

Modeling Garage Parking

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Abstract. Described is a simulation model of cruising for garage parking, intended both for the calibration and evaluation of real-time parking recommendation methods, and as a base for predictive guidance to available parking. The model combines the event-based and agent-based simulation approaches to represent the parking garage and the driver behavior. It is validated by simulating a real-world parking garage and comparing the model's output with observations. The validation results show the model's capability to predict a garage's state over the course of an operational day, even though specific results are not yet precise enough for the intended use.

After an introduction to scope and aims, the paper shares some background on garage parking and related work, followed by a description of the simulation model, and its validation based on a representation of a real-world parking garage.

Introduction

With a significant part of inner city traffic consisting of drivers cruising for parking (on average 30%, see [1]), and with ever growing parking garages containing 2,000 or more individual parking slots (see figure 1), computer based systems providing predictive recommendations to find available parking in these major structures are significantly beneficial to users, and also improve resource utilization for infrastructure providers. One way to predict availability of parking slots is by simulation, starting out from the real-time

state of the garage. Even if a parking guidance system is not predictive, but only considers real-time information, its strategies have to be carefully calibrated and evaluated before their application in the field. Another use of a garage parking model is therefore to evaluate recommendation strategies in a simulated environment.



Figure 1: A parking garage with approx. 2,000 parking spaces on six levels.

This paper presents a simulation model of cruising for parking in parking garages, which will serve both as a prediction model, and as a virtual testbed for calibrating and evaluating garage parking guidance algorithms. The model applies a combination of two simulation approaches: while the basic mechanics, e.g. the arrival of cars, are modeled in an event-based fashion (see [2]), the agent-based paradigm (see [3]) is utilized for modeling the drivers' decision making behavior.

The paper continues with sharing some background of garage parking modeling and related work (section 1), followed by the presentation of the simulation model (section 2), representing both the parking garage and the individual driver's behavior. Then, the model's output is validated based on a real-world example (section 3). The paper closes with a summary of the lessons learned and a short outlook on future work (section 4).

1 Background

1.1 Garage Parking

The term garage parking refers to the process of entering a building at least partially designated for car parking, finding and navigating to an available parking slot, leaving the car unoccupied at that slot for a while, and then de-park by finding the shortest or most convenient path from the parking slot to a vehicular exit. As the intended application for the developed model is to test recommendation algorithms which are concerned with reducing the time spent cruising for available parking, the last part of the process, de-parking, is beyond the scope of this paper and will not be discussed further. The described buildings are often referred to as parking garages, but also as multistorey car parks, parkades, or parking structures.

Garage parking, together with parking lot parking, is often described by the more general term off-street parking. This contrasts with on-street parking with its diverse modes, e.g. parallel parking, angular parking, perpendicular parking.

The parking garage usually consists of a number of connected levels, which are themselves composed of a number of areas. Each area contains a set of parking slots fit for individual cars. The readers will know this decomposition from their own experience: “I parked my car in a slot on level 3, in area C.”

Vehicular access to the parking garage is granted, often at the ground floor, by entry and exit lanes, which are usually unidirectional. Pedestrians access the garage via elevators or stairways, or on the ground floor by doorways. Pedestrian access ways are usually bidirectional.

1.2 Related work

Corresponding to its importance in planning and design of public spaces, on-street parking has seen a lot of research attention, both in general modeling (see e.g. [4], [5], [6], [7], [1], [8], [9], [10]) and in simulation modeling (see [11], [12], [13], [14], [15], [16]). Most of the more recent simulation models are at least partially agent-based (see [11], [12], [14], [15]). Dieussaert *et al.* (see [12]) and Horni *et al.* (see [14]) combine agent-based modeling with the cellular automata paradigm, while Gallo *et al.* (see [13]) construct a multi-layer network supply model. Some authors (see [12], [15]) utilize the described models to evaluate pricing and other

policy considerations, while others (see [11], [13], [14], [16]) apply them to analyze technical methods to reduce cruising time and thereby traffic in general.

