `netconvert` tool also recognized some smaller parking facilities.

For trip chain modeling, we used SAGA [13] to obtain activity and home locations. Instead of cross-validating the abstract model with SAGA, our goal was to test the auction-based parking lot assignment mechanism. Hence, we kept only starting positions (let us call them home locations, analogously to the above mentioned) from the output of SAGA. For each home location, we added roadside parking lots to the corresponding edges. Activity generation is

[8]In November 2020.

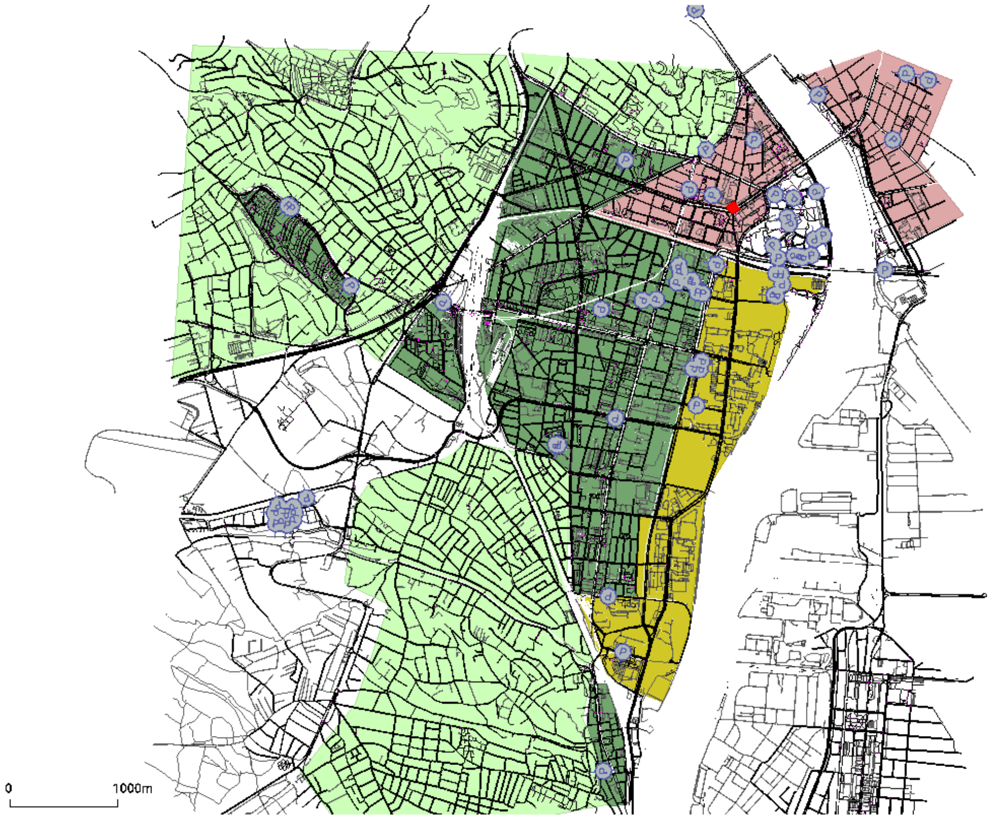

Figure 8: The simulated road network of 11th district of Budapest. The historical downtown area is brick red. High density residential areas are darker, while low density residential areas are lighter green. The yellow area is mainly occupied by industry and services. White areas either have other functionalities or are unreachable. P+R parking lots, with capacity for at least 100 vehicles are depicted by letter Ps in blue circles. The central point for curbside parking pricing is at the red polygon.

similar to the one presented in Section 5.1.3. The only difference is that we draw activity locations evenly from edges containing parking areas.

This setup is like the abstract model of Section 5.2.2 as it covers an approximately identical area. They have almost the same expected vehicle parking capacity: the abstract model provides parking space for 10700 vehicles, meanwhile the Budapest 11th district scenario offers parking lots for 9857 vehicles.

Finally, we defined the center of the map at the intersection of Budafoki and Irinyi streets, as indicated in Figure 8. Moreover, we can use driving distances provided by SUMO.

