Travelling Officer Problem: Managing Car Parking Violations Efficiently Using Sensor Data

Wei Shao, Flora D. Salim, Tao Gu, Ngoc-Thanh Dinh and Jeffrey Chan

***Abstract*—The on-street parking system is an indispensable part of civil projects, which provides travellers and shoppers with parking spaces. With the recent in-ground sensors deployed throughout the city, there is a significant problem on how to use the sensor data to manage parking violations and issue infringement notices in a short time-window efficiently. In this paper, we use a large real-world dataset with on-street parking sensor data from the local city council, and establish a formulation of the Travelling Officer Problem with a general probability-based model. We propose two solutions using a spatio-temporal probability model for parking officers to maximize the number of infringing cars caught with limited time cost. Using real-world parking sensor data and Google Maps road network information, the experimental results show that our proposed algorithms outperform the existing patrolling routes.**

***Index Terms*—Parking Sensor Data, Parking Violation Management, Smart Cities, Intelligent Transportation Systems (ITSs)**

I. Introduction

With cities growing rapidly in population and traffic volume, traditional parking management techniques face many challenges such as inefficient resource management, high human capital needs, and data noise. The Internet of Things (IoT) provides the capacity to deal with such challenges, as the IoT can be designed to capture sensor data for monitoring areas of interest in smart cities. Recently, researchers have explored the potential usage of the IoT in public transportation services and urban computing [1]. An increasing number of cities try to use an IoT-based framework in local transportation system management. Most existing works focus on finding car parking spaces for drivers; several models have been proposed to provide drivers with real-time information about available car parking bays nearby [2]. Only a few studies have been done to help the government manage on-street parking more effectively and efficiently. Over the last few years, the Melbourne Transportation Council installed thousands of in-ground sensors in car parking bays located in the Melbourne City Centre (CBD) [3]. These sensors can detect car parking events by recording the arrival time and the departure time of a car. The parking system can check whether a car has overstayed the maximum permitted period within parking rules. These sensors will send a signal to the central station within 5 minutes while a car is in violation. Parking officers will be dispatched to specific locations to stick parking infringement notices on cars in violation.

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Due to the lack of parking officers, in many instances, drivers are able to escape infringement notices. Therefore, catching violators in time is a critical issue for the local transportation council, not only for the potential financial benefits, but also for ensuring public compliance of local laws, and reducing repeat offences.

The current patrolling methodology works on a "first-come first-serve" (FCFS) basis. The parking officers will go to the next parking space with the earliest violation time. The existing system works well in a small area with fewer violations, though it is inefficient in busy areas. This is because the existing system does not consider the temporal and spatial information of violations, as well as the probability of a car leaving after a violation, but before officers have arrived.

In this paper, we formulate car parking fine collection as a Travelling Officer Problem (TOP), which aims to find an optimized path to maximize the probability of catching cars in violation, with limited time cost. We take into account the walking speed and behaviour of an officer, and also use spatio-temporal and historical information (probability of violation period). Based on this model, we propose two solutions using observed spatio-temporal information. The first solution is a greedy algorithm that employs probability estimation, and the second solution is a path-finding algorithm based on Ant Colony Optimization (ACO) [4]. The results show that the ACO-based algorithm performs more stably than both the existing approach, and the greedy algorithm. Both algorithms utilize Google Maps road network information, and an observed distribution of parking violations. We also build a system to simulate the real case, and conduct extensive experiments using real-world parking data provided by the Melbourne City Council [5]. The experiment results show that both algorithms perform much better than the current approach.

Figure 1 illustrates a simple example of our problem and results from different algorithms. There are four car parking slots in violation around the CBD area from P1 to P4. The patrolling officer needs to go through four parking slots to give infringement notices to each car in violation. The information centre sends the events sequentially as "P1, P2, P3, P4". The first diagram of Figure 1 shows the officer's path under the current methodology, denoted by the blue line. The complete trajectory is 1km long as measured by Google Maps. Using the greedy algorithm with a car-leaving probability estimation, the patrolling officer tends to look for car parking plots with the highest probability of the car not leaving. The Green line (around 928 m) denotes the walking path determined by the greedy algorithm, shown in the second diagram of Figure 1.

