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Design and Control of Park & Charge Lanes for Carsharing Services with Highly-Automated Electric Vehicles ⋆

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Abstract: Carsharing operators could benefit from vehicle automation even before full vehicle automation is available city-wide: so-called Park- & Charge Lanes (PCL) installed in closed environments can increase customer convenience and reduce costs for parking space and charging operations. The concept introduced in this study comprises the stacking of vehicles in several lanes of optimized width, the division of lanes into charging and parking areas, and control strategies for efficient operation. Compared to conventional parking lots with two lanes and two perpendicularly arranged parking spaces, the stacking of vehicles allows for space reductions of up to 43 %. Additional cost savings can be achieved, since it is not necessary to equip every parking space with an inductive charging plate. Splitting each lane into a parking and a charging area makes the optimal control problem non-trivial: In order to provide the vehicles with a battery level that is high enough to serve customer requests, the PCL has to be controlled in a smart way. Both rule-based and model-predictive control policies are developed for assigning arriving vehicles to lanes and selecting vehicles for customer requests. An event-based simulation framework is created in order to test the performance of the introduced policies for the resulting dynamic and stochastic PCL problem. The best of the four described rule-based policies performs nearly as good as the implemented model-predictive control approach in the numerical experiment. The model-predictive control policy outperforms the random lane selection by 27 %, which clearly reflects the benefit of using advanced control strategies.

Keywords: Autonomous vehicles; Electric and solar vehicles; Automatic control, optimization, real-time operations in transportation; Modeling and simulation of transportation systems; Charging infrastructure; Parking; Carsharing

1. INTRODUCTION

In recent years, there has been a growing interest in mobility-on-demand systems like ride-hailing and carsharing services. These services can be a booster for electric mobility: The analysis of app call and booking data of a carsharing provider in Munich, Germany, suggests that customers prefer electric over conventional vehicles and shows that the vast majority of trips is short enough to be covered by electric vehicles (Niels and Bogenberger (2017)). In order to ensure a good spatial and temporal availability of vehicles and a high reliability of the technology (e.g. a level of charge that is high enough), staff is required to relocate and recharge the vehicle fleet to meet customer demand (Weikl and Bogenberger (2015)). With an increasing level of automation, requirements regarding availability and reliability could be fulfilled more easily: The vehicles could be relocated and recharged automatically at low costs. Assuming fully automated operations, autonomous carsharing and autonomous ride-hailing services are very similar concepts. Customers request a trip anywhere within an operating area, the autonomous vehicle drives to the customer, picks them up and drives the customer to her destination (Dandl and Bogenberger (2018)). This service could be offered at a cheaper price than today's carsharing and ride-hailing services, because costs for ride-hailing drivers could be omitted (Bösch et al. (2017)), and a carsharing fleet could be used more efficiently (Dandl and Bogenberger (2019)). Until full automation is available city- or even region-wide, automated driving functions can improve the maintenance and customer comfort in carsharing services in specific situations: automated driving in limited areas without human-vehicle interactions seems feasible in very near future. Examples are the projects for automated valet parking developed by several car manufacturers worldwide, see e.g. Hard (2015); Islam (2016); Pluta (2019).

Automated valet parking offers a higher comfort for customers, because they can leave the vehicle at the entrance of the car-park and do not need to worry about finding and maneuvering into a narrow parking spot. Additionally, as passengers leave the vehicle at the parking entrance, the average space per vehicle is estimated to decrease. Without human drivers and pedestrians in the parking area, the driving lanes can be narrower, elevators and staircases can become obsolete, and the required room for opening a vehicle's doors becomes unnecessary. The space efficiency

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can further be increased by compactly stacking the vehicles in several lanes, one behind the other. In combination with inductive charging plates, the parking facilities can be used for charging as well. In this paper, a new concept for these car-parks, denoted as Park & Charge Lanes (PCL), is introduced. In order to optimally use available space and power for charging, the PCL needs to be designed and controlled in a smart way. The objective of the study is to determine the dimension of a PCL for a carsharing operator, and to develop and test policies for organizing the parking and charging processes.

We present related literature in Section 2 and introduce the design of the PCL in Section 3. Section 4 explains the implemented automatic control strategies and presents simulation results, and Section 5 concludes.

