SParking: A Win-Win Data-Driven Contract Parking Sharing System

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ABSTRACT

With a rapid growth of vehicles in modern cities, searching for a parking space becomes difficult for drivers especially in rush hours. To alleviate parking difficulties and make the most of urban parking resources, contract parking sharing services allow drivers to pay for parking under the consent of owners, reaching a win-win situation. Contract parking sharing services, however, have not yet been prevailingly adopted due to the dynamic parking time which leads to uncertainties for sharing. Thanks to the Internet of things technique, most of modern parking lots record vehicles' fine-grained parking data including entry and exit timestamps for billing purposes. Leveraging the parking data, we analyze and exploit available vacant contract parking spaces. We propose SParking, a shared contract parking system with a win-win data-driven scheduling. SParking consists of (i) a parking time prediction model to exploit reliable periods of free parking spaces and (ii) an optimal scheduling model to allocate free parking spaces to drivers. To verify the effectiveness of SParking, we evaluate our design on seven-month real-world parking data involved with 368 parking lots and 14,704 parking spaces in Wuhan, China. The experimental results show that SParking achieves more than 90% of accuracy in parking time prediction and the average utilization rate of contract parking spaces is improved by 35%.

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CCS CONCEPTS

• **Human-centered computing → Empirical studies in ubiquitous and mobile computing**.

KEYWORDS

Parking Sharing, Usage Prediction, Online Scheduling

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1 INTRODUCTION

Searching for a vacant parking place is difficult for drivers and brings extra street travel, especially during rush hours. According to a recent survey [7], 45% of the street traffic is caused by searching for parking spaces, which results in severe traffic congestion and air pollution. To alleviate the pain of parking, many researchers have investigated the problem pertaining to parking. Some studies propose approaches to exploit vacant parking spaces in public parking lots [16, 25]. In addition, researches propose scheduling algorithms to alleviate the public parking pressure [13, 19].

Different from existing studies, we propose a contract parking sharing system inspired by sharing economy ideas. We introduce the concept of *contract parking sharing* to make the best of the urban parking resources. For instance, parking in the hospital is difficult during work hours because of massive parking demands and limited hospital parking places. At the same time, there are abundant vacant parking spaces in surrounding communities since their owners are out at work. If we allow drivers utilize these contract parking places under the consent of owners, the parking difficulty is alleviated. Achieving contract parking sharing is a challenging problem for several reasons. Specifically, the usage of contract parking space is dynamic and uncertain. Furthermore, it is difficult to make an optimal match between contract parking spaces and parking requests and avoid parking conflicts between owners and secondary users under the uncertainty of supply and demand.

Thanks to the development of the internet of things techniques [8, 15, 20], most of modern parking lots record vehicles' fine-grained parking data including entry and exit timestamps using various sensors. Leveraging the fine-grained parking data, we propose *SParking*, a data-driven contract parking sharing system, which aims to make the best use of contract parking space resources and provide an optimal solution for the online contract parking sharing problem.

To achieve this goal, we first introduce a entropy based model to decide those valid vacant contract parking spaces whose utilization are regular enough for sharing. Then we propose an idle time prediction model to predict the available time of contract parking places. Finally, *SParking* conducts the parking scheduling between parking requests and available contract parking spaces with an optimal scheduling algorithm. The main contributions of this work are summarized as follows.

- To the best of our knowledge, this is the first work which proposes contract parking sharing to solve parking problems. *Contract parking sharing* improves the utilization rate of parking spaces and realizes a mutually beneficial win-win situation for temporary parking drivers, contract parking space owners and parking lot managers.
- Based on real-world parking data, we propose a prediction model which aims to predict the available parking time for contract parking sharing taking the spatio-temporal, meteorology and holiday factors into consideration. Furthermore, we propose (i) an optimal scheduling algorithm for contract parking sharing using dynamic programming, and (ii) its corresponding online version.
- To verify the effectiveness of our design, we evaluate our design on seven-month real-world parking data involved with 368 parking lots and 14,704 parking spaces The experimental results show that the accuracy of parking time prediction is higher than 90% and the average expectation of the utilization rate of contract parking spaces reaches more than 95% of the optimal utilization rate. To benefit the community and make our work reproducible, we will release one week data utilized in this paper.

