Social Simulation Seminar Report
Parking Simulation Model

Parking Search and Stated Preference Model

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Abstract. Traffic plays a huge role in modern life; everybody is influenced by it even if we do not participate in it. Thus, lawmakers need to be able to get precise feedback on how future changes to our laws and policies impact the current status. The model implemented in this paper simulates the traffic in the city center of Mannheim and with it, the influence of parking search behavior of the individual agents on the traffic can be investigated. The latest version updated the agent preference model, which influences which parking spots are chosen, to use a combination of a utility-based approach and various overarching parking strategies. In particular, the utility function takes into account user preference, misinformation, and the increasing urge to find a parking spot over time. The strategies can be divided into two categories: informed and uninformed agents.

Keywords: Agent-Based Model · Parking Search Model · Stated Preference Approach · Netlogo

1 Introduction

With an ever-increasing population size and thus raising numbers of cars, especially in cities, it is important for city planners and regulators to understand and predict future car flows depending on the choices of individual drivers and traffic policies. Therefore it is vital to gain an understanding of the behavior of people within the interactive environment of traffic because small actions by individuals can affect the whole system; see traffic jam wave theory [1][2]. A critical point to look at is the parking search behavior as parking spaces are scarce especially in cities compared to the number of people entering them for various tasks. This factor is underlined by the fact that a significant amount of traffic can be attributed to the search for a parking space [3] and that a car on average is parked 95% of their lives [4]. Furthermore, the layout of cities and their parking spaces makes the whole process much more complicated and thus inefficient [4]. Thus, a realistic parking simulation can vastly support the creation of good parking policies which reduce congestion and improve economic and ecological benefits.

The previous model had several shortcomings concerning real-world parking scenarios that can be replicated with the model. In particular, the model only incorporated a very primitive parking behavior such that preferred parking lots were only considered based on the distance to the target and agents did not follow any individual preferences. Therefore, the model did not include an actual parking search based on utilities or any parking strategies, that describe different parking behavior and preferences by agents. Even though the model included agents' willingness to pay (WTP), this only gives a price limit set by the agents but no stated preference in terms of importance compared to other factors. Based on the previous shortcoming, we took several measures to incorporate a search function and several strategies to illustrate parking search behavior by agents.

This paper outlines the theoretical groundings, the implementation process, and the evaluation of the stated parking model. At the start, a brief overview of previous research conducted in the field of parking search behavior and parking strategies is given. This serves as a theoretical basis for the implementation described in the following section. Then the experimental setup and the results are reported which are discussed in the following section. The report is concluded with possible future research topics.

The NetLogo model, additional codebase and experimentation results are available at the following GitHub repository: github/ social_simulation_seminar.

2 Literature Review / Previous Work

The following section elaborates on the research used for the implementation described in section 3.

Waraich and Axhausen demonstrated the successful utilization of utility-based agents in a parking search simulation. The utility function was used to evaluate the quality of different daily plans which are lists of sequential tasks an agent has to perform (e.g., go shopping at building x, then go home) and it consists of various parts such as travel time, travel cost, perform activity and parking. Those components were aggregated with a weighted sum to get the overall utility score for the given agent's plan [5]. A shortcoming of this paper is the fact that they did not use a parking search model which results in embellished results due to the general traffic density being drastically reduced.

Next, Thompson and Richardson created a parking search process where the search process itself is defined as "a number of linked decisions based on updated knowledge gained from experience" [6]. Based on two surveys in Wollongong and the University of Melbourne, they explain the flow of the process as follows: After starting to search, the agent would examine and evaluate a car park. If they accept the spot, they will check if it is available and if not the case wait and reevaluate from time to time. If the spot is available the agent will park and the search is finished. On the other hand, if they directly decide to not accept the spot, they will drive to the next spot and redo the procedure for this parking spot. The authors work with the calculation of "car park disutility" [6] with which the evaluation of the spot is performed. The explaining variables are divided into "access costs" (costs while traveling to the car park), "native costs" (i.e. monetary costs), and "waiting costs" (costs for queuing in front of a car park) [6]. These different factors thereby underlie several estimation calculations and introduce uncertainty to the model. Moreover, the paper introduces a stopping rule formulation for the search process which is based on the economic search principle of ”expected gain in utility” [7]. That means they calculate the net change between the utility of the current car park and the utility of other car parks in the choice set. Also, the direction of the search is being calculated with an estimation of turning movements. Overall, they found their parameters to be reasonable and consistent with prior expectations.

Further, Rodríguez et al. created a microsimulation parking choice and search model to assess dynamic pricing scenarios [8]. The respective parking space choice model is based on a utility calculation for different groups of users such as residents, non-residents, and among the non-residents, uninformed as well as informed users. Uninformed users do not know the parking costs in the target zone, but they are able to learn throughout the search process so that they gain more information (about costs) over time. Informed users, on the other hand, are aware of the parking price charged as well as free or occupant spaces in the target area [8]. In terms of the utility function applied, the authors use a multinomial logit (MNL) model that is computed in dependence on the parking type, such as paid on-street parking, free parking, and off-street private parking. Hereby, variables such as parking price, time to the destination, search time, space occupancy, parking time limit or search time are taken into consideration and calculated individually [8]. In order to combine both the parking lot utility calculation as well as different user types, “the combined choice of the type of parking and section consists of the specification of a Hierarchical Logit (HL) model in which the utility of the on-street alternative depends on the maximum expected utility of the related alternatives” [8]. As part of the parking search, the user is guided to the parking area with the maximum utility and can either park on the way to the assigned parking area if the convenience falls into a predefined range, park in the assigned lot, or, depending on a pre-defined threshold, is assigned the next maximum utility spot in case that the initial spot is occupant [8]. In general, the parameters of the model “were estimated from data collected in the city centre of Santander (Spain) and from a stated preferences survey asked to users of parking spaces” [8].

