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COORDINATION OF HOSPITAL PARKING AND TRANSPORTATION SERVICES: A SIMULATION-BASED APPROACH

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ABSTRACT

Motivated by hospital parking problems that limit the access of patients and visitors, we study a hospital parking setting comprising an on-site parking lot with an occupancy-based dynamic tariff and a free shuttle service from an off-site free parking lot. We developed a discrete event simulation model to study the system's dynamics and find the preferable coordinated tariff and shuttle schedule that maximize revenue for the contractor operating the hospital's parking services under a predefined service level. We use a case study from Hadassah Medical Center in Ein Kerem, Jerusalem, to demonstrate the effectiveness of our method. Our results show that the coordinated solution provides significantly better performance: more than a 30% increase in service level, a 25% (about $5,000) increase in daily revenue, and a 53% decrease in average waiting time for a shuttle.

1 INTRODUCTION

Hospitals in urban areas experience severe parking problems (McGrath 2015; Yan-ling et al. 2016; Chen et al. 2018; Ji et al. 2023), which cause patient access delays, stress and unsatisfactory service/medical experiences. In Shanghai, China's Huashan Hospital, for example, the average waiting time to park during peak hours is more than twenty minutes (Ji et al. 2023). In an Australian metropolitan hospital, the cost of parking was identified as a significant expense faced by adult patients undergoing treatment for blood cancer (McGrath 2002; McGrath 2015). Costly parking at public hospitals increases public criticism since it may prevent low-income patients from receiving the medical care they need and low-income visitors from visiting their loved ones at the hospital. Motivated by this troubling issue, we seek to find a solution that will allow *all* visitors/patients access to the hospital parking.

One challenge in addressing hospital parking issues is the imbalance between demand and supply. Hospital parking demand is variable. It is much higher during the day when outpatient services are being delivered and patients receive their visitors; at night, however, the demand is much lower. The fixed number of parking spaces (supply) creates a demand–supply imbalance – long waiting times and insufficient parking spaces during the day and many vacant parking spaces at night. Unlike other time-varying service systems in which staffing levels can be adjusted throughout the day, parking capacity is fixed. We, therefore, seek another way to align operations with the demand time-variability.

Accordingly, and in order to ensure maximum access rate, we consider a hospital parking setting with an on-site for-pay parking lot (usually near the administration/main building) and an off-site parking lot that provides a shuttle service to and from the hospital. Arriving patients and visitors have the option of either parking in the expensive on-site lot or in the free-of-charge off-site lot and waiting for a shuttle to take them to the hospital. The decision of where to park is influenced by the parking rate, with a higher charge leading to a greater likelihood of visitors choosing the second option.

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Within this setting, we study two operational levers: (1) an occupancy-based dynamic pricing mechanism at the on-site parking lot, and (2) a dynamic demand-based shuttle service between the off-site parking lot and the hospital. To minimize the total cost within a desired service level, these two levers need to be fully coordinated. During high demand hours, for example, occupancy levels and thus parking rates in the on-site parking lot will rise; this might prevent those who cannot afford it from using the lot and feeling ”forced” to use the off-site lot. To avoid negative parking experiences, shuttle service during these hours should be frequent, thereby assuring a high service level to those who opt to use the off-site lot.

The system's operator needs to establish a shuttle schedule that will maximize revenue (the total income from the on-site lot minus the shuttle service cost) while meeting the service level constraint. To do so, the on-site lot needs to be fully utilized to ensure a minimum number of shuttles. Since the decision of which parking lot to choose is fee dependent, and the fee is occupancy dependent, balancing the number of customers between the two lots and setting the shuttle service schedule is a highly challenging task.

Due to the model's complexity and dynamics, analytical results are hard to attain. In this context, the fallback alternative is discrete event simulation, the main tool for performance evaluation and optimization of such systems (Glynn and Asmussen 2007).

Using a discrete event simulation model and data from Hadassah Medical Center in Ein Kerem, Jerusalem, we constructed a shuttle timetable that ensures a service level of above 98% without additional costs. Our findings suggest that this model can help hospitals improve their patients' and visitors' accessibility and service experience without harming their profitability. In Section 4 we compare our results to the current situation with a fixed parking rate and uniform shuttle distribution throughout the day, and show that our solution can increase revenue by 25% while providing better service to incoming patients and visitors.