Only a few models (see [17], [11], [12], [8]) consider off-street parking: Asakura and Kashiwadani (see [17]) apply a model to examine the effect of different types of on-street and off-street parking availability information on overall system performance, but do not examine the drivers' behavior inside of individual parking lots. Benenson *et al.* (see [11] and also [6]) develop a spatially explicit model of parking search and choice, with simulated drivers cruising through an artificial or real-life city center model, giving them both on-street and off-street parking options. Dieussaert *et al.* (see [12]) also are interested in the traffic patterns generated by cruising for parking. They model on-street parking as well as parking lots and garages, but consider parking lots and garages as simple sinks, not modeling their interior. Van der Waerden *et al.* (see [8]) develop a simple cellular automata based sub-model for choosing parking spaces inside a parking lot, but clearly set their focus on modeling traffic patterns resulting from the whole, city-wide process of traveling and parking.

None of the described models considering off-street parking is detailed enough for the evaluation of garage parking recommendation systems.

2 Modeling Garage Parking

An agent-based model usually includes two components (see [3]): the agents themselves, and the environment they interact with.

The agents are usually self-contained and autonomous; they have attributes whose values change over the course of a simulation run. Their behavior is determined by a set of rules, and they interact dynamically with other agents and the environment they exist in. In more complex models, agents are often goal-directed and adaptive, and may even be heterogeneous. Individual agents usually only interact with a local subset of the environment and other agents, and therefore consider only local information.

In addition to their communication with their set of neighbors, agents interact with their environment. This information might provide only basic information, e.g. the agent's position in the environmental model. It may also provide more detailed information, e.g. the capacity and real-time rate of occupancy of parking garage areas. While in many cases the environment might be

modeled as an attributed graph structure, it sometimes is built as a complex simulation itself, e.g. based on cellular automata.

In the proposed model (which is based on a simpler model described in [18]), drivers and their cars are modeled as agents adhering to a set of rules and acting on local information, while the parking garage is modeled as an attributed neighborhood graph, and constitutes the agents' environment.

2.1 Modeling parking garages

The parking garage is modeled as an attributed graph $G(A, E)$ representing the garage's layout and the internal neighborhood relations. A node $a \in A$ represents an area of the parking garage, an edge $e(a_i, a_j) \in E$ with $a_i, a_j \in A$ represents a direct connection between two areas a_i and a_j which is traversable by car. If all lane segments in the parking garage are two-way, the garage can be modeled as an undirected graph. If some or all segments only allow for one-way traffic, a directed graph can be established. As it is the garage planner's basic objective to ensure reachability of each parking area, the graph consists generally only of one connected component.

Each node $a \in A$ is attributed by its total number of parking slots z_a , the number of currently occupied slots $o_a(t)$ at time t , by extension also the number of free slots $f_a(t) = z_a - o_a(t)$ at time t , and the average time r_a a car needs to traverse and search the area. The recommendation methods to be tested (see [19]) explicitly consider only these areas, and do not depict individual parking slots. Therefore, a spatially explicit modeling of these individual slots is not necessary.

Each edge $e(a_i, a_j) \in E$ is attributed by a time r_e a car needs to move from area a_i to area a_j . In cases where areas are directly adjoining, $r_e = 0$ can be assumed.

In this simplified model we assume an infinite traversal capacity for nodes and edges, therefore ignoring congestion resulting from multiple cars cruising the same area.

The garage's entry lanes are modeled as special nodes $a_e \in A_e \subset A$ with $z_{a_e} = 0$, which serve as sources for the transient car agents. As is customary in discrete modeling (see [2], pp. 209-210), interarrival times are approximated with an exponential distribution with an arrival rate of $\lambda_{a_e}(t)$. The distribution parameter is established for each entry lane a_e and each period t by input data analysis. Technically, the agents are gener-

ated by the event-based framework at each entry node at appropriately distributed simulation times.

Figure 2 shows a simplified layout of a parking garage level, while figure 3 shows the corresponding partial model graph.

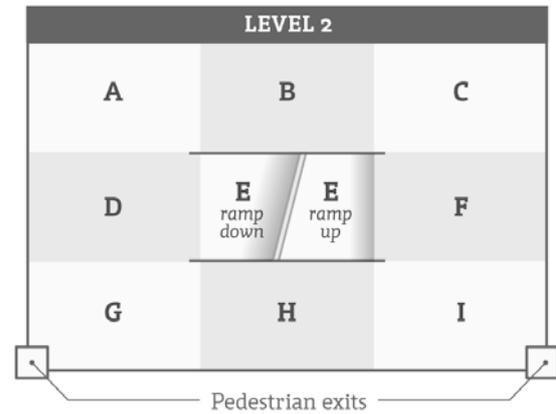


Figure 2: Simplified parking garage level with two pedestrian exits, two bi-directional ramps, and nine areas.

