ONLINE OPERATION STRATEGIES FOR AUTOMATED MULTISTORY PARKING FACILITIES

Yineng Wang[a], Fang He[a], Xi Lin[b], Meng Li[b]

[a]*Department of Industrial Engineering, Tsinghua University, Beijing 100084, P.R. China*

[b]*Department of Civil Engineering, Tsinghua University, Beijing 100084, P.R. China*

January 4th, 2020

Keywords: urban parking; multistory parking facility; online operation; reinforcement learning

1. INTRODUCTION

Up to the first half of 2019, the average ratio of parking lot gap remains 76.3% in Beijing, Shanghai, Guangzhou and Shenzhen (He, 2017), which results in the problem of parking difficulty in megacities. Parking fee can relieve the parking problem to some extent, but it results in excessive monetary cost for car users.

The idea of automated multistory parking facilities is proposed. An automated multistory parking facility is a dedicated building for parking with multiple levels adopted for pick-and-place of vehicles such that ramps for the transport of vehicles and drivers are not necessary. However, due to the limited capacity on elevator and incomplete knowledge of coming needs, the service efficiency of the elevator system is restricted. At the time that the demands are intensive, drivers may experience long waiting time before successful parking or picking. The question is: how to acquire the optimal operation strategy in a stochastic and dynamic environment?

This paper develops an intact methodological framework for the online operation of automated multistory parking facilities. The overall framework is designed as a two-tier online model. The first tier, which we call it placement tier, utilizes a reinforcement learning approach to determine the parking spots of the vehicles to be placed. Once the parking spots are acquired, the second tier named execution tier will solve an integer programming model to obtain the action sequence of the elevator until the next iteration.

2. METHODOLOGY

2.1 Basic settings

We assume a multistory parking facility with L levels along with a starting level, i.e., level 0. At level 0, the driver leaves his/her vehicle, or pick up a vehicle. On level 1 to level L, there are C parking spots uniformly distributed on a circular parking space on each level. For the elevator, it has M plates reaching out from the center pole spreading evenly like a round pan. We divide the time horizon into some periods. In each period, the elevator unloads the retrieved vehicles. The objective of the online operation is to minimize the customers' loss.

2.2 The placement tier

The placement tier determines where to store the vehicles on the elevator in each operational period. This study proposes a reinforcement learning approach. RL method's goal is to find the optimal policy π^*, indicating the best action a to take given a specific state $s \in S$. In this problem, the facility state s is composed of three parts, $s = (l, m, e)$. $a \in A_s$ decides the distributed parking spot for each vehicle on the elevator.

The value function of state-action pair $q^\pi(s, a)$ is the expected return after taking action a at state s under π (Sutton, R.S., Barto, A.G., 1998).

$$q^{\pi}(s,a) = E_{\pi}[\sum_{k=0}^{\infty} \gamma_k R_{t+k+1} | S_t = s, A_t = a] \quad (1)$$

The approximation of $q^{\pi}(s,a)$, Q value is defined by Eq.(5) as the average of all returns that have been generated from experience passing state s. α is the step size of learning.

$$Q^{\pi}(s,a) \leftarrow Q^{\pi}(s,a) + \alpha[G_t - Q^{\pi}(s,a)], \qquad S_t = s, A_t = a \quad (2)$$

We apply a $\epsilon - greedy$ method at each time step.

2.3 The execution tier

Upon the determination of parking levels for the vehicles on the plates, the execution tier accomplishes the order given by the placement tier by optimizing the action sequence of the elevator.

Consider a directed graph $J_{t\mu} = (N_{t\mu}, A_{t\mu})$ at period t for the μth action sequence planning of elevator, where $N_{t\mu}$ and $A_{t\mu}$ represents the node set and the arc set respectively. Five features are labelled to each node $d_{t\mu}^{k}$ in D_{tu} to describe the request about to accomplish, $d_{t\mu}^{k} = (h_{t\mu}^{k}, l_{t\mu}^{k}, c_{t\mu}^{k}, s_{t\mu}^{k}, p_{t\mu}^{k})$.

The arc set $A_{t\mu}$ are made up of the transition arcs between nodes. Each arc $a_{t\mu}^{i,j}$ in $A_{t\mu}$ refers to the specific arc from node i to node j.
In this formulation x_{ij} and z_{ij} are two kinds of decision variables. x_{ij} are binary variables that indicate whether arc $a_{t\mu}^{\mathrm{i,j}}$ is admitted to the action sequence of elevator or not. And z_{ij} is its integral order in the action sequence once it enters.