Although our main motivation in this study is to ease patients' and visitors' access to the hospital, our suggested method can easily be modified to fit other systems such as amusement parks and airports. Better coordination between parking lots and shuttle services has the potential to reduce costs and increase customers' satisfaction.

The remainder of the paper is organized as follows. We complete this section with a brief literature review. In Section 2, we present our model and characterize the parking and shuttle systems. Section 3 includes our two-step approach for coordinating the parking and shuttle systems and building the schedule. In Section 4, we offer our case study simulation analysis and results. Lastly, Section 5 presents our concluding results and a few promising future research directions.

1.1 Brief Literature Review

Hospital parking problems are a well known issue. Liang et al. (2013) analyzed some of those problems, providing insight on what needs to be done to make hospital parking more accessible. Our study aims to tackle some of those problems and find a worthy solution to the general problem of hospital parking. Similar to us, Van der Heijden et al. (2000) examined the use of shuttle services and off-site parking for employees who work inside cities with scarce parking resources. While their study focused on setting the shuttle frequency so that the employees would choose to use the shuttles, we attempt to coordinate dynamic occupancy-dependent parking rates in addition to the shuttle schedule in order to maximize revenue.

Another article that looked at using shuttle services in a discrete event simulation is that by Zulkepli et al. (2018). Their study showed that it is possible to schedule a shuttle system for a university given data on course times and potential passengers. The system they proposed keeps the current wait time for the shuttles the same, while lowering the number of shuttles to a minimum. Our goal is to lower the number of shuttles in coordination with a dynamic tariff at the on-site parking lot, and while meeting a specified service level.

Numerous studies have focused on drivers' parking decisions. Gillen (1978) developed and tested a model that characterizes the parking location decisions of individual drivers. The research examined the different factors that affect their decision such as the parking rates and location.

To increase revenue from the on-site lot, we use a dynamic pricing model for parking, as used in Poh et al. (2023), which developed deep reinforcement learning-based dynamic pricing. They sought a dynamic pricing system that would work to counter the growing demand for parking spots due to an increase in population. Their model found that dynamic pricing is highly efficient at both peak and low hours. This finding is crucial to our study, given that in systems such as hospitals, peak and low hours happen on a regular basis.

Many studies such as McGrath (2015) and Ali (2021) attempted to find ways to resolve the lack of hospital parking spaces or the high cost of such parking. The field of occupancy-based parking rates was also studied in Qian and Rajagopal (2013) who formulated the parking choices under user equilibrium conditions using the variational inequality approach. In the study by McGrath (2015), the researchers compared the dynamics between the occupancy and pricing of two parking lots rather than one farther away from the driver's destination offering free shuttles, as ours does. In the former system, a 'preferred lot', which was closer to the desired location, was used as in our system. Their study was extended by Qian and Rajagopal (2015) where, again, optimal dynamic pricing based on the parking lots' occupancy was studied.

Our model works to combine the above studies and tackle the two issues of hospital parking and shuttle timing. Furthermore, our model's goal is to maintain a low operating cost and accrue high revenue, allowing any organization – from hospitals to airports – to overcome their parking problems and use a shuttle-based solution.

2 THE MODEL

We consider a hospital parking setting with N customer classes. (Visitors and patients arriving for outpatient services are termed customers.) The number of visitors for each patient in each ward/department is distributed in a discrete triangle distribution in terms of their cars.

Each customer class is characterized by a non-stationary Poisson arrival process with rate $\lambda_i(t)$, $t \geq 0$, $i = 1, \ldots, N$, which captures the time variability throughout the day. The different classes represent different types of outpatients and visitors. The latter is determined by the distribution of the number of hospitalized patients in each ward. The parking time for each customer class is distributed exponentially at a rate of μ_i, $i = 1, \ldots, N$.

The hospital parking setting, illustrated in Figure 1, includes an on-site parking lot and a shuttle service from an off-site parking lot.