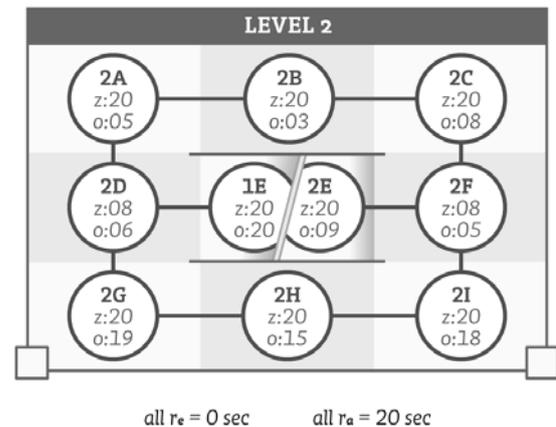


Figure 3: Partial model graph of a parking garage level.

2.2 Modeling driver behavior

Agents enter the model from one of the entry lane nodes $a_e \in A_e$, and in the course of the simulation move iteratively from node a_i to node a_j along edge $e(a_i, a_j) \in E$. On any given node $a_i \in A$ the agent, after spending a time of r_{a_i} searching the area for available parking, has to take two decisions: It has to decide whether to park in the current area (parking decision), and, if not, where to go next (routing decision).

To enable the agents to take these decisions, the model considers a number of aspects:

Basic routing: To avoid moving in an infinite loop, an agent administers a counter $v(a_i)$ representing the number of times an area a_i has been visited by that agent. If an agent always chooses one of the routing options a_j with the lowest $v(a_j)$, every loop will eventually be broken. In addition, as cars are rarely seen to turn on the spot in a parking garage, agents can never move onto the area they just left.

Attractiveness: The model assumes that a driver prefers to park in a slot which is as attractive as possible. The model therefore assumes an order of attractiveness on a parking garage’s areas: $1.0 \geq c(a_{i_1}) \geq \dots \geq c(a_{i_n}) \geq 0.0$ (see figure 4). Agents prefer areas with greater values of $c(a_i)$ to areas with lower attractiveness. Attractiveness orders are individual to classes of drivers, i.e. customers with distinct destinations. For example, during the day 40% of customers might desire to park as close to a supermarket as possible, while 60% might be attracted by parking slots near a hospital. These distributions could change over the time of day, e.g. when the hospital closes for the evening, but a neighboring cinema starts to attract parking visitors in another region of the parking garage. As these classes of preferences are generally shared by many drivers, only a few different orders of attractiveness represent all drivers’ intentions for any given garage.

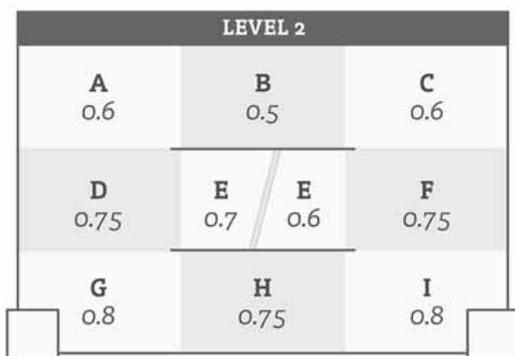


Figure 4: Parking garage level with attractiveness values.

Real-time availability: Drivers also consider real-time availability: if they observe that no spaces are available in a specific area, they are not attracted to

it. Obviously, without technical measures the drivers cannot have total knowledge of the current state of the garage, but can look ahead only locally. To model this, we assign a look-ahead set $L_{a_i} \subseteq A$ for any current area a_i . An agent has access to $c(a)$ and $f_a(t)$ only if $a \in L_{a_i}$.

Classes of parking decals: Some parking providers offer different classes of parking decals, with some classes having more options than others: at a university campus, administrative and faculty/staff might be allowed to park at any given area, while students might only park at labeled student parking. A business park’s parking provider might distinguish executive, employee, and visitor parking. This is modeled by assigning each agent a decal class, and by assigning each slot to one of these classes. The number of slots visible to an agent is then defined by that class. Non-compliant parking is thus not permitted to the agent.