The rest of the paper is organized as follows. Section 2 introduces the necessity and the feasibility of our system. Section 3 presents the system architecture and challenges of the contract parking sharing system. Section 4 and Section 5 describes the design and implementation of our system. Section 6 evaluates the performance of SParking. Section 7 discusses lessons learned and limitations. In Section 8, we review the related work, followed by the conclusion of this paper in Section 9.

2 MOTIVATION

In this section, we explain the insight of contract parking sharing which aims to alleviate the difficulty of parking. Through empirical data analysis, we show the potential of sharing contract parking spaces.

Parking Difficulty and Traffic Congestion

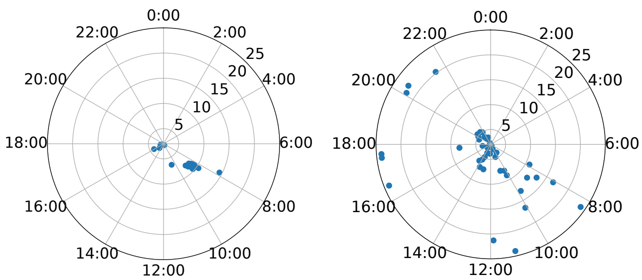
According to statistics, in the third quarter of 2018, the estimated number of vehicles in the United States reached 281 million, an increase of about 7 million compared with the previous year [4]. In 2018, 31.72 million vehicles were newly registered in China and the total number of vehicles has reached 327 million, an increase of 10.51% compared with the previous year [5]. In addition to the difficulty of parking, the traffic generated by searching for parking spaces exceeds 30% of the total traffic [21].

Figure 1: Distribution of contract parking lots in Wuhan

Facing enormous parking pressure, it is difficult to alleviate the existing parking problems completely relying on the limited public parking space. In this paper, we propose to explore the potential of contract parking sharing services.

Potential of Contract Parking Sharing

We collect parking records in Wuhan by monitoring probes which are deployed in 366 community parking lots. Based on the dataset, we show more than 300 parking lots in Wuhan City in Fig. 1 and the parking lots basically cover the business districts of Wuhan. Through data analysis, we find that the parking behaviors of a certain number of parking space owners are regular and these contract parking spaces are suitable for sharing purposes under the consent of owners.



(a) (b)

Figure 2: Parking behavior of a contract parking space owner

Considering the time boundary and indefinite parking time, we apply scattered points to characterize parking behaviors of the car owners with the starting time and the parking duration. Fig. 2 shows the parking behaviors of two contract parking space owners. The round angle indicates the time when the contract parking space owner goes out and the parking space starts to be idle. The radial length of the circle means the length of the available parking duration. For example, the coordinate $[0°, 8]$ represents that the contract parking space owner goes out at 0 o'clock and goes back home after 8 hours, which indicates that the parking space starts to be idle at 0 o'clock and the available parking duration is eight hours.

As shown in the left picture of Fig. 2, the distribution of scattered shows that this contract parking space owner almost goes out at 8:30AM and goes back home after 8-10 hours. However, the parking behavior of the contract parking space owner on the right in Fig. 2 is irregular. As shown in Fig. 2, a parking space has more regular outing time and outing duration if scattered points are closer, which has the potential to be shared contract parking space.

3 SYSTEM OVERVIEW

Parking Data Collection

Our vehicle parking management platform collects information about parking lots off-street in the city, and realizes on-street and off-street parking data exchanging and sharing. The intelligent parking lots management system includes several modules including parking vehicles entry and exit, online traffic flow guidance and parking fee collection. The vehicle enters and exits a parking lot by swiping a card or being photographed for image recognition. Vehicles entering or leaving the parking lot will be recorded. This is the important data that we use to analyze parking behaviors.

Design Requirements

To solve the difficulty of parking, we propose a contract parking sharing system, which is designed to meet the following requirements. Except for providing basic functions, i.e., (i) a contract parking sharing platform needs to be established. In order to ensure the smooth implementation of contract parking sharing system, the operation should be as simple as possible to achieve user-friendly applications; (ii) due to the different parking habits of different contract parking space owners, the contract parking spaces need to be a designated parking space, rather than any parking space in the parking lot. So the system needs to identify the specific free parking spaces and accurately guide the drivers who need parking to the contract parking space.

Challenges

To meet these requirements, two major challenges need be addressed in developing the contract parking sharing system.