Polak and Axhausen [9] identified five different parking search strategies based on the responses of drivers in Kingston and Birmingham. The result, including the distribution, of this study, is the basis for our parking search strategies for informed drivers. Additionally, seven distinct search strategies were also used by drivers in Karlsruhe. Some of them were then applied in our Netlogo model to distribute the weights for the different strategies. It is an insightful paper, although as usual with surveys, it depends heavily on the respondents and may not be representative of the general audience.

Chaniotakis and Pel [10] conducted a series of stated preference experiments in the form of internet-based questionnaires about drivers’ choice behavior in an unfamiliar area, under uncertain parking availability and search times. According to the result of the questionnaires, the parking strategies that the uninformed drivers mostly employ are ”deciding upon parking area pre-trip, start searching once they arrive at destination, and start searching before arriving at destination” [10]. The distribution of the values from those questionnaires and in particular for the last two parking strategies mentioned in the paper is what we decided to implement for our Netlogo model. The paper also mentions that ”after waiting for more than 5 minutes and still not being able to find a parking spot, they will change their strategy and park at the nearest parking spot” [10]. In addition to that, it also presents us with a table about the contribution of some factors, such as cost and distance to destination, to the total utility, which were then used for our weight distribution. Same as in the previous paragraph, questionnaires also depend heavily on the respondents and may not be representative of the general audience.

3 Implementations

Based on the different findings from the papers discussed in Section 2, we aimed to implement a search and stated preference model which is closer to reality. In this section, we will explain the approach we took to receive an improved parking simulation. We thereby focused on the employment of two general novelties: First, the introduction of a utility function according to which agents should decide on their preferred parking spot, and secondly, the introduction of different parking strategies an agent could have that influence the agent's utility accordingly. Following, we will first explain the general construction and computation set up for the utility function of a single parking spot for an agent and afterward discuss the different possible agent strategies.

3.1 Utility Function

General Construct First, when constructing the basic structure of the utility function, we had to decide which type of function would be most appropriate. As remarked in the literature review (Section 2), there are different possibilities to construct a utility function. At the moment, a weighted sum over the considered attributes seemed to be the most reasonable. It is a simplistic form of a utility function that assumes a linear relationship between variables but could be implemented straightforward. Moreover, the used weights in the sum should add up to one in order to make them comparable against each other. For this purpose, we normalized each weight by the sum of all weights. The most important factors regarding the latest research are used within the construction of the utility function. Nonetheless, there are a variety of factors that are either too hard to capture or implement or just too specific for single agents. Including all influencing components would be impossible, due to being disruptive and computationally infeasible for the model. In order to still capture the influence of unconsidered factors, an uncertainty factor ε has been added to the function. Moreover, each considered attribute in the function has been normalized to its respective maximum value. A more detailed calculation will be explained later.

Overall, the utility function is then being maximized and signs of attributes have been assigned accordingly to this maximization intent. We end up with a simple maximization optimization problem that can be formulated as Eq. (1).

$$\max_k U_k = \max_k \sum_{i=1}^{n} w_{ki} \cdot X_{ki} + \varepsilon_k, \qquad \text{where} \sum_{i=1}^{n} w_{ki} = 1 \tag{1}$$

U_k represents the utility of parking lot k and w_{ki} and X_{ki} the ith weight and attribute of that respective parking lot with $1 < i < n$. Moreover, ε_k captures the discussed uncertainty factor for unconsidered variables at parking lot k.

As another novelty to the model, we decided to divide attributes into two general groups: *previous knowledge before starting a trip* and *information right in front of a trip*. In reality, there exist factors agents can inform themselves about before going on a trip for example by searching on the internet for parking information of the city, the webpage of a garage, or Google Maps. But there are also factors that can only be known when they arrive right in front of a parking spot. Additionally, agents could then be divided into *informed* and *uniformed* drivers as two supersets for various strategies. Which variables exactly a certain agent is informed about will be decided by their respective strategy and discussed in Section 3.2.

Considered Attributes and Their Computation After an overview of the various components and assumptions underlying the utility function, the following section discusses them in more detail. Similar to Thompson and Richardson [6] we divided the variables into different groups according to their main functionality. Four main categories emerged: *time costs*, *monetary costs*, *service preferences*, and *uncertainty*.

Time costs thereby include the *distance from the parking lot to the target*, i.e. walking distance, and *distance from the current location to the parking lot*, i.e. the distance an agent has to consider for driving from his current location to the lot [6]. The walking distance was adopted from the previous model and is calculated in the NetLogo model when an agent is at a parking spot and attempts to park. The model thus uses their current location and calculates the distance from there to the final target. Here, it needs to be mentioned that "Turtles and patches [already] use the wrapped distance (around the edges of the world)" as a default option within NetLogo instead of a simplistic line of sight [11]. Therefore, this distance calculation is very close to reality, at least to a city with the model's street architecture. The calculation of the *distance from the current location to the parking lot* follows a similar approach. Every time the utility function is called, the distance is determined from the location the agent is currently at to the position of the parking lot for which the utility is to be computed. Time costs are not calculated based on the travel time of the agent to the parking lot, but on the distance in the model. Although there might be some traffic congestion, this cannot be predicted beforehand and therefore it is assumed that the travel time is proportional to the distance.

Next, the *monetary costs* are represented by the *expected price to pay*, so the amount of money an agent should expect to lose when they park at the respective spot. The calculation of the *expected price to pay* is performed in a separate reporter procedure *compute-price*, which accounts for two possibilities: If the agent is a parking offender and their WTP is higher than the product of the expected probability for a fine and the fine amount they would need to pay, the expected price is set to exactly that product. Otherwise, if the agent is not a parking offender, the amount will consist of a combination of the known parking fee of the lot and the park time they aim to park. It is therefore only an estimation of the monetary costs beforehand for the calculation of the overall utility of the spot and not the actual price they pay.