6.2 Running Simulations with Eclipse SUMO

Our simulation setup contained a *backend*, a Jupyter Notebook, that controlled the running of the tests and carried out non-SUMO-specific tasks. Traffic Control Interface (TraCI) provided the connection between the backend and Eclipse SUMO.

The road network with its *additionals* (i.e. parking lots) was identical within each simulation run. However, the trip chains were regenerated at the beginning of each run. In this case, we used $c_{fp} \in \{0.0, 0.2, 0.6, 0.8, 1.0\}$ free cruising parameter and the $d_r \in$ {500 m, 1500 m, 2500 m, 4000 m, 7000 m, 10000 m} empty cruising distance regulation pairs. Again, we simulated a whole working day within each simulation run.

The backend, which had a 180 s timestep, controlled the SUMO simulation; conducted the actions, and also registered the occupancy of the parking lots. In every *backend step*, we collected the actual beginning and terminating activities. To perform each of these activities, a new vehicle was inserted into SUMO via TraCI. Its origin was either its home location or the parking lot it had won in the previous auction. Its destination was the position of the terminating activity. When a vehicle picks up its passengers at these locations, it transports them to their next activity.[9] After an AV has carried out these tasks, it terminates. When a passenger has additional activities, new vehicles will be inserted to serve this travel demand.

In the simulations, besides the cumulated distances and total parking prices, the following values were measured:

- *Average speed:* Average speed of the vehicles in the simulation, calculated as follows. The *cumulated distance* that AVs traveled was measured together with the *cumulated travel* times. The ratio of these two metrics results in the average speed.
- *Cumulated waiting times:* The total amount of time that AVs spent waiting (i.e. the time in which the vehicle speed was below or equal 0.1m/s[10]). This metric helps understanding how free parameters influence the traffic flow.

We emphasize that our measurements are intended to provide qualitative results only. Therefore, in our experiments with Eclipse SUMO, we did not differentiate the empty cruising for parking from the *effective movements* (when AVs are carrying passengers) when calculating the cumulated distances. As the activity chains have identical distributions, effective movements are considered to cover the same route lengths on the average. The true variance is caused by the parking lot assignment mechanism in the cumulated distances. Hence, effective movements are only an offset to the cumulated distance data.

Unfortunately, the simulation runs require a significant amount of time on an average PC[11]. Therefore, simulation runs were repeated for 3 times for each given $(d_r \times c_{fp})$ pair.

6.3 Results of Experiments with SUMO

Firstly, total parking prices, obtained by SUMO measurements, are similar to that we have seen by the abstract model, see Figure 9. It only implies that consistent distance metrics do not influence the auction method. We can also notice that parking prices are significantly lower when $d_r < 2500$ m. It is in agreement with the conclusion of Section 5.2.2, as too strict empty cruising regulation makes numerous parking lots out of range.

On the other hand, the curves of cumulated distances are not alike as we would expect because smaller c_{fp} free cruising parameters seem to enlarge them. To understand this phenomenon in Figure 10, we shall investigate the traffic flow related parameters as well. As Figure 11 shows it, average speeds are also lower when the c_{fp} is lower (at higher d_r cruising regulation levels). Higher waiting times, see Figure 12, indicate congestion forming in these

[9] If the activity is the first in the activity chain, we consider that the passenger and its AV are at their home location. Hence, we do not simulate the picking-up movements.

[10] https://sumo.dlr.de/docs/Simulation/Output/TripInfo.html [accessed: August 14, 2021] [11] Intel Core i5 4200H CPU with 8 GB of RAM.