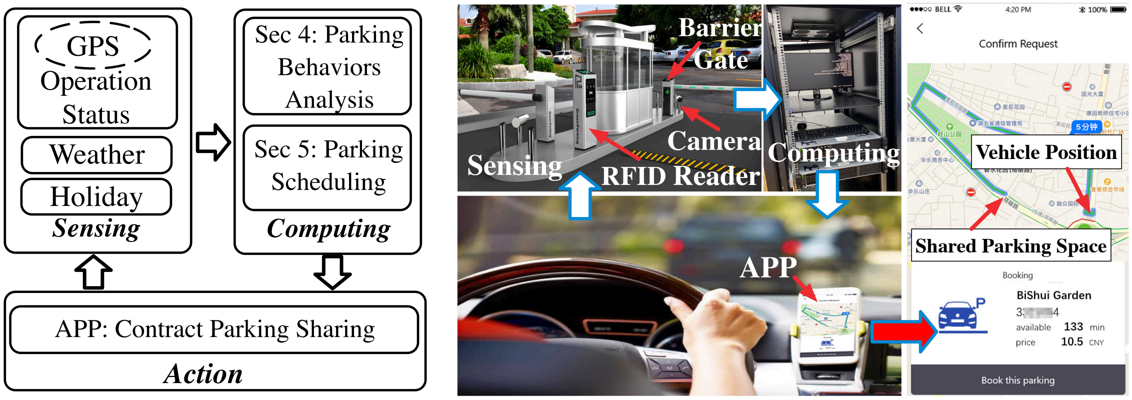
- As mentioned in Section 2, it is difficult for drivers to find parking spaces in public parking lots. To make full use of private parking spaces, our system needs to find the available contract parking spaces and predict their available parking time accurately.
- In order to conduct real time parking scheduling, our system needs to efficiently calculate the recommended contract parking spaces while maximizing the utilization of contract parking spaces.

System Architecture

Our contract parking sharing system is based on the original parking lots management system, using the original system to obtain data, processing and scheduling parking spaces on the platform. As shown in Fig. 3, our system is composed of three components.

Sensing Component: The sensing component serves as the data feeding module, which collects five datasets: (i) the historical parking records of the parking spaces, (ii) the departure information of the vehicles daily, (iii) the user's location, (iv) the required parking duration, and (v) the weather data. The weather data come from the Meteorological Bureau, user information is collected through the app and others come from the IoT system in the parking lot. These sensing datasets are sent to the server in the dispatching center in real time and served as the input of the computing component.

Computing Server: The computing server receives these uploaded data. Then it provides real-time available parking time analysis. When a new parking demand appears, the computing center allocates an appropriate free parking space as soon as possible. Finally, the results are sent to the Client APP.



(a) System diagram (b) Physical infrastructure

Figure 3: The architecture of parking sharing system

Action Component: After receiving dispatching results from the server, the Client App app is responsible for guiding the target parking space.

4 PARKING BEHAVIOR ANALYSIS

As mentioned in Section 2, not all parking behaviors of contract parking space owners are regular. Parking spaces with irregular parking time are not suitable for sharing. We use information entropy to quantify the regularity of parking behaviors. After selecting parking spaces that are suitable for parking, we propose a prediction model based on prophet to predict available parking duration of parking.

Entropy of Parking Behaviors

To obtain potential contract parking spaces, we need find contract parking spaces with regular parking behaviors. We utilize information entropy to represent contract parking space owners' parking behaviors. The information entropy is defined as:

$$H(U) = E[-logp_i] = -\sum_{i=1}^{n} p_i logp_i \tag{1}$$

Where U is the complete set of random variables and p_i is the probability of the i-th random event. The greater the information entropy of contract parking spaces, the more irregular parking behavior. The parking behaviors of parking spaces owners become more diverse as the information entropy increases. In order to avoid conflicts, we select parking spaces with less information entropy as shared contract parking spaces.

Feature Selection

Since real-world environmental factors introduce high dynamics in parking behaviors, it is important to select proper features to improve prediction accuracy. As shown in Fig. 4, we can see that the available parking duration follows similar patterns over time. In addition, we notice that there is a special highlight on June 9, 2016 and the next three days are also different from other periods. This is because June 9, 2016 to June 11, 2016 is the Dragon Boat Holiday in China, and the original weekend, June 12, needs to work due to the adjustment of the holiday. Therefore, it is reasonable to select time stamp as a crucial feature.