2. RELATED LITERATURE

The advances of the PCL have the goal to improve customer comfort and cost efficiency of a carsharing operator by combining concepts from various branches of research: automatic (e.g. inductive) charging technology for electric vehicles, vehicle automation and its impact on parking infrastructure, and control theory. Inductive charging (Lu et al. (2016)) can potentially remove the necessity of carsharing customers or staff plugging in charging cables. With the additional automation of driving capabilities, valet parking concepts further increase the comfort of customers and potentially reduce the risk of vehicle damages (Schwesinger et al. (2016)). Several factors reduce the complexity of the automated driving task within a PCL: (i) there is no human-vehicle interaction within the PCL; (ii) the maximum driving velocity within a PCL can be very low; (iii) a high-definition map of the parking lot can be available and the parking lot can be equipped with infrastructure sensors. These factors simplify and can thus accelerate the implementation of the concept (Wachenfeld et al. (2016)). Automatic driving capabilities also allow to save space for parking. While car-parks for manually driven vehicles are usually designed according to guidelines published by local governments which impose restrictions on parking and driving space dimensions and orientation (see e.g. Bayerisches Staatsministerium des Innern (1993)), the advent of highly automated and autonomous vehicles allows for using space more efficiently. Passengers can leave the vehicle before it arrives in its final parking position, thus allowing the reduction of spaces between the sides of vehicles. The design of so-called k-stacks (Timpner et al. (2015)) is especially space-efficient. Therefore, stacking is commonly used in storage systems. However, retrieving a blocked item, which is in the middle of the stack, requires rehandling, which should ideally be minimized. Parking facilities designed for privately owned vehicles need to take that into account: car owners will of course expect to drive home with the same vehicle that they used to come to the car-park. Nourinejad et al. (2018) present an optimal car-park layout that considers both space savings and necessary relocations. The relocation problem is somewhat relaxed when considering carsharing or ride-hailing vehicles: it can be assumed that the customer does not request a specific vehicle. Nevertheless, customers will expect a certain battery charge level that is sufficient for their planned trip, and carsharing operators will want to maximize the overall battery level in order to be able to perform several trips without interruption. For the maximization procedure, it is beneficial to design a model and test control strategies. Vehicle arrivals, charging processes and departures can in principle be modeled as a traditional queuing problem as introduced in Newell (2013). Assuming that not all parking slots are equipped with charging plates, the proposed design of the PCL results in a non-trivial dynamic and stochastic optimization problem. Different rule-based policies and model-predictive control algorithms are presented, implemented and tested in this paper. The relevant literature that is necessary to understand the control algorithms are presented along with the policies in Section 4.

3. DESIGN OF PARK & CHARGE LANES

In the following, we introduce a concept denoted by *Park & Charge Lanes* (PCL). The goal of the concept is to provide enough space, charging plates and energy for incoming vehicles while minimizing costs for necessary infrastructure. Subsequently, the determination of the number of rows and charging units within a PCL is discussed.

3.1 Concept of Park & Charge Lanes

The use case is depicted in Fig. 1: customers leave and accept carsharing vehicles in two reception zones on the left (leave) and the right (accept) of Fig. 1. Customers are not allowed within the PCL area, such that this area represents a delimited area, in which automated driving functions of the vehicles can be applied in a controlled environment. The area is divided into lanes, and each lane consists of a charging and a parking area. Vehicles enter into the part of the lane equipped with inductive electric chargers. The new concept of this study is to coordinate charging and parking in lanes similar to the k-stacks arrangement of Timpner et al. (2015). In order to reduce risks of vehicle and infrastructure damages and achieve a very high precision of matching the electric surfaces of vehicles and chargers during re-parking, the lanes are strictly separated and vehicles are only allowed to stay within the lane they are assigned to at the beginning of the PCL.

PCL should be placed in locations, where the carsharing operator has large numbers of incoming vehicles and vehicle requests. Additionally, vehicles should idle at that location for a duration, in which significant amounts of energy can be recharged to the respective vehicles. Typical examples are stations near residential areas, where vehicles can be charged over night, or early-day destinations such as airports or stations in business areas, where vehicles can charge during the day. Empirical analysis of rental data can help identifying these locations, see e.g. Schmöller et al. (2015) and Hardt and Bogenberger (2018).

The space efficiency of the lane arrangement is especially advantageous in places, where parking space is expensive. In an automated valet parking system which is currently being tested in a parking garage in Boston, the average space per vehicle is assumed to decrease by two square meters (Chin (2015)). Fig. 2 illustrates a typical arrangement of parking lots and the PCL arrangement with their