With the additional *service preferences* category, we introduce a binary variable to the model which accounts for various service types that could influence an agent's preference, e.g. security or credit card payment. For simplicity and because we assume detailed information is especially not given for curbside lots or all garages, we just use it as a binary variable instead of a range. The variable *service* thus is either 0 or 0.25 indicating if a certain service level is met (0 for "no", 0.25 for "yes"). The second number was chosen according to the final value range we ended up with the utility function averaged over all agents since *service* should not influence the utility to a much higher degree than the other components.

Lastly as mentioned before, it is also tried to account for *uncertainty* factors which are not yet included in the utility. These could be very personal preferences that vary per agent like convenience or if the parking lot is in the shade. This is reflected by the addition of an ε in the model and drawn from a normal distribution with a mean of 0 and variance of 0.125. The mean of 0 was chosen because the noise should be able to alter the utility score in both directions (make it smaller with negative values and bigger with positive). The variance was set to 0.125 to be within the interval defined by the utility function and be big enough to have an influence but not too big to overshadow the other factors.

Additionally, to the four main categories, the increasing impatience or urge to find a parking spot is also considered. Since not every parking spot an agent arrives at is available or satisfies its expected utility, it will not always park at their first choice. Considering this, each passed opportunity is counted and multiplied by a factor of 0.1. Therefore, making it more likely that the next parking spot will be taken. The exact check-up for the minimum utility will be explained later. Moreover, this creates a soft upper bound for the number of parking spots an agent will pass on.

As already mentioned before, all attributes except the uncertainty factor and the additional time-increasing component have been normalized leading to an overall data range of -13.72 up to 0.44 with a median utility value of -0.30 so that the minimum values calculated can be considered outliers. Each attribute in the utility function is normalized by dividing the respective value by the global maximum value. Hence, the expected price is divided by the maximum fee of all the lots times the parking duration. The distance from the parking lot to the agents' target is divided by the distance of the parking lot that is farthest away from the chosen target. At last, the distance from the current location to the parking lot is divided by the distance to the parking lot that is farthest away from the current location.

Calculation Setup The general calculation flow of the model for navigation works as follows: We utilize a newly defined *navigate* reporter that navigates each agent to its favorite parking spot. The procedure is thereby dependent on the target of the agent. In the previous navigation procedure, a fixed ranged list with parking spots has been calculated to navigate the agent from spot to spot until it finds a suitable spot to park or the last element of the list is reached. The latter behavior is discarded in favor of calculating the best parking spot at the current moment for the agent each time a parking spot is passed on. The best parking spot for the agent is calculated with the utility function defined in the *compute-utility* reporter procedure. Since factors like *distance from the current location to the parking lot* change with the location of the agent, a recalculation of utility results in a more realistic setup. Hence, we calculate the best parking spot for the agent at the initiation of the model and every time they decide not to park at the arrived location and the best new spot gets evaluated. If agents get initialized while the model is already running, the utility will be calculated in the initialization procedure. The decision of whether an agent will use a parking spot or not depends on the calculated utility score for the parking spot exceeding a predefined threshold which is set in the UI. Upon arrival at the designated parking spot, the agent will recalculate the utility score (using the same procedure *compute-utility* as before) as the information provided at the start of the journey may have been inaccurate or may have changed. If the calculated utility score still exceeds the minimum utility threshold the agent will use said parking spot or else find the next one to drive to.

3.2 Parking Strategies

Strategies, Values, and Weights Distribution for Different Agents The baseline search model assumes that all agents are uninformed and do not have a particular parking search strategy. Essentially, the stated preference knowledge is missing from the baseline search model implementation. We improve upon this behavior by encoding different parking strategies with a fuzzy weighting mechanism that assigns different importance weights to different attributes in the utility function. The parking strategy behavior of the agents is further governed by the prior knowledge that is available to them about the Central Business District (CBD) and Controlled Parking Zones (CPZs). We conditioned parking strategies on agents being informed and uninformed. Informed agents are aware of the CBD map with corresponding CPZ location knowledge uninformed agents are unaware of them.

Search Strategies	**Sample Percentages**	
	Birmingham *(N=147)*	Kingston *(N=624)*
"I always go to the same parking place"	39	33
"I have a private or reserved place"	3	16
"I have a private or reserved place"	18	18
"I have a private or reserved place"	26	18
"I drive around the streets looking for a free space"	11	8
Other	3	7

Table 1: The Distribution of Nominal Parking Search Strategies in Kingston and Birmingham [9]

Additionally the five strategies *(ignoring others, simplicity purposes)* stated in the Table 1 value different factors from the utility function based on their preferences as discussed in Section 2. For example, strategies like "I always go to the same place" *(same park)*, "I have a private or reserved place" *(private park)* prefer to give additional weightage to the *Service* factor which represents aspects related to the security. Whereas strategies like "I drive to my destination and then start to look" *(destination park)*, "I go to the car park nearest to my destination" *(nearest goal park)* values parking *(P)* closely to the target destination *(T)* more in comparison to *Service* factor. But these strategies in their own different ways assign importance to the current location *(CL)* and parking location *(P)* distances as shown with different hard weight vectors in Table 2. And, the most flexible "I drive around the streets looking for a free space" *(active lookup park)* values pricing and empty parking for convenience reasons the most. Considering these strategy differences, we create corresponding fuzzy weight vectors based on the hard threshold-based weights expressed in Table 2. These weights give more importance to the preference determining factors of the utility function based on the Section 2 literature and the informed nature of the agent.

For the uninformed drivers, as previously stated in Section 2, there are two different parking search strategies: "I drive to my destination and then start to look" *(destination park)* and "I drive around the streets looking for a free space" *(active lookup park)* [12]. Since the sample distribution of these similar strategies is available in the Table 1 for the CBD environment, we directly use the same distribution for representative comparison between uninformed and informed agents. The corresponding weights for these strategies are designed based on the coefficient values of the random-utility-maximization multinomial-nested-logit model (RUM-MMNL) measuring panel effects for uninformed drivers, and appropriate noise for avoiding biases is also added [10]. Table 2 highlights the comparative probability distribution of the uninformed strategies with informed strategies. And additionally, Table 2 expresses the corresponding hard threshold weight vectors for uninformed strategies from which fuzzy weight vectors are generated.