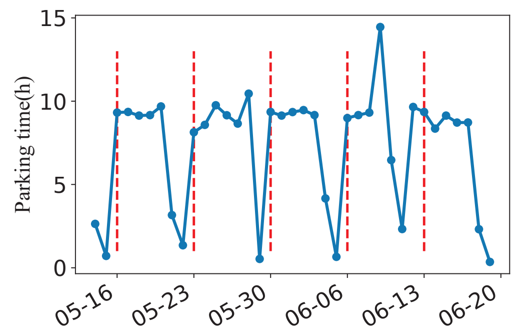


Figure 4: The available parking time in a parking space

Weather condition is another important factor that dramatically influences parking sharing services. We assign sunny day to 1, windy, cloudy to 0.5, rainy, snowy or other inconvenient weather day to 0. As shown in Fig. 5, weather changes basically do not affect the available parking duration of contract parking spaces on weekdays. On weekends, contract parking space owners tend to stay home under bad weather conditions, and the available parking duration is shorter correspondingly. Thus, we collect weather condition data and add relative labels to the original dataset.

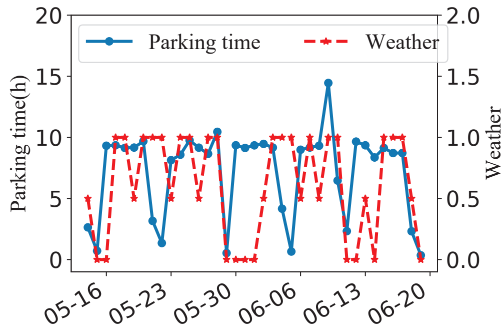


Figure 5: Relationship between weather and available parking time

The Prediction Model

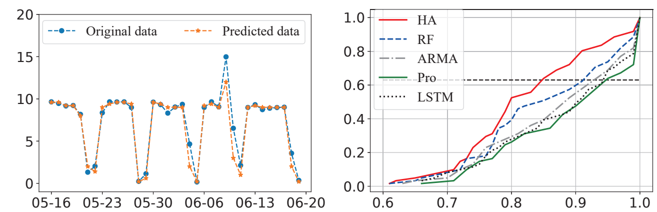
After selecting proper features, we build up learning based models to predict the parking duration of contract parking spaces. In our system, we conduct time prediction based on Prophet model [24]. Prophet is a framework for predicting temporal fishing and hunting data, which considers multiple non-linear trends [3]:

- Hourly, daily, or weekly observations with at least a few months of history.
- Strong multiple "human-scale" seasonalities: day of week and time of year.
- Important special days that occur at irregular intervals, such as holidays and special weather.
- A reasonable number of missing observations or large outliers.

In our model, based on the analysis of parking behaviors of the contract parking space owners, we choose three main components to build a time series including trend, periodicity, and vacation.

$$r(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{2}$$

where $g(t)$ is a non-periodic trend function. Our model automatically detects the trend change by selecting trend change points from the data. $s(t)$ represents the weekly or monthly or yearly cyclical changes which are applicable to the Fourier series modeling. The period of the cyclical change in contract parking space owners' behaviors is one week. $h(t)$ represents the effects of special days that occur from time to time. ϵ_t is an error term which indicates some special changes. We select a piece of prediction results and show it in Fig. 6. Our model provides prediction values, which is quite close to the ground truth. The difference between the predicted value and original value on weekdays is small. On the weekend, the prediction tends to be more conservative. The model's overall prediction effect is better and conservative prediction results will not cause disputes between the contract parking space owners and drivers.



(a) Prediction Results (b) Average Accuracy

Figure 6: The prediction results of our method and the average accuracy of different prediction methods

In order to further verify the effectiveness of our prediction method, we compare the performance of Prophet-based model with three other widely used prediction models. Historical Average (HA)[10] is a basic model in time-series prediction, which utilizes the average of historical observations for the same time and location to forecast the future data. Auto Regressive Moving Average (ARMA)[2] provides a parsimonious description of a stationary stochastic process in terms of two polynomials: the momentum and mean reversion effects (AR) and the shock effects observed in the white noise terms (MA). Random forests(RF)[23] are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. Long Short-Term Memory (LSTM)[1] is a recurrent neural network architecture with feedback connections. It is widely applied for time series prediction problems.