Upon arrival at the on-site parking lot, customers see the current hourly parking fee. These customers may then choose whether to park there or drive off and park in a free-of-charge off-site parking lot and wait for a shuttle to bring them to the hospital. Our model generates each customer's decision that takes into account the current parking fee, which is set by a dynamic occupancy-dependent pricing model. In Section 2.1 we elaborate on the decision model and parking fee mechanism.

A shuttle service is offered for those who park in the off-site parking lot. The timetable of the shuttle service is determined by our simulation model, which aims to generate the fewest number of shuttles possible while meeting a set customer satisfaction level, thereby achieving minimum operational costs. Customers parking in the off-site lot have to wait in a shuttle queue to get to the hospital. In Section 2.2 we characterize the shuttle service and service level requirement.

The system's operator needs to set the dynamic parking rate and shuttle schedule that will maximize revenue while satisfying the service level constraint. The system's revenue includes the total income from the on-site lot minus the cost of the shuttle service, which depends on the number of shuttles that leave the off-site lot every day.

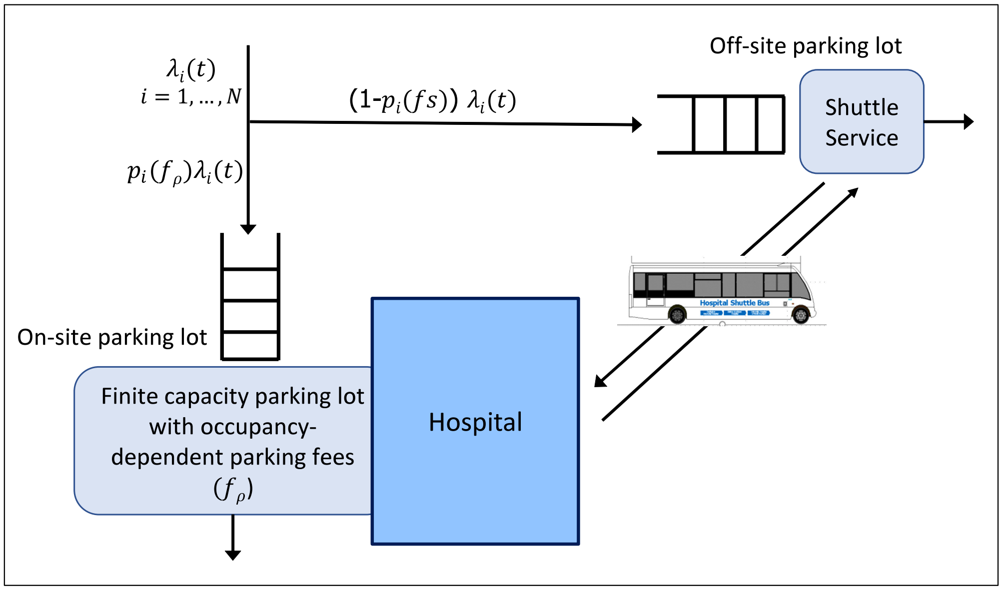

Figure 1: The hospital parking setting.

2.1 Parking System

The decision whether to park in the on-site parking lot depends on the current parking rate, which as noted above is occupancy dependent. Let f_ρ denote the parking fee for occupancy level ρ. The parking fee changes dynamically throughout the day, according to predefined occupancy thresholds. Consider K rate change thresholds: A_k, $k = 1, \ldots, K$. The parking fee f_ρ is set according to the corresponding tariff at $\rho \in [A_k, A_{k+1})$. The current occupancy of the lot as well as the thresholds A_k, $k = 1, \ldots, K$ are in percentages, removing the model's lot size dependency. Instead of parking in the on-site lot, a customer may decide to park in the off-site lot and use a shuttle service. With the help of fee sensitivity calculations and assumptions, for each on-site parking fee f_ρ we set the probability $p_i(f_\rho)$ of a Class i customer opting for the off-site lot. Obviously, the probability grows in line with the increase in the parking fee.

We use simulation in an attempt to fill the parking lot – this will allow us to minimize the number of required shuttles.

2.2 Shuttle System

A customer who decides not to park in the on-site parking lot drives to the off-site lot, which we assume has ample capacity. There, the customer waits in a first-in-first-out queue for the next shuttle to the hospital. We define the service level as the percentage of customers who had to wait more than a predetermined amount of time, T for the shuttle.