Long-term experience and expectations: Instead of having to explore an area’s attractiveness while driving through a specific garage, a driver with long-term experience already knows the attractiveness of each area, and can also estimate the individual areas’ occupancy to a certain degree. These experience and expectations can be modeled by extending the look-ahead set to the whole graph, and by replacing the exact knowledge $f_a(t)$ by a “guessing function” $h_a(t) = f_a(t) \pm random$ which includes a small random component. The agent now knows the attractiveness of each area, and has imprecise knowledge of the areas’ availability.

Based on these considerations, and starting out from the current position a_i as root, an option tree is constructed. This is accomplished by considering all neighboring areas a_j reachable from a_i via an edge $e(a_i, a_j) \in E$, and from thereon iteratively to succeeding neighbors with a maximum depth of d (see figure 5). The branch starting with the area last visited is removed from the tree, adhering to the no-turn-around rule.

For each node a_j in the option tree, a conditional attractiveness $g(a_j)$ is calculated: if $a_j \in L_{a_i}$ and $h_{a_j}(t) > 0$ then $g(a_j) = c(a_j)$, else $g(a_j) = 0$. Thus, if the agent assumes an area to have zero slots currently available, it is not at all attracted to that area. In a next step, for each immediate neighbor a_j of a_i an assumed utility $u(a_j)$ is

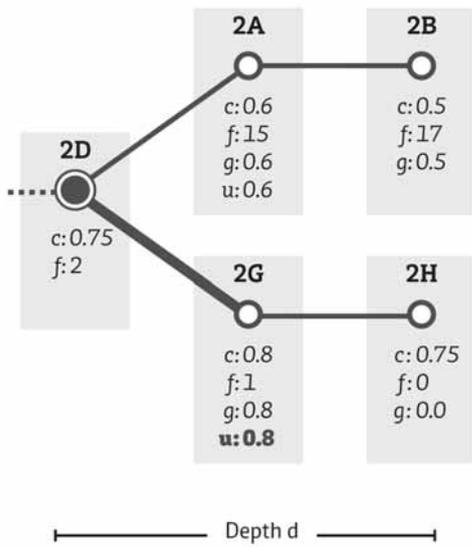


Figure 5: A simplified option tree, with the selected option being highlighted.

calculated by assigning $u(a_j) = \max_{a \in T_{a_j}} g(a)$, with T_{a_j} being the partial option tree with root a_j (again see figure 5).

At each simulation step, the agent takes a parking decision, followed by a routing decision if necessary. To take a *parking decision*, it selects the a_* with the maximum $u(a_*)$ out of the current area a_i 's immediate neighbors. If $f_{a_i}(t) > 0$ and $c(a_i) \geq u(a_*)$, the agent decides to park at the current area a_i . If not, it moves on with the routing decision.

To take the *routing decision*, the agent only considers the options with the lowest $v(a)$. From these, the agent selects the option a_j with the maximum $u(a_j)$. It moves to that area via edge $e(a_i, a_j)$, completing the movement after a time of $r_{e(a_i, a_j)}$.

If all areas have been visited, i.e. all $v(a) > 0$, and no available parking slot has been found, the agent concludes that the parking garage is full, stops searching, and is subsequently removed from the simulation.

3 Validation

3.1 Modeling Florida International University's Parkview Housing Garage

The Florida International University (FIU) Parkview Housing Garage provides students living in adjacent dorms with 282 parking slots on three levels. Access

to the garage is controlled; students swipe an identity card for the entry and exit barriers to open. The building consists of 16 areas with an average of 17.6 slots. Its layout is translated to a model graph as described in section 2.1 (see figure 6), with the attractiveness values being assigned by considering the areas' distances to both the vehicular entry and the pedestrian exits in accordance with information gathered from local experts. The traversal time for each area $a \in A$ is set to an average of $r_a = 10 \text{ sec}$. As all areas are immediately adjacent, the time necessary to move between areas is set to $r_e = 0$ for all $e \in E$. The agents' interarrival times are modeled based on a typical day's observed entry events per hour. By correlating the registered entry and exit events over a longer period, the average parking duration (and its standard deviation) based on entry times is modeled. As Housing Garage parking is only available to students living nearby, a high degree of experience can be assumed. The agents' look-ahead set is therefore extended to include the whole model graph.