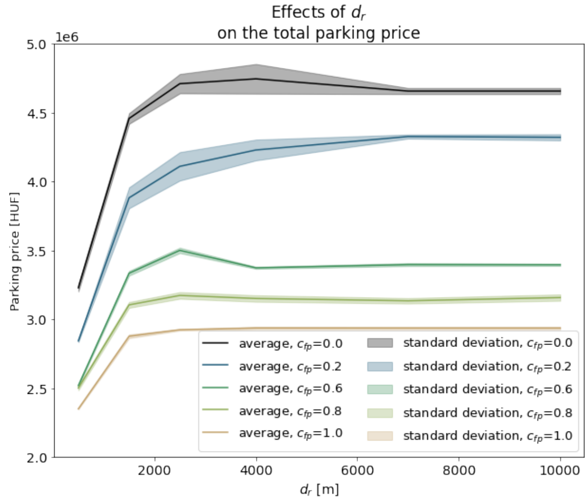

Figure 9: Parking prices for different c_{fp} and d_r levels measured in SUMO simulations

cases. As the simulated vehicles try to optimize their travel times, they are likely to take detours to avoid getting congested. That naturally results in higher traveling distances.

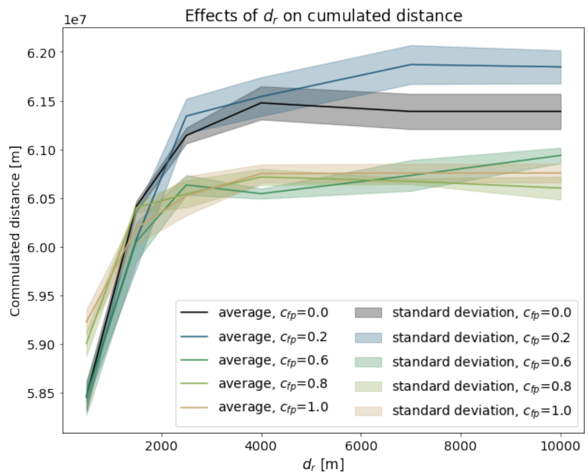

Figure 10: Cumulated distances for different c_{fp} and d_r levels measured in SUMO simulations

We suspect that this congestion has a principal cause. The low c_{fp} parameter forces AVs to find parking lots closer to the destination of their passengers. As human activities are likely to be concentrated in small areas, many AVs try to park there, thus forming congestion. When AVs can or have to[12] go further for parking, the vehicle density in the road network will be more balanced. Therefore, we conclude that c_{fp} shall have a minimum value too, e.g. $c_{fp} \in [0.2, 0.8)$.

[12]Because, for example, there are not enough parking lots within range.

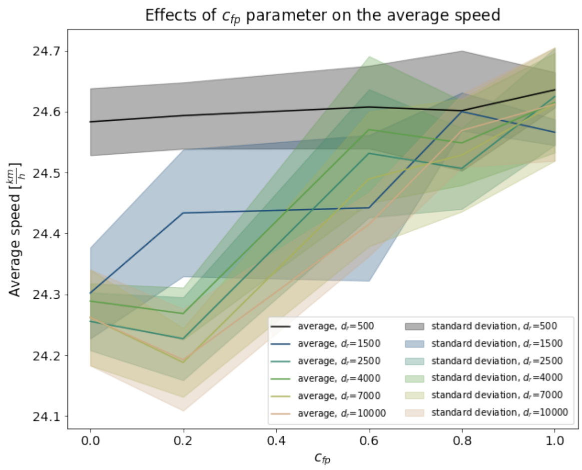

Figure 11: Average speeds for different c_{fp} and d_r levels measured in SUMO simulations

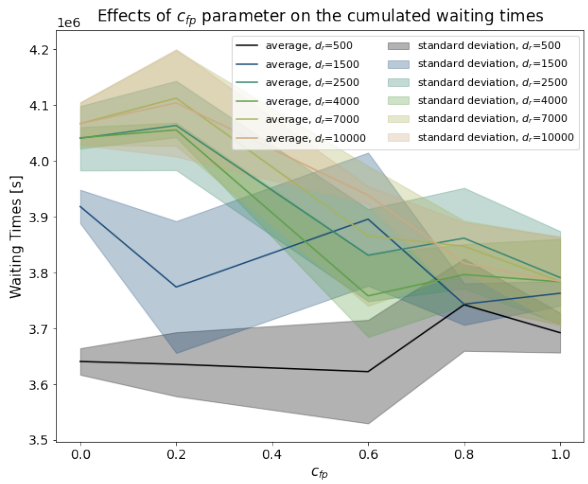

Figure 12: Cumulated waiting times for different c_{fp} and d_r levels measured in SUMO simulations

We may see another difference between the abstract and the SUMO based results in Figure 10. Namely, smaller d_r values do not necessarily cause higher cumulated distances. As parking lots are likely to have a higher density around frequented activity locations in real-world cities, it is more likely that an AV can find an empty parking place within a smaller area. However, it is still true that many parking facilities might be out of range when the empty cruising regulation is too strict (d_r is too small).