For parking duration prediction, assuming that the predicted value is pv and the original value is tv, we define the accuracy p_{ac} as: $p_{ac} = \frac{|pv - tv|}{tv}$. Among them, the time length is accurate to every 1 minute. It is considered to be accurate if the parking duration error is less than 1 minute. The CDF of absolute errors is compared in Fig. 6. Our Prophet-based model clearly outperforms the baseline methods.

5 PARKING SCHEDULING

In this section, we define the parking scheduling problem, and then propose its solution. We propose an algorithm to calculate the maximum contract parking space utilization.

Definition of Parking Scheduling Problem

Scheduling problems can generally be understood as the allocation relationship between machines and jobs. Multiple jobs are assigned to multiple machines according to a certain algorithm. Most of these problems are NP-hard problems[14]. In our system, we recommend available contract parking spaces in several nearby parking lots to drivers who are searching for parking spaces.

The optimization goal of our scheduling algorithm is to maximize the total utilization time of parking spaces. We suppose that there are time periods for m parking requests, n parking spaces and satisfy $n < m$. We define the i-th available parking space idle time period as: $P_i = [a_i, b_i), i = 1...n$. a_i indicates the time point when the i-th parking space starts to be idle. b_i represents the point when the i-th free parking space is occupied by its owner. We define the time period of the parking request issued by the j-th user as: $R_j = [s_j, f_j), j = 1...m$. s_j represents the time point when the j-th parking request starts. f_j represents the time point when the j-th parking request ends.

In our parking scheduling problem, we adopt a hierarchical interval scheduling method to reduce complexity. We assume that at most l of the n idle time periods are coincident, and divide the n idle time periods into l subsets $S_h (h = 1, ..., l)$. So that the time periods in each subset are mutually exclusive. We S_h is called the h-th layer.

Optimal Solution

Dynamic programming is a method to solve complex problems by decomposing the original problem into relatively simple sub-problems.

After the layering process, we improve the dynamic programming algorithm based on the following modeling ideas. We assuming that there are x layers that meet the demand for parking end time f_n, and then f_n is placed in one of the x layers Layer, or no layer, that is, there are $x + 1$ cases for the demand f_n. Assuming we know the best in the remaining idle time period of the remaining $f_0 - f_{n-1}$ requirements Allocation, the optimal allocation method for the optimal allocation in the remaining idle time period of $f_0 - f_n$ needs will be the allocation method with the longest idle time in $x + 1$ cases. Through the bottom-up iteration method, the optimal result of the model is obtained. The details of the algorithm are shown in Algorithm 1.

Algorithm 1: Optimal Layer Scheduling(OLS)

Input: i,$Parkings\{P_i\}_{i=1}^{n}$, $Requests\{R_j\}_{j=1}^{m}$,$R'$,$Totaltime$
Output: R'
if $i == m$ **then**
  if $Totaltime \geq besttime$ **then**
    $besttime = Totaltime$;
    return R';
else
  // not put R_i in;
  $OLS(i + 1, P, R, R', Totaltime)$;
  // try put R_i in;
  for $t = 1 : len(P)$ **do**
    // put R_i in;
    if $match(P_t, R_i)$ **then**
      $P_{n+1} = park(R_i.end, P_t.end)$;
      $P = P \cup P_{n+1}$;
      $P_t.end = R_i.start$;
      $R' = R' \cup R_i$;
      $OLS(i + 1, P, R, R', Totaltime + R_i.time)$;
      $P_t.end = P_{n+1}.end$;
      remove P_{n+1} from P ;
      remove R_i from R' ;
      break if;

6 SYSTEM EVALUATION

In this section, we evaluate the contract parking sharing system design on real-world parking datasets involved with 368 parking lots and 14,704 parking spaces in Wuhan, China.

Compared Algorithms

We compare three scheduling algorithms.

- First-Come-First-Served Algorithm (FCFS): Parking requests are served according to their generation time. The first parking request has the highest priority. This is a common scheduling algorithm.
- Longest-First-Served Algorithm (LFS): Parking requests are served based on the length of parking duration. The longest parking request will be scheduled firstly.
- SParking: The dynamic programming algorithm calculates all possible dispatch schemes for parking requests and selects the scheme with the largest parking space utilization. DP achieves the optimal dispatch solution, but it is time-consuming.