The shuttle service operates according to a fixed shuttle timetable. In Section 3 we explain how the fixed shuttle timetable was constructed using a discrete event simulation model and data from Hadassah Medical Center, Ein Kerem. The fixed timetable is then used on a regular daily basis while meeting the required service rate.

3 THE TWO-STEP METHOD FOR GENERATING THE SHUTTLE TIMETABLE

We use a discrete event simulation model to set a fixed timetable of shuttles to be used on a regular daily basis, while maintaining a given service level. The desired service level is determined ahead of time in order for the simulation to be able to output a timetable. The timetable aims to generate the least amount of shuttles, thereby achieving minimum operational costs, given the service level constraints.

Our suggested method includes two simulation-based steps. The first generates an initial shuttle schedule according to predefined rules for a shuttle departure; the second step adjusts the first-step's schedule to assure that the desired service level is achieved.

3.1 Generating an Initial Shuttle Schedule

To find the fixed timetable we run the simulation for J days, while paying special attention to cars parking at the off-site lot. Every passenger (some cars may have only one occupant but others may have more than one) waits in line for the next available shuttle. A shuttle leaves T minutes after the previous shuttle or when enough waiting customers can fill up a whole shuttle. A shuttle will not leave if there are no customers waiting in line. The shuttle departure times are recorded for each simulation run.

Next, we divide each day into 24 intervals/hours; the index of each interval is i, $i = 1,\dots,24$. Each day in the simulation is indexed by j, $j = 1,\dots,J$. Let N_i^j denote the number of shuttles that left the off-site lot during the i interval of day j. The average number of shuttles for each interval i is, therefore,

$$\bar{N}_i = \frac{1}{J}\sum_{i=1}^{J} N_i^j, \quad i = 1,\dots,24.$$

As expected, the average number of night shuttles was very low whereas during peak hours it was much higher. For each daytime interval i, $i = 1,\dots,24$, we set the number of shuttles leaving the off-site lot to be the average number of shuttles rounded up $\lceil \bar{N}_i \rceil$. We then uniformly distribute the shuttle departure times within each interval. Specifically, the fixed timetable for interval i is

$$\left\{ \frac{k}{\lceil \bar{N}_i \rceil} \right\}, \quad k = 0,\dots,\lceil \bar{N}_i \rceil - 1, \quad i = 1,\dots,24.$$

3.2 Adjusting the Initial Shuttle Schedule

With the fixed timetable generated as output from the first step, we commence another simulation run of J days – this time, with shuttles leaving only at the times dictated by the initial timetable. As before, the wait times of each customer at the off-site parking are recorded as a measure of the service level. We observed that customers' waiting times did not meet the desired service level of up to $X\%$ of customers waiting less than T minutes.

To meet the desired standard, we add additional shuttle runs to the timetable, which later on are added to the final timetable. The idea is to add a minimal amount of extra shuttles to keep the costs of operation at their lowest. At this stage, the simulation is run again, this time while scheduling the shuttles using the timetable from the first round of simulations, with an additional rule that if a shuttle departs and there are more than Z customers waiting in line, an additional (unscheduled) shuttle is called to pick up these customers and promptly leaves.

After examining the times of the average number of extra shuttles per day $\bar{N}_s$, a decision can be made regarding how many extra shuttles should be added to the timetable. Using the extra shuttle times, it is possible to identify the ideal times to schedule these additional shuttles. In Section 4 we demonstrate how to implement the two-step method. Running the simulation a third time, this time using the new timetable, will give insight into the updated service pace and allow the user to decide if enough extra shuttles have been added. We note that the second step of the method is not always required. It is possible, and even likely, to achieve a satisfactory service level after just the first step. Obviously, this scenario depends on the required service level.

4 CASE STUDY: HADASSAH MEDICAL CENTER AT EIN KEREM

We demonstrate our method and its effectiveness using a case study from the Hadassah Medical Center at Ein Karem, which is a university hospital in Jerusalem. The facility has 1,200 inpatient beds and is considered one of the most advanced hospitals in Israel.