The model was implemented utilizing an in-house event-based modeling and simulation framework. To validate the model's results, the individual areas' occupancy was measured in the Parkview Housing Garage over the course of two weeks at 10:00, 13:00, 17:00, and 20:00.

3.2 Results and Discussion

The described model was applied to simulate 100 operational days, with output measurement beginning after a 72 hour initialization phase. A simulation run generates approx. 1,700,000 events of nine event types. An average operational day thus consists of approx. 17,000 events, with the majority of these considering searching areas and moving through the graph (see figure 7).

The simulation's results are shown in table 1 and figure 8. At 10:00, the average number of simulated cars is 1.7% higher than the average number of observed cars. The average deviation of simulated to observed occupancy ratios is 8.7%. The other measuring points at 13:00, 17:00, and 20:00 show comparable results: On average, 2.5 more agents (1.4%) are simulated than cars were observed, while the average occupancy ratio over all areas and all measurement points deviates by 9.1%.

The model's validation shows its capability to predict a garage's state over the course of an operational day, even though specific results with their deviation of 9.1% are not yet precise enough for a feasible recommendation system. One major weakness of the de-

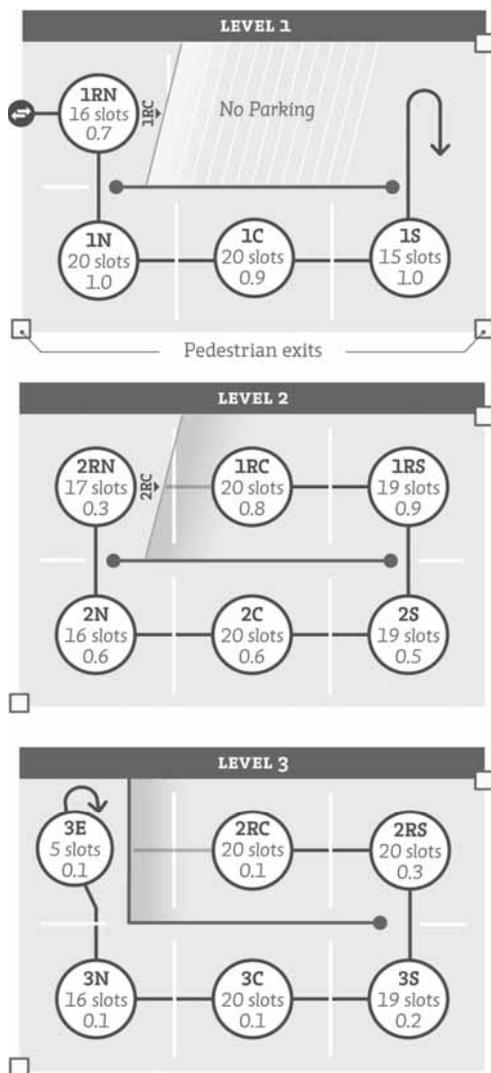


Figure 6: FIU Housing Garage: Model graph and attractiveness levels.

scribed validation process is that the occupancy measurement was executed on different days than the registration of entry and exit events. There was therefore no way to calculate the number of cars already present in the garage at the start of the registration period. Currently, FIU’s parking data collection is being converted from batch processed reports to real-time data streams, in addition to replacing the parking garage’s card swiping mechanisms with license plate recognition cameras at entry and exit lanes. As these new data streams will be continuously available, occupancy rates can be measured for periods with available entry and exit events. By utilizing these improved data sources, higher qual-

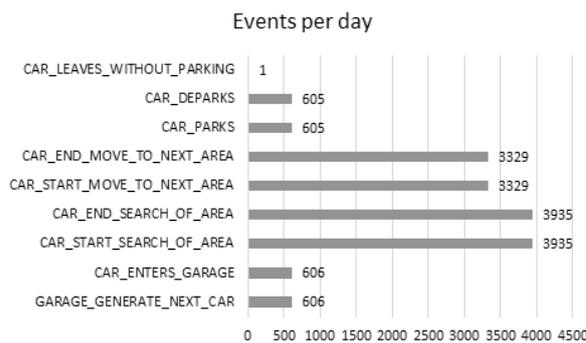


Figure 7: Number of simulation events per operational day.