Evaluation Metrics

Our *SParking* is evaluated based on three different real world constraints. (i) **Parking Duration** to show that how long the contract parking spaces can be used. (ii) **Utilization of Parking Duration** to show the occupancy rate of parking time. We define the utilization of parking duration as $\frac{T_o}{T_{av}}$, where T_o is the parking duration scheduled by three algorithms and T_av is the total available parking duration. (iii) **Operation Time** to show that how long it takes from the user's parking request to the completion of the recommendation.

We obtain the distribution features of vehicle entry and exit based on the real-world parking lot entry and exit records. In experiments, we generate a large number of parking requests which meet the distribution rule. Each experiment is repeated one thousand times. Our system tends to give results within half a minute, in other words, parking requests within half a minute will be scheduled together. This time will vary in a small range with the peak parking period.

Experiment Results

Parking duration of different algorithms. We take a community with 10 parking spaces as an example, and plotted the parking duration. As shown in Fig. 7, the community provides 3914 minutes for parking in a day. SParking gets the longest parking time of 2221 minutes. The performance of FCFS and LFS is slightly worse. Our system increases the utilization of contract parking spaces by more than 50 %.

Fig. 8 shows the utilization of three different scheduling algorithms. It can be seen that our algorithm is better than FCFS and LFS.

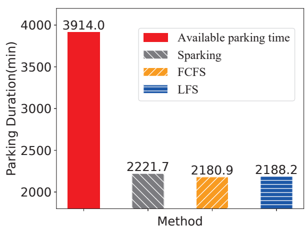


Figure 7: Parking duration

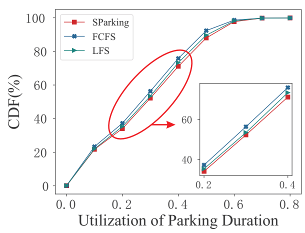


Figure 8: Utilization

Operation time of different algorithms. Fig. 9 shows the operation time of three algorithms at different parking request numbers.

We observe that as the parking request number increases, the operation time for FCFS and LFS are negligible compared to the running time for SParking. This is because that our parking scheduling problem is NP-hard, and SParking uses dynamic programming to obtain the solution, which leads to a longer running time. However, the number of parking requests in a short time and a small range is not large, so the complexity of SParking is acceptable.

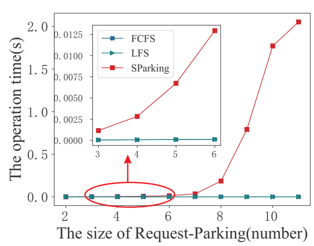


Figure 9: Time comparison

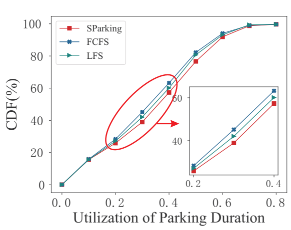


Figure 10: w/ 80% participants

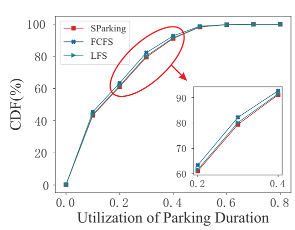


Figure 11: w/ conservative strategy

Impact of available parking spaces. One of the most typical and important factors that affects system performance is the number of available parking spaces. We have obtained the results with all available parking spaces data. But in practice, not all contract parking space owners are always willing to share their parking spaces.

We consider that only 80% of contract spaces owners are willing to participate in the contract parking sharing project. Fig. 10 shows that as the number of parking spaces decreases, the maximum utilization rate of parking spaces rises instead. This is because as the number of parking spaces decreases, the number of possible allocation schemes decreases. However, the total parking duration decreases.

Impact of fluctuation of parking time. Another key impact factor is fluctuation of parking time. In our system, the estimated parking time is entered into our app by drivers. Therefore, there are cases that the actual parking time of drivers exceeds the time they input. Besides, the available duration of contracted parking spaces comes from the prediction of our model, and we also need to consider the prediction error. Through the analysis of parking data, we find that most of the parking time fluctuations are within 5%. Thus, we add more conservative time strategy to real-time scheduling. As shown in Fig. 11, the utilization rate of three algorithms is reduced. But the performance of SParking is still better than FCFS and LFS.