3 Results

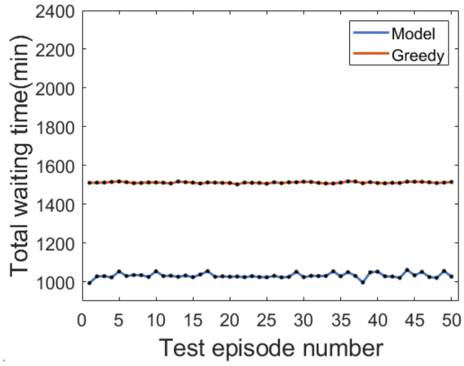
The test horizons of all experiments are 12 hours from 6 am to 6 pm. The multistory parking facility is with 8 floors for storage, and on each floor there are 6 parking lots; the elevator owns 2 plates. For a quick look, we take *Experiment 3* as an example.

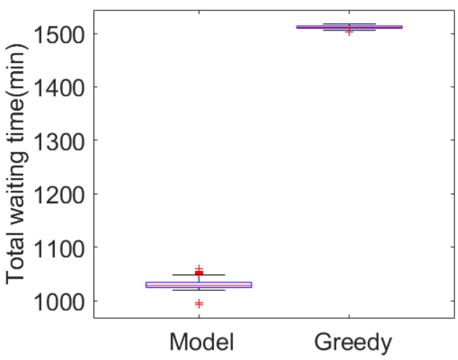
3.1 Experiment design

This experiment is established to model a mixed parking of commute and temporary visits; some park for work and others park for eating, shopping, etc.

3.2 Experiment results

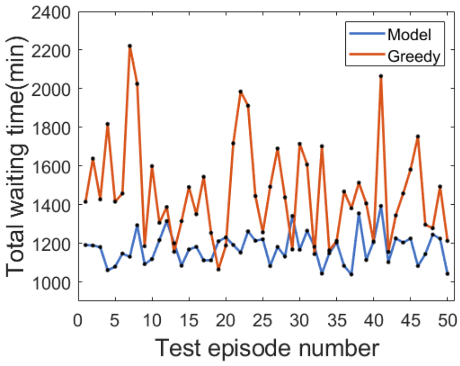
In this experiment, we still have two sub-experiments (1) and (2). In both sub-experiments for that commute visits are less flexible than temporary visits. In the plot and box plot of 50-episode-test, the model reduces the total waiting time of customers by 31.76% in SE-3(1). And in SE-3(2), the model has reached an unstable optimized result though there is an average of 20.05% improvement in saving customers' total waiting time as in Fig.1 .

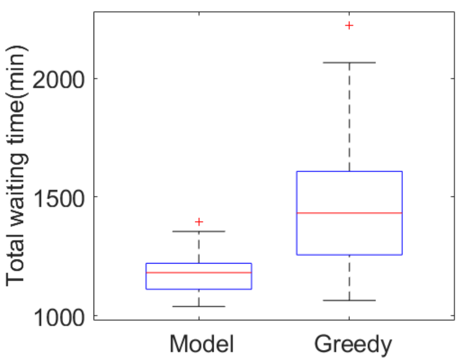




(a) 50 episodes plot in SE-3.(1)

(b) 50 episodes box plot in SE-3.(1)





(c) 50 episodes plot in SE-3.(2)

(d) 50 episodes box plot in SE-3.(2)

Fig.1 A test of 50 episodes under pattern 3

We again look into the facility state over the day with larger perturbation in SE-3(2), as is shown in Fig.2. Under the original pattern of *Experiment 3*, the 15^{th} vehicle and the 16th vehicle divide the first time part and the second time part, and the 51st vehicle and the 52nd vehicle divide the second time part and the third.

In Fig.2, after the 16th vehicle's arrival, vehicles who parks for commuting purpose arrives continuously and are distributed to higher levels. Until the first vehicle for temporary purpose arrives, the commuting vehicles has occupied all of the parking spots on the top four levels except one parking spot. This proposed operation can be interpreted intuitively in that the model tries to minimize the utilization of the elevator, and therefore reducing the total waiting time of customers. For commuting vehicles with long parking time, parking at higher levels reduces the elevator's extra movement to upper spots which is time-consuming. Once the higher levels are occupied, the temporary vehicles are distributed to parking spots as if parking in a sub-parking facility with less levels.