Informed Drivers: { $\mathbf{P}(i) = \mathbf{0.67} : i \in \mathbf{N_A}$ }, [9]				
Parking Search Strategies (S)	$\boldsymbol{D}\{\mathrm{P}\rightarrow\mathrm{T}\}$	$\boldsymbol{D}\{\mathrm{CL}\rightarrow\mathrm{P}\}$	Cost	Service
Same Park, *P(S|i)=0.36*0.67=0.24*	1	1	0	1
Private Park, *P(S|i)=0.14*0.67=0.09*	1	0	0	1
Destination Reach, *P(S|i)=0.19*0.67=0.13*	1	1	1	0
Nearest Goal, *P(S|i)=0.21*0.67=0.14*	1	0	0	0
Active Lookup, *P(S|i)=0.09*0.67=0.07*	0	1	1	0
Uninformed Drivers: { $\mathbf{P}(u) = \mathbf{0.33} : u \in \mathbf{N_A}$ }, [10], [12]				
Destination Reach, *P(S|u)=0.67*0.33=0.22*	1	0	1	0.25
Active Lookup, *P(S|u)=0.32*0.33=0.11*	0	0	1	0.25
Changed Strategies [13], [10]				
Nearest Free Park	0	1	1	0
Nearest Park	0	1	0	0

Table 2: Parking search strategy distribution and hard weight values for the utility function factor attributes based on the parking strategy literature review [9], [10], [12], [13], [10]

The simplicity and lesser number of nominal strategies for uninformed drivers can be attributed to our assumption that uninformed users are specifically having no prior information about the different parking places. Additionally, they are only aware of the goal location through some secondary sources like the CBD layout map. This especially means they cannot use the 'same park', 'private park', and 'nearest goal park' strategies because they are not aware of these parking locations. Additionally, we also accounted for the driver's impatience by adding a more flexible strategy change alternatives in case an agent doesn't find parking after periods of wait time [13], [13]. Axhausen and Polak [13]'s work discusses this strategy switch after a wait time of 2.5 to 5 minutes to the 'nearest free park' strategy. Additionally, upon additional wait after 5 minutes the parking price factor loses relevance in the 'nearest park' strategy [10]. The fuzzy weights shown in Table 2 for these two strategies are determined by qualitative analysis of strategy change literature by Axhausen & Polak [13] and Chaniotakis & Pel [10].

Strategies Implementation For implementing the parking strategy module, we created three different flags, namely: 'informed flag', 'agent strategy flag', and 'switch strategy flag'. The 'informed flag' variable indicates whether an agent is informed or not, which is based on uniform random assignment. Where the value 0 denotes uninformed agent strategy and 1 denotes informed agent strategy. The 'agent strategy flag' indicates which strategy is assigned to the agent conditioned on the 'informed flag' variable value. The selection of values of this variable for both informed & uninformed agents is based on the conditional probability distribution highlighted in Table 2. The 'switch strategy flag' is additionally used to indicate when the driver decides to change their strategy. The swap itself is based on the absolute 'wait time' which increases iteratively with *go function* when the agent halts completely. If the 'wait time' is between 2.5 to 5, it changes the agent strategy to the 'nearest free park'. And, if the 'wait time' is more than 5, it changes the agent strategy to the 'nearest park'. Additionally, values 2.5 and 5 functionally represent 'some wait' and 'additional wait' in minutes when comparing values with the 'wait time' variable. The relationship between these three flags and the corresponding functional meaning for the values of these flags is outlined in Figure 1.

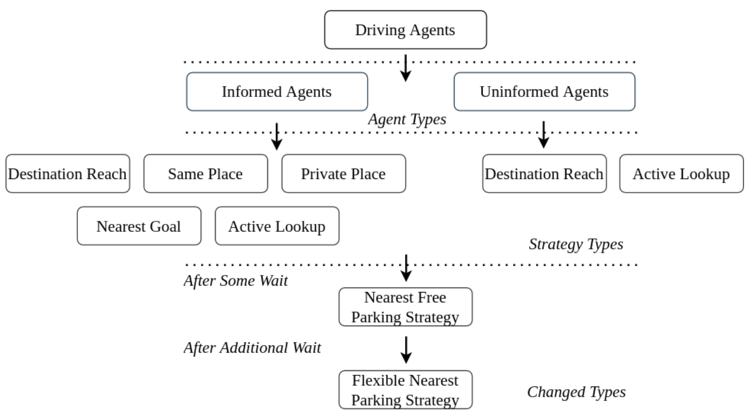


Fig. 1: Parking search strategies for informed and uninformed agents with the strategy changing alternatives after additional wait during the parking process.

Moreover, we also create two new vectors that influence the parking search strategy behavior factors for the utility function. These vectors are implemented as lists 'hard weight list' and 'fuzzy weight list' in the NetLogo implementation [14]. The 'hard-weight-list' is a strict threshold-based weight vector that is assigned four different weights, which represent the distance from parking to target, distance from current location to parking, parking cost, and service respectively. The 'fuzzy weight list' vector is prepared by reducing the hard weight vector values and adding normal noise with a mean 0 and a standard deviation of 0.125. This fuzziness is added to account for any confounding factors that might be affecting the survey samples for the parking strategy distribution [9]. Finally, each weight of this fuzzy vector is also standardized by the *max-min* score standardization.

For example, the 'agent strategy flag' with a value of 2 representing 'private park' is assigned a hard weight vector [1 0 0 1] for the utility function. This vector strictly considers only distance from parking to target and the service factors only whereas distance from the current location to parking and the parking cost is rejected completely. This absolute decision does not represent a realistic decision-making process for many drivers because in realistic scenarios some entropic uncertainty is always present. Therefore, we generate corresponding fuzzy weight vectors represented by [0.78 0.13 0.13 0.78] to represent a more realistic decision process. This vector is further standardized with *max-min* normalization to [0.70 0.12 0.12 0.70] before the final utility calculation.