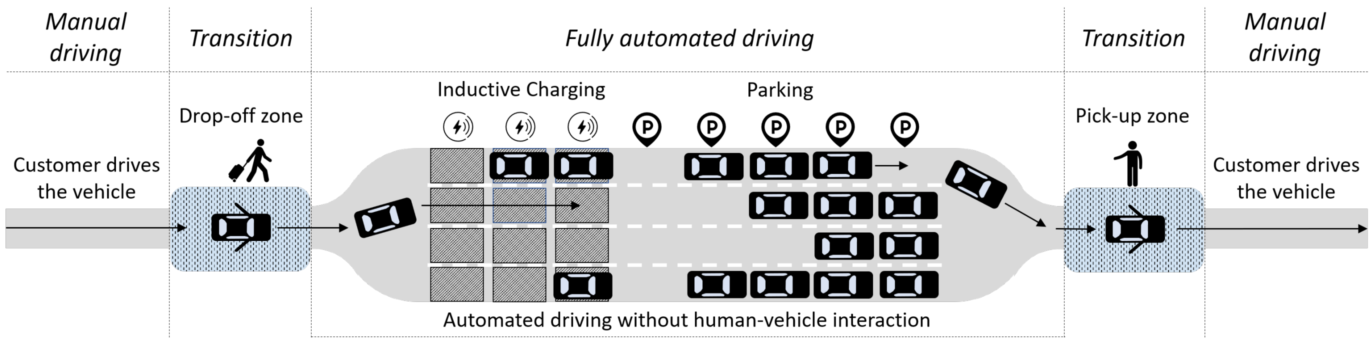


Fig. 1. Concept of Park&Charge Lanes for carsharing vehicles.

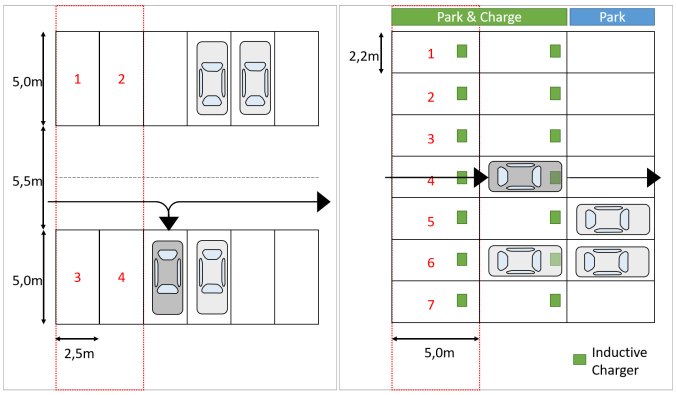


Fig. 2. Space requirements for conventional parking (left) and PCL (right).

respective space requirements. No people have to get in and out of cars for re-parking, thereby allowing the lanes to be as narrow as possible. As vehicles do not have to turn by 90 degrees in order to arrive in the parking position, the space previously reserved for driving to and from parking lots is not necessary in the PCL design. As shown in Fig. 2, two rows of a conventional perpendicular parking arrangement require the same amount of space as a PCL with 7 lanes. Hence, the additional vehicles in the same area can be counted easily:

$$\frac{N_{PCL}}{N_{conv}} = 7/4 = 175\% \tag{1}$$

Assuming a fixed number of required vehicle slots, an operator can save approximately $3/7 = 43$ % of space, which can translate into significant cost savings.

Additionally, the operator does not necessarily have to equip all parking slots with charging units. In a conventional park-car arrangement, vehicles have to execute quite a few rather complex driving maneuvers in order to switch between parking lots with and without charging units, which costs time on the one hand, but also increases the risk of damages on the other hand. In contrast, vehicles simply have to drive one or more slots straight ahead within a PCL.

In the following, the most suitable dimension and equipment of PCL for a carsharing provider is discussed.

3.2 Dimensioning of Park & Charge Lanes

Knowledge of the average vehicle idle time and distribution of vehicle states of charge (SOC) at arrival are critical for right-sizing the charging and the parking areas of the PCL. The capacity of the PCL, which is the number of lanes N_L times the number of available slots per lane N_S, can be derived from the cumulative difference of vehicle arrivals and departures due to customer requests:

$$N_L \cdot N_S = \max_t \left(\int_{t-24h}^{t} A(t') - R(t')\, dt' \right) \tag{2}$$

where $A(t)$ and $R(t)$ are the rates of vehicle arrivals and requests (departures), at time t, respectively. The number of lanes will often be constrained by the available width of the infrastructure; equation 2 will be sufficient to determine the size of the PCL. The average idle time $\mathbb{E}\left[t^{idle}\right]$ of vehicles can be computed on a macroscopic level as well:

$$\mathbb{E}\left[t^{idle}\right] = \int t' \cdot (A(t') - R(t'))\, dt' \tag{3}$$

The carsharing operator aims to charge the vehicles as much as possible so that the vehicles can perform multiple trips before recharging again. Hence, the number of slots N_C^P equipped with an inductive charging plate of power P should provide sufficient power to replenish the average state of charge $\overline{S}$ of the arriving vehicle batteries in the average idle time of vehicles. Let B be the average battery capacity of vehicles that park and charge in the PCL. Then:

$$N_C^P \cdot P \geq \frac{\mathbb{E}\left[(1-\overline{S}) \cdot B\right]}{\mathbb{E}\left[t^{idle}\right]} \tag{4}$$