7 Conclusion and Further Research Aims

In this paper, we presented the usage of Eclipse SUMO to test an auction-based parking lot assignment mechanism developed in an abstract city model. The results of SUMO helped to analyze aspects oversimplified in the abstract simulations.

As the downward refinement consistency empirically holds for the obtained abstract and SUMO results, broadly speaking the two models are consistent for the investigated problem. However, further validation of the abstract, mathematical model may be necessary for the future research. Luckily, more and more publicly available SUMO scenarios have appeared recently. By using a variety of these scenarios, we would be able to test the abstract model more profoundly. For example, we may make hypothesis testing of the mentioned metrics (i.e. empty cruising distances, total parking prices). Then, unless being able to reject it, we shall consider the abstract model valid.

The scenario of Section 6.1 also lacks some details. E.g. the transit traffic through the 11^{th} district of Budapest was not modeled here. As a qualitative test, instead of optimizing the traffic flow, we focused on how the c_{fp} and d_r parameters form the traffic for parking. In this interpretation, the parameter set that is less likely to cause (local) congestion is more favorable.

Our further research covers studying machine learning algorithms connected to parking lot seeking. To keep the generality of the results, and to minimize the calculation times, a more detailed mathematical city model formulation is required. When the developed method is mature enough in the abstract world, we will also test it by publicly available SUMO scenarios to show its efficacy.

Finally, we would like to point out that city planners will have to prescribe cruising limitations carefully. As we saw in Section 5.2.2, if the d_r value is too small, AVs will not find a suitable parking place. A similar precaution is advised when tuning something like the c_{fp} free cruising parameter. A small c_{fp} value[13] is more likely to cause (local) congestion. On the other hand, a higher c_{fp} can increase empty cruising distances, more vehicle kilometers traveled, consequently more energy usage. Therefore high c_{fp} values are also to be avoided.

References

[1] S. Alberton and G. Guerra. *Il comportamento dei consumatori in materia di mobilità nei principali centri commerciali del cantone Ticino.* CODE, Centro per l'osservazione delle dinamiche economiche, c/o IRE, Instituto di Ricerche Economiche, Lugano, 2008.

[2] L. Alekszejenkó and T. Dobrowiecki. Auction based parking lot assignment and empty cruising limitation of privately owned autonomous vehicles in a simple city model. (submitted to the IV21 32nd IEEE Intelligent Vehicles Symposium, Nagoya, July 11-17, 2021).

[3] L. Alekszejenkó and T. Dobrowiecki. Using auction mechanism for assigning parking lots to autonomous vehicles. In *Proc. of the 28th Minisymposium of the Department of Measurement and Information Systems Budapest University of Technology and Economics*, pages 32–35, Budapest, Hungary, February 2021. https://inf.mit.bme.hu/sites/default/files/minisymp/28Minisy_proceedings.pdf.

[4] L. Alekszejenkó and T. P. Dobrowiecki. Sumo based platform for cooperative intelligent automotive agents. In M. Weber, L. Bieker-Walz, R. Hilbrich, and M. Behrisch, editors, *SUMO User Conference 2019*, volume vol. 62 of *EPiC Series in Computing*, pages 107–123. EasyChair, 2019.

[5] W. Alonso. *Location and Land Use – Toward a General Theory of Land Rent.* Harvard University Press, 1964.

[13] We believe, human drivers have a really small c_{fp} value. That means most driver prefer paying more for parking over walking longer distances.

[6] F. Bacchus and Q. Yang. Downward refinement and the efficiency of hierarchical problem solving. *Artificial Intelligence*, vol. 71:43–100, 1993.