Utility Attributes Importance for Parking Strategies First, for the informed drivers, the parking cost additionally contributes to the utility function value for the 'destination reach park' and 'active lookup park' strategies. The *Service* attribute, which represents aspects like security, is something that agents with 'same park' and 'private park' strategies additionally care about. Distance from parking *(P)* to target *(T)* is important for all the agents, except for the agents with 'active lookup park' strategy. And the distance from current location *(CL)* to parking *(P)* is also important for all, except for the 'nearest goal park' strategy. Second, for the uninformed drivers, the additional factor that contributes to the utility function is the parking cost. The *Service* factor, like security, is something that the uninformed agents are often not aware of to a greater extent, whereas distance from parking *(P)* to target *(T)* is only important for the 'destination reach park' strategy. Finally, for drivers that changed their strategy after waiting for 2.5 to 5 minutes, the distance from the current location *(CL)* to parking *(P)* plays an important role in determining the utility because these agents will switch to next nearest free parking. Upon further waiting, the parking cost also becomes a less important factor, and only the distance from the current location *(CL)* to parking *(P)* is important for the utility function.

4 Experiments and Results

Experimentation Setup To investigate the agents' behavior and the parking distribution within the model, the model was run and evaluated with various settings. Table 3 shows several setting configuration examples that were used to investigate different outcomes and agent behavior. Parking lots in our experiment design always have staggered pricing with more expensive parking lots closer to the city center, such as *yellow lots* and cheaper parking lots located rather on the outskirts of the city, such as *blue lots* or *teal lots*. Parking lot prices shown in Table 3 represent prices for yellow, green, teal, and blue lots in the respective order represented by the *(y-g-t-b)* keyword. To investigate differences in parking lot capacity utilization of the model, we adjust the number of cars in the model as well as change the minimum utility as a prerequisite for the agent to park for different runs while keeping the lot distribution and general occupancy stable. All models with their respective configurations are run with roughly 8000 ticks to ensure a good evaluation basis. For experimentation consistency, we run the model with the dynamic pricing strategy, and the number of garages is always set to two.

NetLogo Model Configurations						
Setting	# of cars	Min. Utility	Lot Prices (y-g-t-b)	Lot Distribution (%)	Target Start Occupancy	Parking Cars (%)
1	300	-0.2	10-8-6-5	0.50	0.40	61%
2	300	-0.3	10-8-6-5	0.50	0.40	61%
3	500	-0.5	10-7-5-4.5	0.50	0.30	60%
4	600	-0.4	10-8-6-5	0.50	0.40	61%

Table 3: Different model configuration settings for comparative analysis

Results Results of several models that were run with different settings were recorded using the *document-turtles* function as well as different plots incorporated within the Netlogo Model. Regarding the agents' utility, we looked at the calculated utility score for all agents and lot over time as well as average utility values for different settings and different income groups.
Next to the overall utility scores that were calculated while running the model, we were interested in the utility score of parked cars. Table 4 displays the average calculated utility for all agents and lots as well as the utility score of the agents that managed to park. Results show that the average utility value of cars ranges from -0.4 to -0.38 depending on the model settings described in chapter 4. In addition, when comparing the utility of parked cars, all settings yield quite similar results with utility values ranging from -0.15 to -0.13.

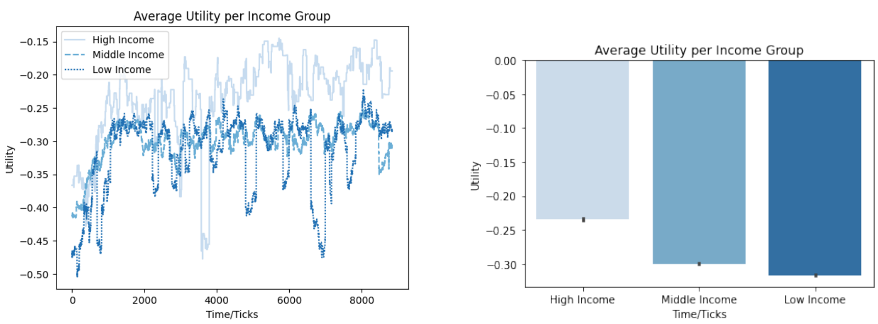
In addition to the average utility value of the agents, Table 4 also shows the average search time of cars that parked. As indicated in Table 4, regardless of different numbers of cars initiated, the average search time of cars that parked

NetLogo Model Configurations				
Setting	Overall Average	All Parked Cars	Avg Search Time	Distance Parking Target
1	-0.39	-0.14	388.16	19.77
2	-0.38	-0.13	368.62	17.0
3	-0.4	-0.15	550.32	17.97
4	-0.38	-0.13	671.87	16.13
Previous Model	-	-	804.45	20.72

Table 4: Comparison of average calculated utility values and utility of parked agents for different settings

within the model is, for all settings, far less than the search time of the agents within the previous model. Moreover, the distance to the target is on average 17.7 for the different settings of the current model and the distance to the target for the previous model running with 300 cars is 20.72.

As we were particularly interested in comparing results for different income groups, Figure 2 displays all calculated scores per income group over time (Setting 3).



(a) Moving Average over Time

(b) Mean Utility Score

Fig. 2: Average Calculated Utility Score per Income Group (Setting 3)

Figure 3 shows the average utility score for each income group, namely high, middle, and low-income for the model run with setting # 3. The mean utility score of the parked cars is -0.15 and, as the figure indicates, the high-income group achieves the highest overall utility score with -0.11 compared to the other two income groups. Hereby, the maximum utility score is 0.18 and the minimum utility score is -0.60. All settings yield the same result of the high-income group achieving the highest utility value overall.