Equation 4 only constrains the product of N_C^P and P in order to supply sufficient power. Operators might define sufficient power to be higher or lower than that; they could add a buffer in order to accommodate for fluctuations or choose a slightly lower value since it is not necessary to fill all vehicles to 100 % SOC. Either way, operators wish to choose the power of chargers and the number of chargers by optimizing the investment costs while satisfying Equation 4. Depending on the costs per charging unit with power P, this optimization is likely to suggest more, but cheaper and less powerful charging units. Finally, the chargers have to be distributed among the lanes. The simplest approach is to divide them evenly with N_C charging units per lane.

4. AUTOMATIC CONTROL OF PARK & CHARGE LANES

4.1 Problem Formulation

For the following, we consider a PCL with N_L lanes, N_C charging slots per lane and N_S total slots per lane. The objective of the operator is to maximize the amount of charge that is transferred to the carsharing vehicles in the charging part of the PCL. Furthermore, vehicles assigned to customers should have an SOC above a threshold $\tilde{S}$ defined by the operator. In the objective function of the resulting optimization problem, assigning a vehicle v_{req} to a request with SOC $S(v_{req})$ is penalized with

$$\Xi_{req} = \Xi \cdot \max\left(\tilde{S} - S(v_{req}), 0\right). \tag{5}$$

For a real-time operation of this PCL, the operator needs to (i) assign a vehicle that was left by customers to one of the lanes and (ii) send a vehicle from one of the lanes to a customer who requests a carsharing vehicle. Shunting processes within a lane can be performed optimally in the following way: vehicles in a lane are queued in the charging area until that area is full. When an arriving vehicle is assigned to a lane with full charging area, all vehicles in the charging area are automatically shunted by one position and the vehicle leaving the charging area is queued in the parking area of that lane (see Fig. 3).

Assuming a carsharing system with a homogeneous fleet, the index of a vehicle v can be dropped as soon as it enters the PCL. The evolution of the PCL system can then be described by the variables $x_{ls}(t)$ denoting the occupancy of slot number s in lane l of the PCL ($x = 1$ in case a vehicle occupies the slot) and $S_{ls}(t)$ denoting the SOC of a potential vehicle on this space of the PCL:

$$S_{ls}(t + dt) = \begin{cases} x_{ls}(t) \cdot \max\left(S_{ls}(t) + P/B \cdot dt, 1\right) & s \in C \\ x_{ls}(t) \cdot S_{ls}(t) & \text{else} \end{cases} \tag{6}$$

where we define $C = \{1, ..., N_C\}$ as the set of slots with charging units and the index s is defined to be increasing from left to right in Fig. 3. Let $\delta S_{ls}(t)$ denote the marginal change in SOC at time t and R the set of all requests in the evaluation period $[0, T]$, then the objective of the PCL operator reads:

$$\max\left(\int_0^T \sum_{l,s} \delta S_{ls}(t)\ dt - \sum_{req \in R} \Xi_{req}\right) \tag{7}$$

The PCL problem represents a dynamic stochastic problem as both vehicle arrivals and customer requests are not known at the beginning of the evaluation period, but revealed over time and based on stochastic distributions. Hence, it is likely impossible to find one optimal policy for all problem instances.

We assume that a carsharing operator knows about the distributions of future arrivals (both time and SOC) and request times for a time horizon T^S. Furthermore, an operator could leverage quasi-exact knowledge of incoming cars when customers make use of the navigation module within the carsharing vehicles. For this study, an operator is informed about the arrival time and the SOC S of every incoming vehicle T^A minutes before the actual arrival.

Fig. 3. Simulation framework: high-level flowchart (left) and example of a vehicle arrival event (right) showing the position and SOC of vehicles within the Park and Charge Lanes.

4.2 Simulation Framework

An event-based simulation framework was developed in order to test different operator strategies. Fig. 3 illustrates the principle of the simulation framework: an event requires an action of the operator, and the SOC of vehicles in the charging area are updated in the time between events. An event is triggered when a new vehicle arrives at the PCL or a customer requests a vehicle. Shunting processes are automatically performed in an optimal way.

4.3 Control Strategies

A PCL control policy π determines a lane $l(t_k)$ for a given event k at time t_k; either the lane an arriving vehicle should be assigned to or the lane from which a vehicle is sent to a customer request. One of the simplest policies is the random policy, in which lanes are chosen at random – independent of the state of the PCL system (besides feasibility). Four rule-based policies are introduced in the following. As the mathematical problem is dynamic and stochastic, the impact of a current decision on future states and the total objective value are unclear and non-myopic behavior is important. In order to gain insight on the foresight ability of the best rule-based policy, a model-predictive control approach is also studied.