Patients and visitors have the option of parking their vehicles either in the on-site lot or in the off-site lot and then taking a shuttle to the main building. Visitors have access to 200 parking spots in the on-site lot (the remainder are reserved for hospital staff). The off-site parking has almost unlimited capacity and here we consider it to be of infinite capacity. The hospital runs a shuttle service from the off-site parking to the main hospital building with a maximum seating capacity of 20 seats.

The arrival rate of customers who seek to park is time-varying where during peak hours (10am to 5pm) the average arrival rate is over 210 customers per hour. These rates depend on the number of hospitalized patients and their visitor distribution.

The current hospital parking setting includes an on-site lot with a fixed one-time fee of US $15 (balking probability for this price is 0.6), and a free off-site lot. The free-of-charge shuttle service departs every 10 minutes between 6:30am and 11pm on weekdays. That adds up to 100 shuttles per day. Customers who arrive between 11pm and 6:30am park in the on-site lot because there are no shuttles during these hours. The cost of the shuttle service (based on hospital data) is about $28K per month (each shuttle costs $14). After running our simulation using the current operation data, we compare it with our suggested two-step method.

4.1 The Parking System

To maintain a reasonable number of parking rates, we used five-interval tariffs, as presented in Table 1. Using our simulation model, we systematically examined different permutations of parking rates, f_ρ^k, $k = 1,\dots,K$. We considered only integer-increasing sequences – those in which parking rates increase with occupancy. We noticed that very high or very low parking rates result in low total payments. These outcomes make sense: When the low rates are low, the lot will be constantly full with few transactions being made; when the parking rates are high, however, the lot occupancy will be very low, as most customers prefer to park at the off-site lot. We saw that when markedly increasing the arrival rate, the total payments do increase. The simulation results teach us that there exists a set f_ρ^k, $k = 1,\dots,K$, at which the average daily total payment reaches its maximum, giving us the optimal range of parking rates for the on-site dynamic pricing model.

Table 1 shows the resulting occupancy-based parking rates as well as the probability of the driver to balk (i.e., drive off to the off-site lot). These parking rates ensure both high revenues and high occupancy rates. When the parking rate drops and becomes attractive, visitors will enter and park. When the parking rate increase (i.e., the lot is busy), it encourages customers to park outside and take the shuttle instead. This method provides control over the occupancy of the parking lot and "diverts" a minimum number of visitors to the shuttles.

The income distribution column in Table 1 shows that most of the income is received when the occupancy rate is $70-80\%$. That is, during peak hours when the parking rate is still reasonable enough that most customers are willing to pay it.

Table 1: The resulting on-site occupancy-based parking rate.

Occupancy rate (%)	Parking rate ($)	Balking probability	Income distribution (%)
0–40	7	0.01	10.8
40–70	10	0.1	21.2
70–80	14	0.3	51.6
80–90	17	0.7	16.4
90–100	20	0.9	0

Figure 2 presents the number of parked cars in the on-site lot (left) and the number of balking cars (right) throughout the day. The top plots describe the results of the two-step method, while the bottom plots describe the current situation, as we simulated it. In general, the lot occupancy is higher under our solution with fewer variations throughout the day. During peak hours the occupancy is around 80% according to our solution and around 60% in the current situation. During off-hours, the occupancy is around 30% according to our solution and around 10% in the current situation. With balking, it is the other way around. There is more balking in the current situation, in general, and especially during peak hours when many visitors decide to park in the off-site lot, which can be explained by the fact that the on-site lot's occupancy-dependent pricing has made it too expensive for them. These results show that our method manages to keep the on-site lot at high occupancy while reducing the balking – this, in turn will reduce the number of shuttles required from the off-site lot.