7 DISCUSSIONS

In this section, we first summarize a few insights and lessons learned from field studies. Then we discuss some limitations, privacy issues, and potential implications of this work.

Insights and Lessons Learned

Parking lot management rules: The management rules of parking lots in different cities may be different. Some parking lots are strictly managed and do not allow outside vehicles to enter; some are looser and have no other restrictions or allow vehicles to enter after registering. For the first category, our system is really powerless. But for the second category, our system is still valid and also provides an electronic registration method.

Traffic behavior: It is obvious that the traffic behaviors have different features. However, in practical operation of our system, the traffic behavior finally reflects to drivers' behavior, which can be extracted from datasets. Thus, traffic behavior won't affect the performance of our system in different cities.

Limitations

Implementation in Other Cities: We evaluate our contract parking sharing system based real-world datasets from Wuhan city. However, special local conditions may lead to different parking behaviors, in different cities. Therefore, we must re-extract features from bus operation and transaction datasets to make the prediction model suitable for a new city. So it is extremely significant to implement contract parking sharing in different cities.

Privacy

Anonymization: All data analyzed are anonymized by service providers. All identifiable IDs, such as user IDs, parking space IDs and license plate numbers are replaced by a serial identifier and are not involved during the analysis in this project.

Aggregation: Our contract parking sharing model analyzes the aggregated results and does not focus on individual parking provider or specific user. Hence, the learned model is mainly based on information collected from mass population, and is less likely to reveal sensitive information of specific individuals.

Potential Implications

Reduction idle time Our system aims to minimize the idle time of parking spaces, that is, to maximize the utilization efficiency of each parking space and explore the optimal solution to the problem of parking difficulty. Our contract parking system provides a promising way to reduce idle time of parking places and alleviate the pain of searching parking spaces in big cities.

8 RELATED WORK

Smart city is a hot topic in recent years. It's difficult to achieve large-scale spatio-temporal sensing coverage with low-cost in deployment and maintenance[11, 27–29]. Chen et al.[12] presents a vehicular crowd sensing system to efficiently motivate vehicle agents to match the sensing distribution of the sampled data to the desired target distribution with a limited budget. Parking problem has been investigated by considerable studies because of its importance to people's daily life. We summarize existing works in Table 1 with a two-dimension taxonomy: (i) the data relates to a single parking lot or multiple parking lots; (ii) the system provides coarse-grained or fine-grained estimation. For instance, a system that simply presents collected information to users is defined as a coarse-grained system, while a fine-grained system need to dig more information from the data.

Table 1: Parking demand utilization rate of parking space under different participation rate

Categories	Single parking lot	Multiple parking lots
Coarse-grained	[18][26][6]	[16][25]
Fine-grained	[13][19][9][22][17]	SParking (This work)

Coarse-grained researches on single parking lot: The purpose of these researches is to design an efficient parking space reservation system. This can increase the speed of individual drivers finding parking spaces. However, as far as the whole society is concerned, the number of parking spaces has not increased, and the difficulty of parking still exists.

Fine-grained researches on single parking lot: Aiming at the problem of user's lack of information, there are a lot of researches using IoT devices to detect the available information of parking spaces, and provide these real-time data to users. However, Smart parking systems using dedicated sensors may suffer from the cost issues in installation and maintenance.

Coarse-grained researches on multiple parking lots: Some smart parking systems recommend destinations for drivers. They design scheduling algorithms to alleviate the parking pressure of the same parking lot.

Most of the existing works are related to public parking lots. Few of them consider taking advantage of the contract parking spaces, which are basically idle. Therefore, in this paper, we design a shared contract parking space system, which uses contract parking spaces to solve the problem pertaining to parking.

9 CONCLUSION

In this paper, we design *SParking*, a data-driven contract parking space sharing system. Based on the real-world contract parking space dataset of Wuhan City, we propose a parking time prediction algorithm and a scheduling algorithm. In our *SParking*, we first provide date-driven behavior analysis of the contract parking spaces. And then we provide an accurate prediction model to predict the available parking time of the contract parking space, fully considering the effects of holidays and weather. Finally, a optimal algorithm is proposed to solve the parking space scheduling problem and we proved its performance.

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