Rule-Based Policies We present two rules for arriving vehicles and vehicle requests each. We start with strategies (A1) and (A2) for the arrival process before introducing strategies (R1) and (R2) for customer requests.

(A1): A typical approach in queuing problems is to send arriving vehicles to the shortest queue:

$$l_{A1} = \arg\min_l \left(\sum_{s=1}^{N_S} x_{ls}\right) \tag{8}$$

(A2): A more refined strategy considers the state of the charging area and the parking area separately. Strategy (A2) considers three cases. If the charging areas of all lanes are full, then one of the charging vehicles must be shunted out of the charging area. In this case the choice

$$l_{A2}^{(1)} = \arg\max_l \left(S_{lN_C}\right) \tag{9}$$

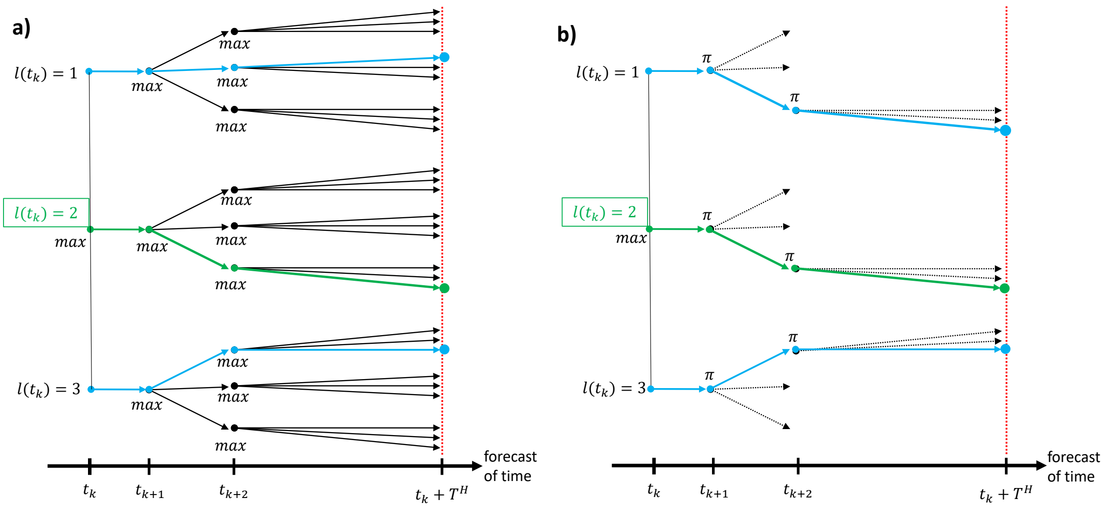


Fig. 4. Model-predictive control with a) exhaustive search and b) policy application. The max operator on an event node compares the results of the objective function to the right, whereas the π operator denotes that the future path at an event node is determined by the selected policy.

makes sense for two reasons: the shunted vehicle would be the most likely to have full SOC before the next event, and choosing this vehicle will create the lowest penalty when it will be sent to a customer later in the day.

Otherwise, there exists at least one lane with at least one free charging spot. Therefore, no vehicles that are not fully charged have to be shunted out of the charging area. The lane for the arriving vehicle is then chosen among all lanes l with $\sum_{s=1}^{N_C} x_{ls} < N_C$ or $S_{lN_C} = 1$. The idea of the following non-myopic strategy is to stack vehicles with increasing SOC such that fully charged vehicles are not stuck somewhere in the middle of the charging area and thereby occupy important space. Let $\Delta_l = S_{ln} - S(v_{arr})$, where S_{ln} is the SOC of the last vehicle (with lowest slot index) that is currently charging in lane l. If there exist lanes with $\Delta_l > 0$, then choose the lane such that

$$l_{A2}^{(2)} = \arg\min_l \Delta_l \tag{10}$$

$$\text{with} \quad \left(\sum_{s=1}^{N_C} x_{ls} < N_C \text{ or } S_{lN_C} = 1\right) \quad \text{and } \Delta_l > 0 \tag{11}$$

Otherwise, a vehicle needs to be assigned to a lane where it follows a vehicle with lower SOC. In this case, we choose the lane such that

$$l_{A2}^{(3)} = \arg\min_l \Delta_l \tag{12}$$

$$\text{with} \quad \left(\sum_{s=1}^{N_C} x_{ls} < N_C \text{ or } S_{lN_C} = 1\right) \tag{13}$$

As empty charging lanes are taken into account here with $\Delta_l = -S(v_{arr})$, they are selected if available.