In addition to the utility score and agents' 'satisfaction' with the parking lot, the overall distribution of agents and utilized lot capacity was investigated. In

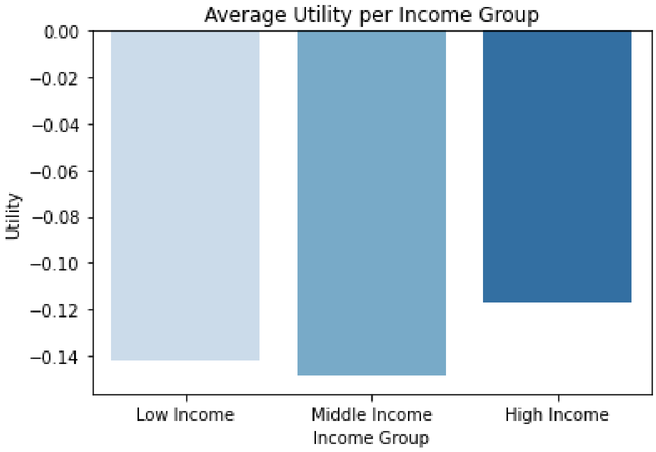
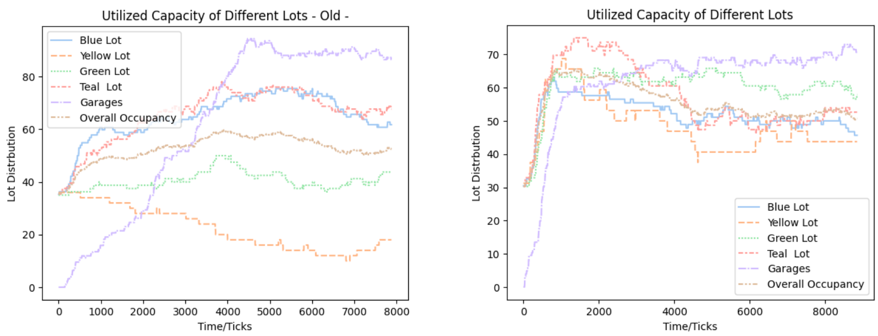


Fig. 3: Average Utility Score of Parked Cars per Income Class (Setting 3)

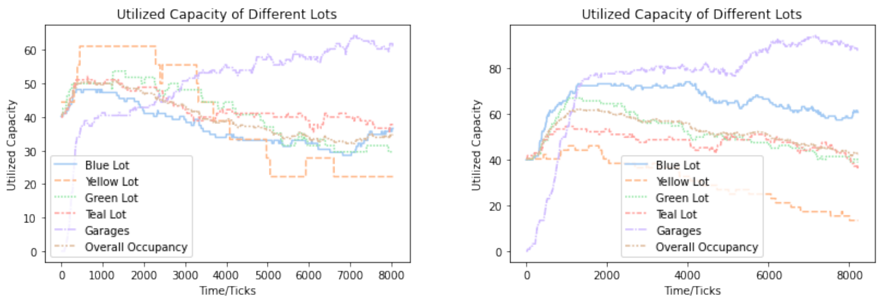
particular, Figure 4 displays the utilized lot capacity for each parking lot over time of the previous model compared with the current model. When initiating the previous model with 300 cars, we yielded the same result of a heterogenous parking lot utilization.
At the same time, however, Figure 5 shows that the distribution of the utilized parking lot capacities also highly depends on the number of cars initiated within the model. While the distribution is quite homogenous for 300 or 500 initiated cars, the utilized capacity is rather heterogeneous when the model is initiated with 600 cars.



(a) Previous Model (b) Current Model

Fig. 4: Utilized Capacity of Parking Lots (Setting 3 - 500 cars)

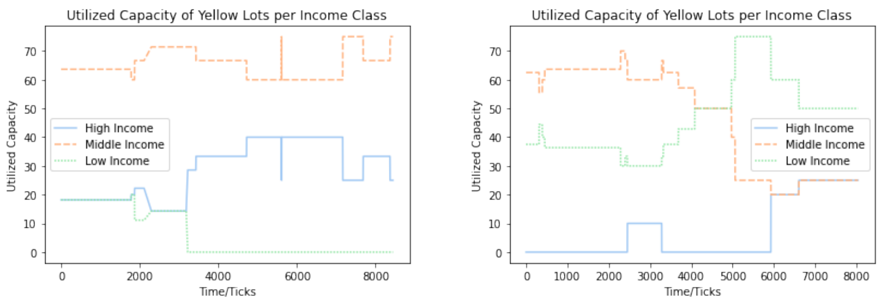
Moreover, the distribution of different income groups on yellow lots – the most expensive and closest to the city center - was investigated. Figure 6 shows a com-



(a) 300 cars (b) 600 cars

Fig. 5: Comparison of Utilized Capacity of Parking Lots (Setting 2 & 4)

parison of the respective share of income groups within the old model and the current model initiated with 300 cars. Results show that the current model causes the low- and middle-income group to use the yellow lots more while the high-income group is rarely parking on yellow lots. This used to be the opposite case within the previous model. Running the current model with different settings and number of cars yields similar results.



(a) Previous Model (b) Current Model

Fig. 6: Share of Income Groups on Yellow Parking Lots (Setting 2 - 300 cars)

In Figure 7 we observe that the distribution of parking strategies approximately follows the probability distribution highlighted in Table 2. Our implementation for the experiment design with 500 cars draws strategies with uniform randomization from the strategy distribution vector, given by [0.24 0.09 0.13 0.14 0.07 0.22 0.11]. Additionally, we observe that 'same park' and 'uninformed destination reach' strategies are the most common strategies. And the strategy distribution at all timesteps is at a quantitatively comparable level with respect to each other, for qualitative statistical analysis of parking metrics amongst the strategies.