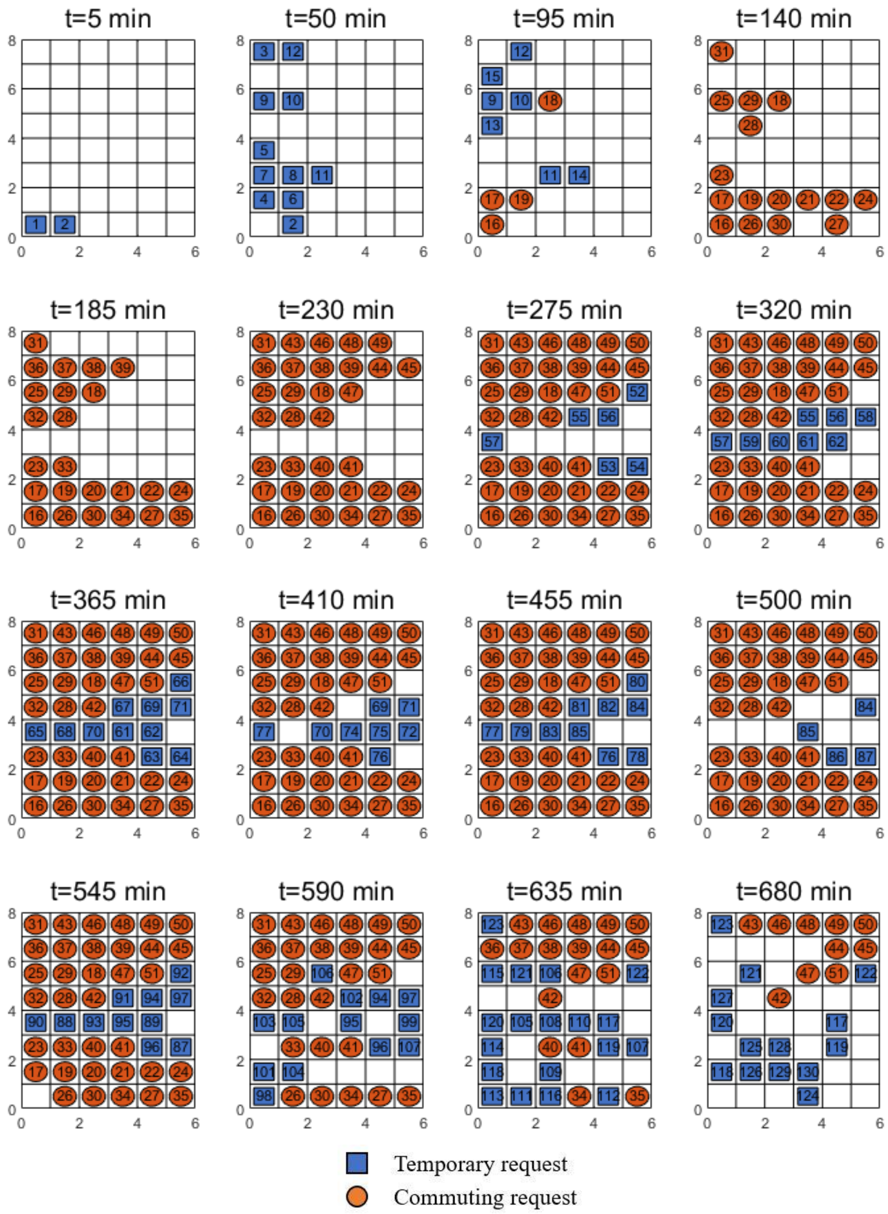


Fig.2 Facility state over time in Experiment 3

5 CONCLUSION

In this paper, we propose an online operation optimization model of two tiers for automated parking facilities under stochastic parking demands. The placement tier distributes the incoming parking vehicles to levels according to the current parking facility state, following the instructions of RL training results, and the execution tier delivers the vehicles in pre-determined sequence solved by network model with the purpose of reducing period length. Numerical examples based on synthetic traffic data of three possible patterns have demonstrated that our model can make use of previous knowledge of request sequences and propose proper operation strategy over the day obviously reducing the customers’ total waiting time. Future research should include a more detailed discussion on the rationality of the basic settings of parking facility.

REFERENCES

He D., 2017. Smart Parking makes city better. People’s Daily, 2017-09-28, <http://theory.people.com.cn/n1/2017/0928/c4053129564103.html.> (accessed 10.06.2019).

Sutton, R.S., Barto, A.G., 1998. Reinforcement Learning: An Introduction. MIT Press, Cambridge, MA.