Obviously, the selection of lanes for incoming requests is always limited to lanes with vehicles in stack. Furthermore, following rules are tested:

(R1): The vehicle from the longest queue is assigned to a request

$$l_{R1} = \arg\max_l \left(\sum_{s=1}^{N_S} x_{ls}\right) \tag{14}$$

(R2): A more intelligent strategy will always try to assign a vehicle from the parking area to a customer request, if possible. If there are vehicles in the parking area, then the first vehicle from the lane with most vehicles in the parking zone is assigned to a request:

$$l_{R2}^{(1)} = \arg\max_l \left(\sum_{s=1+N_C}^{N_P+N_C} x_{ls}\right) \tag{15}$$

Otherwise, the vehicle from the first charging spot that has the highest SOC is assigned to a request:

$$l_{R2}^{(2)} = \arg\max_l \left(S_{l,N_C}\right) \tag{16}$$

Four rule-based control policies (A1_R1), (A1_R2), (A2_R1) and (A2_R2) can be created from the combination of these customer request and vehicle arrival rules.

Model-Predictive Control A typical approach to dynamic optimization problems such as the PCL problem defined in equation (7) is model-predictive control (mpc). We refer the interested reader to literature, e.g. Bertsekas (2005) or Powell (2007) for a detailed description and only describe the applied approach briefly. For each decision, the model extrapolates the implications of the current decision at a time t_k into the future and evaluates the objective function at time $t_k + T^H$. An exact dynamic programming approach would set $T^H = T - t_k$ for each decision and use the Bellmann equation (Bellman (1966)) to recursively check for the best possible outcome for each current decision.

However, the operator has only stochastic knowledge of future requests and vehicle arrivals, and just within a time horizon T^S. Hence, the optimization can only be performed for a rolling time horizon $T^H \leq T^S$. As a consequence, shunting a vehicle v with $S(v) < \tilde{S}$ from the charging to the parking area might not inflict a penalty within T^H, but at some point, this vehicle will have to be assigned to a request and cause a penalty term. Hence, it makes sense to introduce a shunting penalty

ξ_{shunt}, which is the sum of $\Xi \cdot \max(\tilde{S} - S(v), 0)$ for all vehicles v shunted from the charging to the parking area within T^H. Furthermore, it is impossible to optimize decisions based on the exact distributions. Hence, the expectancy value of the objective function is optimized, whereas the computation of this expectancy value can be performed by sampling sets of variables from the stochastic distributions.

Due to the curse of dimensionality, an exhaustive search for the maximum objective function value (see Fig. 4a) becomes infeasible for this problem. Hence, we use an approximate dynamic programming approach called policy application, in which the expected value function at time $t_k + T^H$ is approximated by applying a simpler policy for each expected future event (as illustrated in Fig. 4b). In this study, we use the rule-based (A2_R2)-policy. Formally written, the operator chooses the lane with

$$l_{mpc}(t_k) = \underset{l(t_k)}{\arg\max} \left(\mathbb{E}_\pi \left[\int_{t_k}^{t_k+T^H} \sum_{l,s} \delta S_{ls}(t)\, dt - \sum_{req} \Xi_{req} - \xi_{shunt} \right] \right) \quad (17)$$

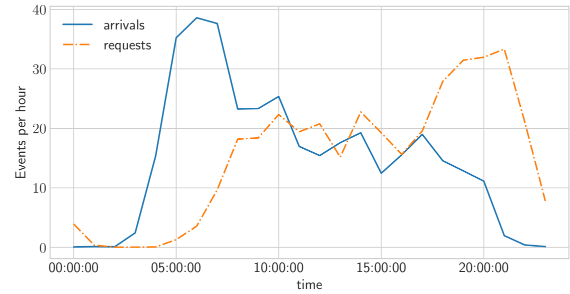
In the following numerical experiments, different rolling time horizons T^H were tested. Furthermore, we noticed that equation (17) often ends in a tie between multiple lanes. Test simulations showed that applying the policy-rules on the tying lanes generates better results than picking the lane with the lowest or highest index, which would be a simpler implementation.