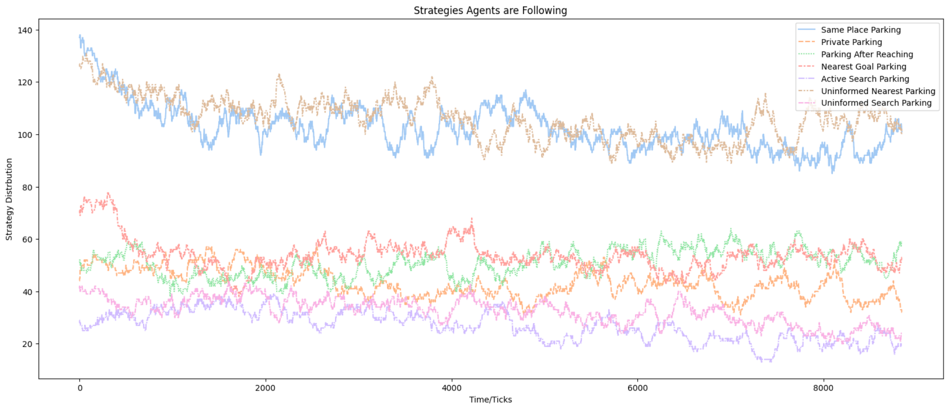


Fig. 7: Parking search strategies distribution from the NetLogo Model with 500 car count configuration.

First, in Figure 8 it can be observed that the average price paid generally increases across all strategies as the traffic increases. This behavior closely resembles the real world where if the number of agents with different strategies increases the average price paid also increases. This can be attributed to the fact that agents are competing for the same number of expensive parking spaces focused on the central region of the CBD. Second, in Figure 9 one can make similar generalizations across different traffic settings but cannot consistently analyze parking offender behavior for different specific strategies. Additionally, in general terms for all strategies, the average parking price paid, and parking offender behavior are almost in inverse proportions for all traffic settings under consideration. Except for some anomalies with this experimentation setup, we also observe this realistic scenario of agents that prefer paying more for parking on an average, often don't engage in parking offending behavior and vice-versa.

(a) 300 cars (b) 500 cars (c) 600 cars

Fig. 8: Parking search strategies distribution for the mean parking offenders values across different traffic configurations.

In Figure 8, we also observe that for 'same park' & 'private park' parking strategies on average the acceptable cost is higher since the *Service* factor is more

(a) 300 cars (b) 500 cars (c) 600 cars

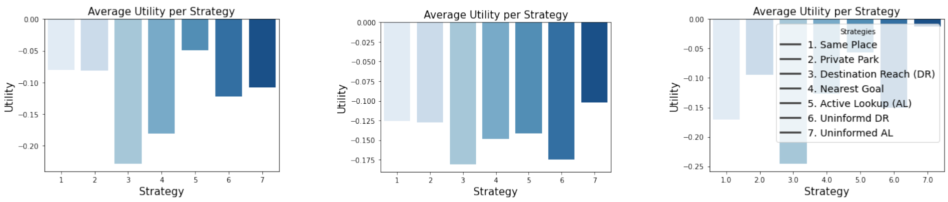
Fig. 9: Parking search strategies distribution for the mean parking price paid across different traffic configurations.

valued, leading them to park quickly in garages. But, for uninformed agents, the average paid price is less *(in 500 car traffic setting)* even though to some extent they also value *Service* factor. This can be attributed to the high parking offender behavior as recorded in Figure 9. Additionally, we also observe that both informed and uninformed 'active lookup' strategies save money for parking by engaging in parking offender behavior relatively more often than other strategies across all traffic settings. This further models a realistic scenario of drivers actively looking for parking are engaging in illegal or off-street parking after failing to find any empty lot. Additionally, we can infer that 'nearest goal' strategy like in real life is the most expensive strategy as the goals are distributed closer to the central region and it would cost them relatively more; generally, agents will choose expensive yellow lots. Also, counter-intuitively the 'destination reach' strategy has lesser mean parking price values for uninformed agents as compared to informed ones. But, in general, the uninformed 'destination reach' are engaging in higher offending parking behavior. Like any realistic scenario, this inference holds, that if an uninformed driver searches for a parking spot after reaching a highly crowded destination spot, they might have a higher tendency to park illegally.

Search Strategies	**Mean $D\{\mathrm{P}\rightarrow\mathrm{T}\}$**			**Mean Search Time**		
	300 Cars	500 Cars	600 Cars	300 Cars	500 Cars	600 Cars
Same Park	15.1	15.8	15.8	417.4	598.2	643.5
Private Park	16.0	13.1	15.1	395.3	536.4	681.7
Destination Reach (DR)	19.0	16.2	18.7	391.4	560.3	656.3
Nearest Goal	9.9	18.2	11.1	391.0	555.0	703.7
Active Lookup (AL)	22.7	19.6	26.2	325.0	556.2	767.3
Uninformed DR	18.7	19.2	16.9	325.5	486.7	660.9
Uninformed AL	24.9	28.0	19.4	255.5	593.7	614.3

Table 5: The comparison of mean parking distance from target goal and mean search time values for different parking strategies.

In Table 5, it can be observed that the mean search time increases across all strategies as the traffic increases. Additionally, we observe that 'active lookup' whether informed or uninformed in general has a lower mean search time which closely resembles a real-world scenario. Also, considering the difficulty in finding parking closest to the target, the 'nearest goal' strategy consistently has a higher mean search time across all traffic settings. Second, in Table 5 we also infer that 'nearest goal' strategy consistently succeeds to minimize the distance between parking and target across all different traffic settings. We also observe that the distance between parking and target across all traffic settings remains almost constant for the 'same park' and 'private park' strategies, this can be attributed to their tendency to consistently opt for garages. The uninformed and informed 'active lookup' search strategies settle for farther parking spots, like the real-world scenario of quickly finding the empty nearest parking spot.



(a) 300 cars (b) 500 cars (c) 600 cars

Fig. 10: Parking search strategies distribution for the mean utility values across different traffic configurations.