[7] M. Balmer. *Travel demand modeling for multi-agent traffic simulations: Algorithms and systems.* PhD thesis, ETH Zurich, 2007.

[8] M. Barthelemy. Modeling cities. *Comptes Rendus Physique*, vol. 20(no. 4):293–307, 2019.

[9] F. Biljecki, J. Stoter, H. Ledoux, S. Zlatanova, and A. Çöltekin. Applications of 3d city models: State of the art review. *ISPRS International Journal of Geo-Information*, vol. 4(no. 4):2842–2889, 2015.

[10] H. Chai, R. Ma, and H. M. Zhang. Search for parking: A dynamic parking and route guidance system for efficient parking and traffic management. *Journal of Intelligent Transportation Systems*, vol. 23(no. 6):541–556, 2019.

[11] L. Codeca, R. Frank, and T. Engel. Luxembourg sumo traffic (lust) scenario: 24 hours of mobility for vehicular networking research. In *2015 IEEE Vehicular Networking Conference (VNC)*, pages 1–8, 2015.

[12] L. Codeca and J. Härri. Monaco SUMO Traffic (MoST) Scenario: A 3D Mobility Scenario for Cooperative ITS. In *SUMO 2018, SUMO User Conference, Simulating Autonomous and Intermodal Transport Systems, May 14-16, 2018, Berlin, Germany*, Berlin, GERMANY, 05 2018.

[13] L. Codecà, J. Erdmann, V. Cahill, and J. Härri. Saga: An activity-based multi-modal mobility scenario generator for sumo. In *SUMO User Conference 2020 – From Traffic Flow to Mobility Modeling*, Berlin, Germany (Online), 10 2020.

[14] L. Codecá, J. Erdmann, and J. Härri. A sumo-based parking management framework for large-scale smart cities simulations. In *2018 IEEE Vehicular Networking Conference (VNC)*, pages 1–8, 2018.

[15] Gy. Fekete and K. Almássy. Smart city megoldások a budapest közút zrt.-nél. *Híradástechnika*, vol. LXXIII.:45 – 53, 2018. (in Hungarian).

[16] N. Kheterpal, K. Parvate, C. Wu, A. Kreidieh, E. Vinitsky, and A. Bayen. Flow: Deep reinforcement learning for control in sumo. In E. Wießner, L. Lücken, R. Hilbrich, Y.-P. Flötteröd, J. Erdmann, L. Bieker-Walz, and M. Behrisch, editors, *SUMO 2018- Simulating Autonomous and Intermodal Transport Systems*, volume vol. 2 of *EPiC Series in Engineering*, pages 134–151. EasyChair, 2018.

[17] A. Lefauconnier and E. Gantelet. La recherche d'une place de stationnement: strategies, nuisances associees, enjeux pour la gestion du stationnement en france, 2005. (research report).

[18] P. A. Lopez, M. Behrisch, L. Bieker-Walz, J. Erdmann, Y.-P. Flötteröd, R. Hilbrich, L. Lücken, J. Rummel, P. Wagner, and E. Wießner. Microscopic traffic simulation using sumo. In *The 21st IEEE Int. Conf. on Intelligent Transportation Systems*. IEEE, 2018.

[19] D. Merchán, M. Winkenbach, and A. Snoeck. Quantifying the impact of urban road networks on the efficiency of local trips. *Transportation Research Part A: Policy and Practice*, vol. 135:38–62, 2020.

[20] 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).*

[21] M. Alonso Raposo, B. Ciuffo, M. Makridis, and C. Thiel. The r-evolution of driving: from connected vehicles to coordinated automated road transport (c-art). 2017. EUR 28575 EN.

[22] G. Soares, Z. Kokkinogenis, J. M. Luiz, and R. J. F. Rossetti. Agent-based traffic simulation using sumo and jade: An integrated platform for artificial transportation systems. In M. Behrisch, D. Krajzewicz, and M. Weber, editors, *Simulation of Urban Mobility*, pages 44–61, Berlin, Heidelberg, 2014. Springer Berlin Heidelberg.