4.4 Numerical Experiment

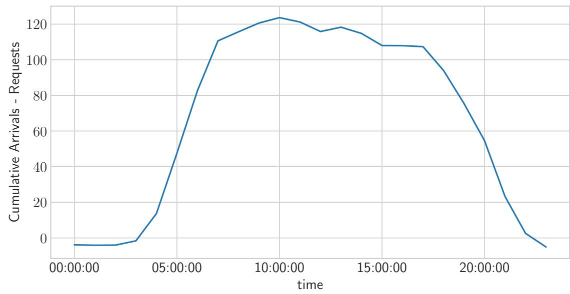
Scenario Setup Average customer-request and vehicle-arrival rates, as well as the SOC distribution for vehicle arrivals in Fig. 5 are based on rental data of a selected zone of a carsharing business in Europe. In order to create scenarios at will, scenario events are created by Poisson processes with various different random seeds. In the underlying data, the number of requests is slightly larger than the number of arrivals and there are some requests right after midnight. For consistency reasons, we add enough vehicles with 100 % SOC in the parking area to ensure consistent scenarios. After all events are drawn from these distributions, the SOC of vehicles are drawn from the distribution shown in Fig. 5c) for arrival events. We assume that the operator has exact knowledge of the arrival time and the SOC of incoming vehicles $T^A = 15$ minutes ahead of their arrival at the PCL.

The battery size of the electric carsharing vehicles is set to $B = 39.7$ kWh, the desired minimal range of vehicles relates to a targeted SOC of $\tilde{S} = 80$ %, and the penalty factor for insufficiently charged vehicles is chosen to be $\Xi = 10$. The power of the charging units is assumed to be $P = 11$ kW.

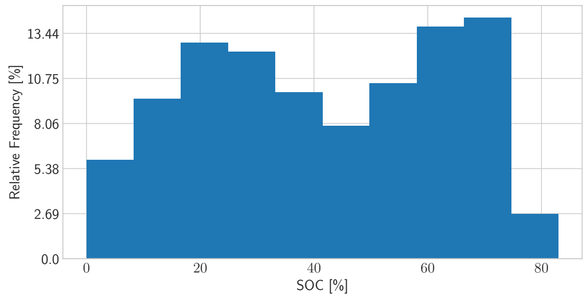
The maximal size of the PCL is estimated from equation 2 with an additional buffer and is set to 175. We assume that the PCL substitutes a parking area with two lanes and perpendicular parking lots. As illustrated in Fig. 2, the available width is sufficient for 7 lanes, which in this case have 25 slots each. The average time of a vehicle inside the



a)



b)



c)

Fig. 5. Stochastic distributions of numerical experiments: a) average rates of vehicle-arrival and customer-request distributions per hour. b) cumulative curve of vehicle-arrivals minus customer-requests. c) SOC distribution of vehicles arriving at the Park and Charge Lanes.

PCL is approximately 4.5 hours (derived from the scenario arrival and request rates with the help of equation (3)) and the required time to charge a vehicle with the mean SOC of the SOC distribution amounts to approximately 2 hours. Therefore, we choose the number of inductive charging units per lane to be 13 for the studied PCL example.

In total, we created 50 scenarios by choosing 50 different random seeds to draw event samples for customer-request times and both vehicle-arrival times and the SOC of the respective vehicles.

Results The simulations show that applying a meaningful policy generates substantial benefits for the PCL operator. Fig. 6 illustrates the objective function defined in equation (7). The scale of the y-axis can be interpreted in the following way: a difference of 1 in the objective function is equivalent to one vehicle being charged from 0 to 100%, or one vehicle with 70% SOC being sent to a customer request. In practice, the difference in the objective function

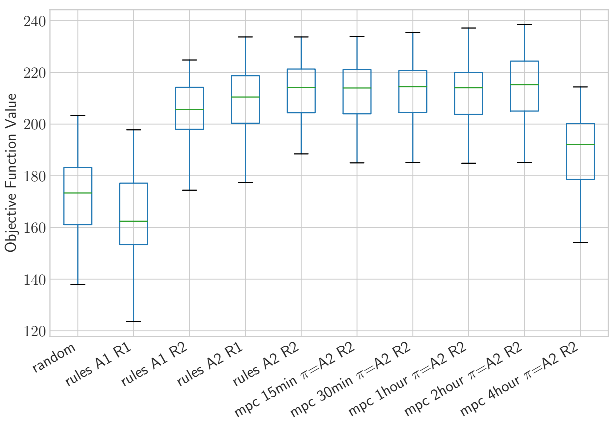


Fig. 6. Objective function results (equation 7) of 50 simulations for the introduced policies.