Time	Obs. cars	Sim. cars	Dev. n/o cars	Deviation occupancy
10:00	194.5	197.9	1.7%	8.7%
13:00	164.5	161.7	1.8%	9.8%
17:00	164.2	166.5	1.4%	8.1%
20:00	169.3	176.4	4.2%	9.9%
Average	173.1	175.6	1.4%	9.1%

Table 1: Validation results.

ity input data distributions can be modeled. We therefore expect the model’s precision to be improved significantly.

4 Conclusions

This paper presented an agent-based simulation model of cruising for parking in parking garages. Beyond the parking structure’s layout and attributes, the model considers basic routing, an order of attractiveness on the garage’s areas, local knowledge of real-time availability, different classes of decals, and a driver’s long-term experience and expectations regarding attractiveness and expected availability. The model’s validation shows its general capability to predict a garage’s state over the course of an operational day based on layout data, attractiveness values, interarrival times, and parking durations. All these values can be easily collected for controlled access garages.

After further validation based on improved data streams, the model will be applied to the evaluation of parking recommendation methods. It will also be extended to accept real-time input data, and then be utilized as a base of a predictive parking information and recommendation system.

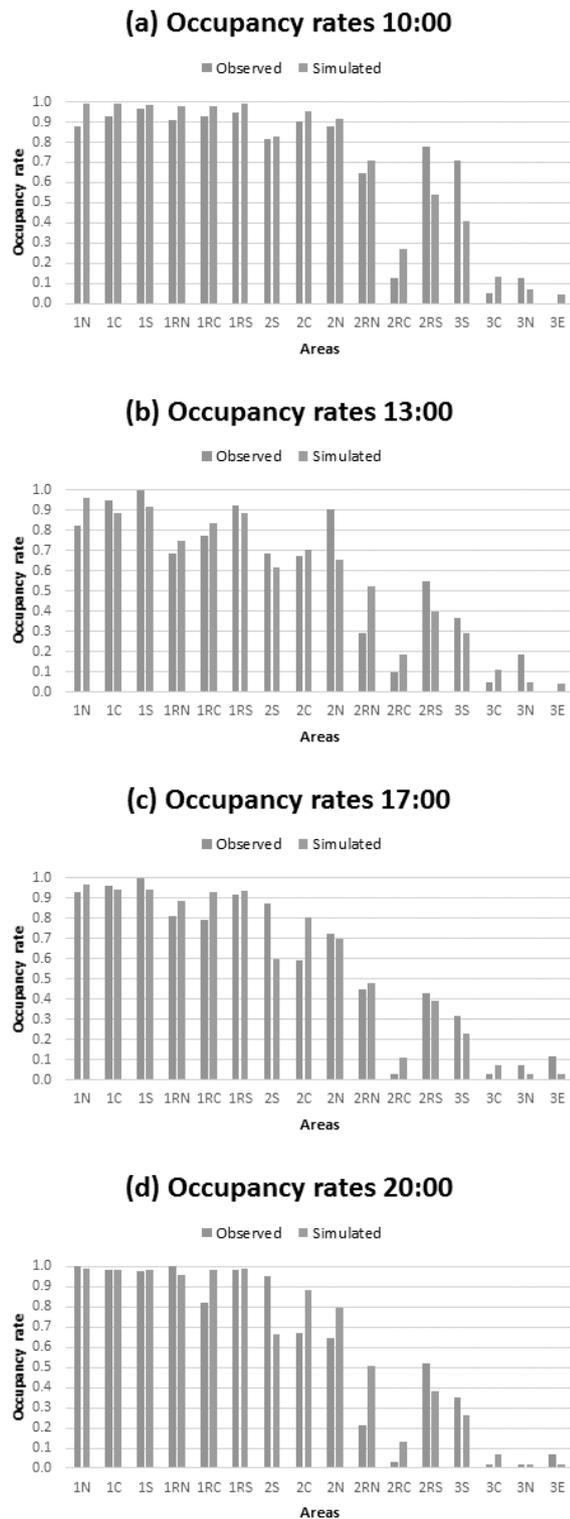


Figure 8: Validation results.

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