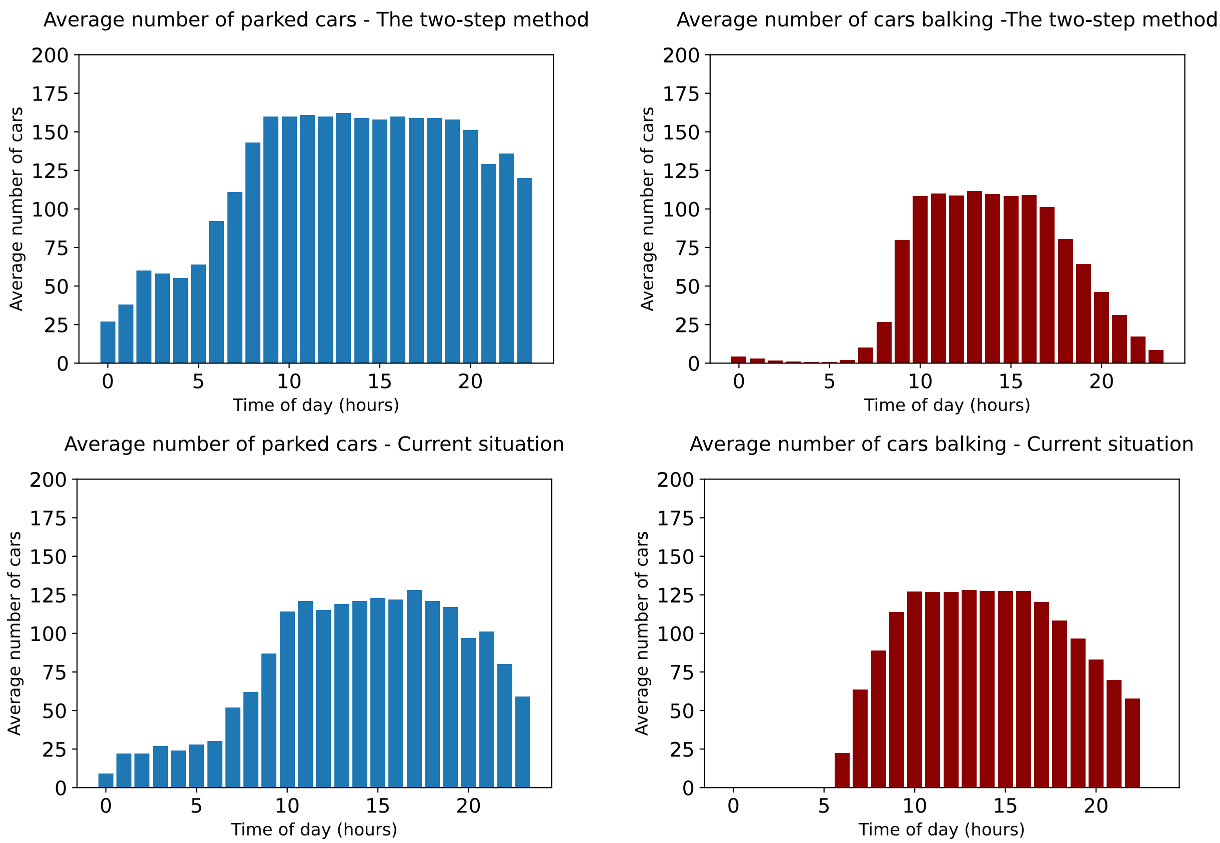

Figure 2: Average number of parked/balked cars per hour – Current situation vs. suggested one.

4.2 The Shuttle System

Using the two-step method described in Section 3, we generated a timetable for the shuttles that guarantees a service level above 98%. That is, 98% of customers arriving at the off-site lot wait less than 30 minutes for a shuttle.

We additionally assume that visitors would prefer to drop off their passengers at the building entrance and save them the wait for the shuttle, thus also reducing the load on the shuttles.

4.2.1 First Step – Generating an Initial Shuttle Schedule

When customers decide to balk and drive-off to the off-site lot, they join the shuttle queue. In the method's first simulation step, a shuttle leaves 30 minutes after the previous shuttle, assuming a visitor is waiting for it or when enough waiting customers can fill up an entire shuttle (20). Shuttles do not leave if there are no customers waiting in line.

To generate the shuttle schedule, meet the required service level, and not drop below it, we round up the average number of shuttles in each interval. The output number of shuttles is distributed uniformly within each hour. An example of a shuttle timetable appears in Table 2.

Table 2: An example of the shuttle timetable after the first step.