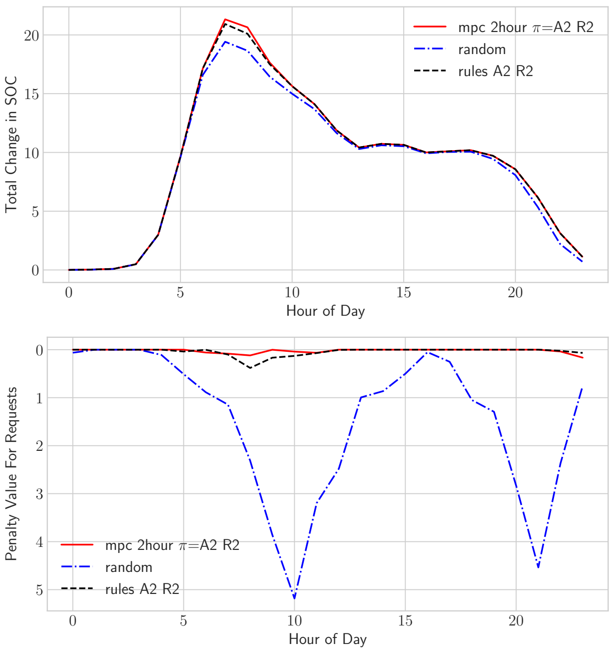


Fig. 7. Hourly contributions to the objective function for selected policies. Top: transferred energy (measured in SOC per vehicle $\in [0,1]$); bottom: accumulated penalty values.

results from changes in SOC and penalties of multiple vehicles in the PCL.

Interestingly, the shortest/longest queue policy (A1_R1), which is a typical approach to queuing problems, performs even worse than the random policy for this PCL example, especially regarding the amount of transferred energy. As soon as either request or arrival strategy are more advanced, the performance increases considerably. A change in the request policy to R2 affects the energy transfer after the morning peak, whereas a change in the arrival policy to A2 also improves the peak energy transfer. Both strategies help avoiding penalties: R2 by intelligently freeing up space in lanes, A2 by reducing the amount of vehicles with insufficient SOC to the parking area.

The results of the model-predictive control policies are almost insensitive to the choice of the time horizon T^H. Only the selection of a 4-hour time horizon yields results that are similar to the random policy. The amount of transferred energy follows the random curve throughout the day, whereas the curve of penalties only looks similar in the morning peak. It seems that for such large time horizon, the randomness of sampling multiple future events (especially with sampling the SOC from the SOC distribution in Fig. 5c) generates near-random lane choice; since there are hardly any events to predict in the night hours, the forecast in that period is more stable and the afternoon/evenening penalty peak of the random policy is avoided. Hence, this policy still performs better than random in the end.

All other mpc approaches (with A2_R2 policy application) generate results which are very similar to those of the underlying A2_R2 policy. The concept behind the underlying rules of this policy are non-myopic thereby producing similar decisions as the model-predictive control approach. For the studied use case, the mpc with a time horizon of 2 hours performs best. In average, the delta in the objective function value between this mpc policy and the best rule-based policy is 1.5. The contributions of energy transfer and penalty value per hour of day are illustrated in Fig. 7 (and only shown for selected policies for clarity). As expected, the choice of policy impacts the results mostly during the peak hours, in which the PCL is filled and many vehicles have to be shunted due to incoming vehicles.

5. CONCLUSION

Before the introduction of fully autonomous vehicles, carsharing providers can benefit from high vehicle automation and inductive charging. Improvements of charging processes and parking space requirements enable both cost-savings and higher customer convenience. The introduction of spatially separated PCL zones ensures that no other traffic participants are allowed within the zone, thereby simplifying the legal framework required for driver-less vehicles and near-future implementation. Since no person has to leave a vehicle within the PCL, vehicles can be arranged with minimal distance to the sides. This allows the concept to generate space reductions of 43 % compared to a perpendicular parking arrangement with two lanes and parking on both sides. Hence, locations with high area costs, but also high carsharing demand are candidate areas for PCLs. The separation of lanes into charging and parking area further reduces costs for charging infrastructure: Since any vertical movements should be avoided to minimize risk of damages, vehicles are only shunted forwards within a lane. Over time, vehicles are charged and move to the front of their respective lane. Hence, the probability of finding fully charged vehicles increases the closer a vehicle is to the end. Therefore, it might be cost-efficient to not equip the near-end slots with charging units.

The configuration with both charging and parking areas makes the control of a PCL non-trivial. Four rule-based strategies and a model-predictive control policy are introduced and tested in an event-based simulation framework. The best rule-based policy was developed in order to obtain vehicle distributions that would be beneficial in future states. This is reflected by only minor gains of less than 1 % from the studied model-predictive control over the rule-based approach. In comparison, the best model-predictive control policy with a rolling time horizon of 2 hours performed 27 % better than randomly assigning arriving vehicles to lanes and randomly selecting a lane from which a vehicle drives to a new customer request.

This study introduces the concept of PCL. It opens the pathway for future studies considering more complex control problems by allowing vehicles to change lanes, including staff that can drive a vehicle on regular roads in order to re-enter a vehicle at the start of the PCL, designing a PCL with different numbers of charging units per lane, assuming inhomogeneous battery sizes, or taking the non-linear SOC-dependent charging behavior into account.

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