Based on the above discussion for averaged out factors like price paid, parking offenders, search time and distance between parking to target we interpret the mean utility values amongst the strategies. First, from Figure 10 we see that for both informed and uninformed 'active lookup' strategies have best utility values associated with them in general, this can be attributed to the fact these agents select the nearest parking spot without being concerned about paying for parking and distance of the parking spot to the target. Essentially, it encourages a selfish and non-ethical approach to parking for drivers. Additionally, we observe that the 'nearest goal' strategy has the lowest utility associated with it as in real-life also it is a very idealistic strategy to follow for any driver. For 'same place' and 'private park' strategies we observe consistently good utility values attributing to quick parking location selection nearest to the central parking region by paying additional costs. This behavior can be realistically interpreted as behavior for office-goers, who would prefer to either have a reserved place or parking in the same place closer to the office without being that concerned about the money. Finally, we observe that the 'nearest park' strategy for informed agents has better utility than uninformed agents in higher traffic settings. This can be interpreted as that informed drivers in high traffic scenarios are successfully able to find better parking spots in comparison to the uninformed agents when both of them intend to park closest to their goal. With the analysis of multiple parking behavior related factors and consistent interpretations of the utility function, we can safely say that our parking strategy implementation successfully captures real-life complex scenarios to a great extent.

5 Conclusion & Discussion

With the currently implemented model, agents have individual preferences for example regarding price or distance and follow different strategies when looking for a parking spot. Compared to the previous model, the agent does not only take the distance to its target into consideration but as mentioned before, has individual preferences towards a suitable parking lot. parking lots are now chosen based on the distance to the target, the distance from the current location to the respective parking lot, the parking lot price, a service preference as well as other (uncertain) factors that are considered as epsilon within the utility function. Furthermore, agents can either be informed or uninformed when looking for a parking spot which represents different parking strategies that agents can follow as well. By incorporating such nuances into our parking model as elaborated in the section we were able to model and encode real-life parking behavior into the agents based on their stated preferences for the parking task. Additionally, we also observed that our findings in general were mostly robust to increasing traffic in the CBD. And all agents utilizing different parking strategies continued to exploit their preferred utility factor for competitively obtaining free parking spots leading to better overall parking lot occupancy throughout the CBD.
By incorporating different variables and weights to determine the importance of the respective variables based on the strategy that the agent follows, the model represents the real-world parking scenario more closely compared to the previous model.
With an average utility score of -0.40 and median utility of -0.30 depending on the model settings, all agents that parked reached a very good utility value of roughly -0.14 compared to the average calculated values. In addition to the optimized utility score of the agents, as Table 4 indicates, the average search time, as well as the distance to the agents' target, decreased significantly across different model configurations testes for all agents.
Furthermore, the results indicate that, depending on the number of cars initiated, parking lot utilization tends to be more homogenous across different parking lots compared to the previous model. Consequently, the utilization is better distributed across lots while agents also follow their (personal) preferences when parking. At the same time, however, the share of different incomes on yellow parking lots, which are most expensive as they are closest to the city center, has changed with the current model setup. Low and middle income groups are now using the expensive parking lots more while the high-income group of agents is hardly using the yellow parking lots.

In general, however, when running the model with the same settings that can be adjusted manually within the interface, we could observe that the model yields quite different results. Such differences are mainly due to the fact that targets and also parking lots are reinitialized when setting up the model so that the individually calculated utilities also vary and the utilization capacity of different lots, for example, can turn out quite differently.
At last, it also needs to be acknowledged that the current model requires more computational resources during setup and while the model is running due to the continuous calculation of the utility score for each agent and (next possible) park-

ing lot as well as the assignment of parking strategies and strategy changes for each agent.
Additionally, as shown in the section, both informed and uninformed drivers with 'active lookup' strategy engage in unethical parking offender behavior. This behavior is an undesirable outcome while we maximize occupancy of the parking lots across different traffic settings. Therefore, adding suitable ethical norms or a centralized governance component for the agents can help in mitigating this unintended consequence [15], [16]. Finally, even though our weights of different strategies and changing strategy logic are based on well defined literature, a more dynamic weight changing approach can help in creating agents that more realistically adapt to parking tasks based on environment interactions. For this parking strategy implementation iteration the weight vector value stabilization would again add to the model complexity.

6 Future Work

The tasks for future projects can be divided into three main areas: Further factors & combination approaches, further strategy exploration, and further granular analysis.

In the latest version of the model's utility function five components are combined (see Section 3.1). Including additional utilities might create an even more realistic behavior for the agents. For example, adding the wait times for garages (synonymously the departure rate if observable) [6], expected parking time, or weather conditions. Besides adding new components to the utility function existing ones could potentially be improved. For example, the *current service* preferences is a binary variable that is hardcoded, this could also be adjusted to take the conditions on-site into account depending if the parking spot is in a garage [17] or a lot [18].

Currently, a weighted sum is used to aggregate the utility score for a parking spot from the different components (see formula 1). It might be interesting to investigate different methods of aggregation like a multiplicative congregation of the utility factors. Furthermore, it might be interesting to look at the results of a transformation of the utility scores e.g. by incorporating a logit function [19].

Additionally, the current model computes the utility score for all lots during the setup of the model but also at each non-available parking lot for each agent. Therefore, further adjustments regarding the initiation and calculation of the utility function could be made in the future to reduce the needed resources and optimize performance.

Presently an agent has seven different parking strategies at its disposal (see Section 3.2), this pool could be extended by adding a strategy with cohesive reserved lots [9] or an imitating strategy [20] or even a rule for special parking spaces for electric cars to account for the latest developments in the greening of traffic [21].

Additionally, the current parking strategy distribution is independent of demographic information like age, gender, income, and education. The conditioned analysis of these factors for the different strategies can further yield better insights for demographic-oriented parking policy planning [9]. Finally, depending on the social parking-related attributes of interest, a plethora of factors can further be investigated for agent modeling while satisfying the correct abstraction assumptions [22].

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