Time interval	Number of shuttles	Schedule
7:00-8:00	1	7:00
8:00-9:00	2	8:00, 8:30
9:00-10:00	5	9:00, 9:12, 9:24, 9:36, 9:48
10:00-11:00	6	10:00, 10:10, 10:20, 10:30, 10:40, 10:50

The required daily number of shuttles after the first step is 83, and the resulting service level is 95.3% – lower than desired 98% (Table 3 summarizes the output measurements of the method's first step). We, therefore, continue to the second step. If, however, the desired service level is achieved after the first step, there is no need to continue to the next one.

4.2.2 Second Step – Adjusting the Initial Shuttle Schedule.

In the second step, we rerun the simulation using the new shuttle timetable to raise the service level to 98%. This time, if ten or more customers are still waiting in line after the departure of a predetermined shuttle, another shuttle would be called to take the waiting passengers.

At the end of this step, the average number of extra shuttles per day (4 in this case) are added to the four most common hours (peak hours) in the timetable that required extra shuttles; see Figure 3, which presents the number of shuttles after the first and second steps. Note that the additional shuttles were added in peak hours to assure service level requirements. . With this new timetable, in another simulation run, we made sure the service level was met. Reducing the number of extra shuttles by one from the new timetable led to a lower service level than desired. In other words, we now have a minimal number of shuttles for the shuttle system that could meet the set service level.

Figure 4 presents the waiting time histogram according to the two-step method and the current operation. In addition to the average waiting time that is reduced from 20 to 9.25 minutes; the variation in waiting times is much smaller under the suggested method (the standard deviation was reduced in half from 15 to 7.2, and the range was reduced by 21.8%). Indeed, about 75% of customers wait less than 10 minutes for a shuttle in our solution. Moreover, while about 25% of the customers currently wait more than 30 minutes, almost no customers wait that much in our solution.

Table 3 compares the system's performance when using our two-step method and the current situation (as we simulated it). Our method significantly improves the current operation. It provides a much higher service level, higher utilization of the on-site parking lot, and higher daily revenue.

5 CONCLUSIONS AND FUTURE DIRECTIONS

In this paper we study a hospital parking setting having an on-site lot and a shuttle service from an off-site free parking lot. To maximize revenue under a predefined service level, we use two levers: an occupancy-based tariff for the on-site lot and a dynamic scheduling for the shuttles. The two levers need to be coordinated to assure high occupancy of the on-site parking lot. To this end, we developed a discrete event

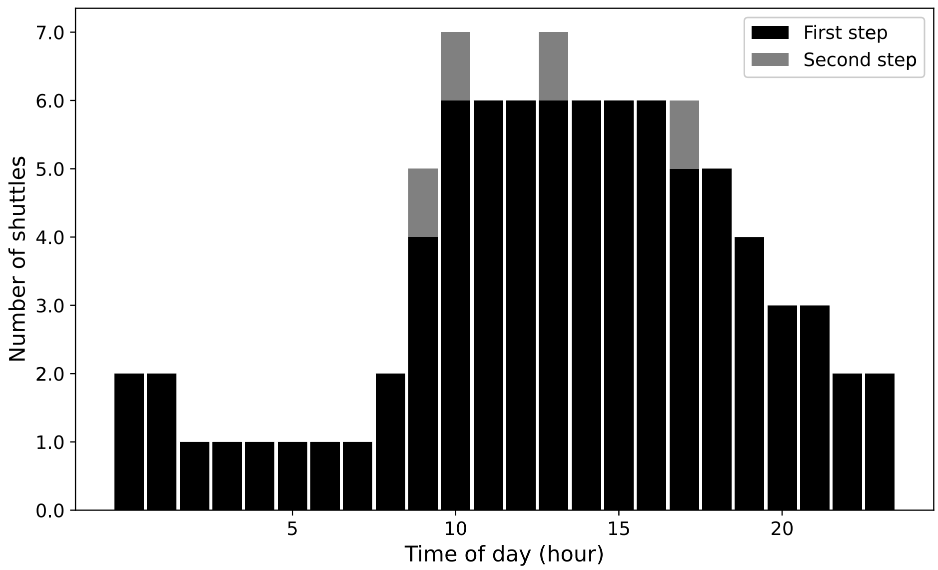

Figure 3: Number of shuttles per hour after the first and second steps.

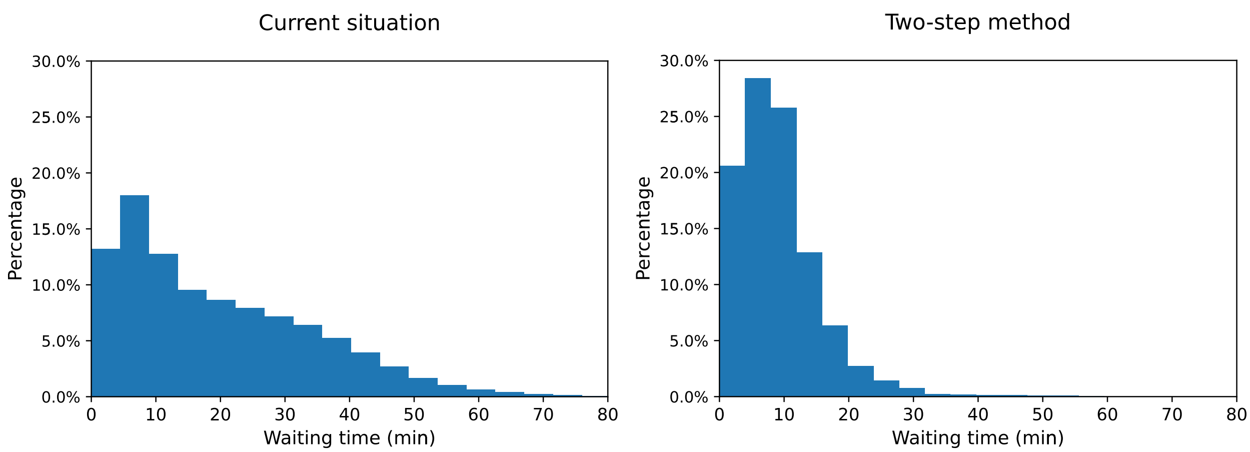

Figure 4: Waiting time comparison – Current situation vs. suggested one.

simulation model that accounts for different customer classes, dynamic occupancy-dependent parking rates, and price-dependent customer choice. Based on this model, we suggest a two-step method for generating a shuttle timetable that will maximize the system's revenue while satisfying the service level constraint. To demonstrate the method's effectiveness we use a case study from the Hadassah Medical Center at Ein Karem. The simulation results show that our method achieves superior results and performance than the current situation. Indeed, with the right balance, we managed to increase the daily revenue as well as the service level – with fewer shuttles each day and higher occupancy of the on-site lot.

We identify three directions for future research. The first includes the attempt to rigorously establish the optimal coordinated solution under simplifying assumptions regarding customers' decision process and the occupation-based on-site parking rate. Second, it would be interesting to include more real-life complications into the model and examine their effect on the system' dynamics and performance. These complications include adding additional customer balking and abandonment, considering day-of-the-week patterns and constructing a corresponding shuttle schedule for each day, etc. Third, our simulation results suggest that incorporating customers' strategic behavior in such a queueing setting with on-site and off-site

Table 3: Comparison between the current situation and the suggested one.

Measurement	Current situation	1st Step	2nd Step	Improvement (%)
Service level (% of customers who waited less than 30 minutes)	75.3	95.3	99	23.7 (31%)
Average number of passengers per shuttle	17.2	15	14.2	-3 (-17.4%)
Average waiting time for a shuttle (minutes)	20	11.5	9.25	-10.75 (-53.8%)
Standard deviation of waiting time for a shuttle (minutes)	15	5.4	7.2	-7.8 (52%)
Number of shuttles per day	100	83	87	-13 (-13%)
Daily shuttles' cost ($)	1,400	1,162	1,218	-182 (-13%)
Average number of parked cars (On-Site)	83	128	128	45 (35%)
Average daily number of cars (On-Site)	1,283	1,970	1,970	688 (54%)
Average daily revenue ($)	19,242	24,037	24,037	4,795 (25%)

parking lots is a promising future direction. On the one hand, it is more convenient to park in the on-site parking lot without waiting for a shuttle service. On the other hand, when parking fees are high, it might be preferable to drive to the cheaper off-site parking lot and commute. Analyzing the equilibrium of such a system and optimizing customers' access rates can lead to a structural solution and further operational insights.

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