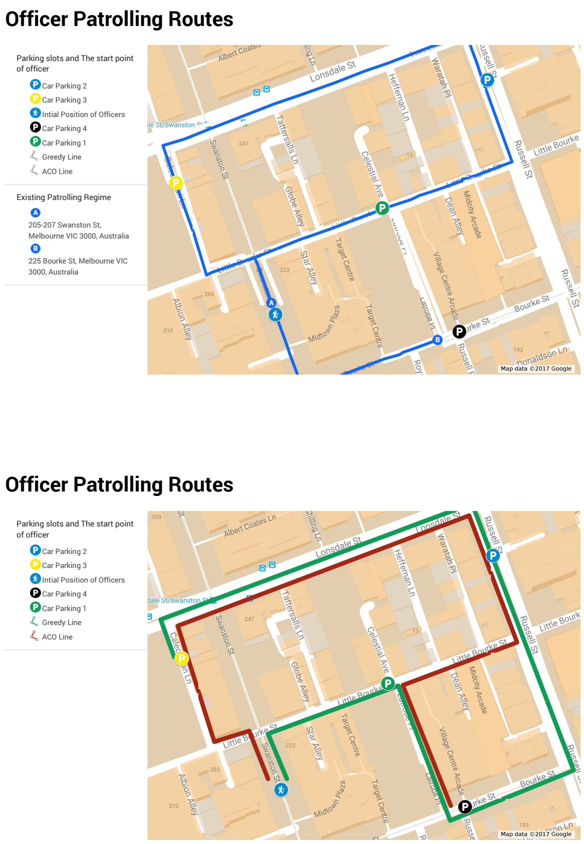

Fig. 1. Officer patrolling routes through three different algorithm. The officer patrols from the initial position to each parking slot by three lines. The Blue line: Existing patrolling regime, The Green line: Greedy algorithm, Red Line: ACO algorithm.

The ACO-based algorithm (red line) leads to the shortest path, with a 750m length. It takes advantage of leaving probability estimation and tricky integrates with the concept of pheromone in ACO algorithm. The example shows that proposed methods perform better than existing regime.

In summary, this paper makes the following contributions:

- This paper defines a new problem called the Travelling Officer Problem; a touring problem faced by officers who need to monitor parking spaces within a given time constraint.
- We propose two algorithms by taking advantage of spatio-temporal information, as well as probability estimation, to issue infringement notices more efficiently by maximizing the number of violators caught within a limited travelling cost.
- We build a system to evaluate our model, and both algorithms. We conduct extensive experiments using a large public dataset provided by the local city council, which has been published online. The results show both algorithms outperform the baseline.

The paper is organized as follows: Section II discusses related work; Section III presents an overview of on-street car parking in the city; Section IV formally defines TOP; Section V gives the details of the two algorithms we propose; Section VI presents the experiments and comparison studies; and Section VIII concludes the paper.

II. Related Work

Orienteering problems such as Travelling salesman problem [6], [7] and its variants [8] are popular in the optimization area. TOP is a problem are based on both TSP and Travelling thief problem(TTP) [9]. Travelling thief problem is an optimization problem which combines two classic problems: one is the TSP, the other is the multiple knapsack problem [10]. It gives more constraints to TSP, which makes it more applicable in real world. This general model is also useful for introducing different types of interdependencies in a more strategic way rather than simply putting different problems together to generate new benchmarks.

Spatio-temporal based problem also become popular recently. Using temporal feature as the constraint of optimization problem is a new trend in transportation area [11], [12]. Spatio-temporal data is one type data with spatial and temporal features which usually generated from sensors and ubiquitous devices. It is different from tradition methodology which is used to solve spatial information based orienteering problems. It can be more complex when the time constraint is dynamic. Dynamic time features need more elaborate methods [13].

III. Overview of On-street Parking in City

A. Background and Motivation

The Melbourne Transportation Council set up in-ground sensor systems around CBD areas. For each car parking area, the sensor can detect parking space availability, and check its violation state with parking rules. The sensors report parking events to information centre periodically, and the system would send the message to the patrolling parking officer who supervises this area when the nearby parking cars are in violation state. Then the patrolling parking officer will go to check the cars in violation, and dispatched to issue an infringement notice.

B. Parking Sensor Data

The parking events data recently has been published online, which attracts researchers to study and analyse [5]. The parking events data were recorded from October 1, 2011, to September 30, 2012 (12 months). A total number of 12,208,178 records were logged. Each record comprises the information of a parking event including area name, street name, street segment and some other parking information. It also provides the spatial information such as the latitude and longitude of the parking spaces. The entire CBD is divided into 23 areas by the city council, and each area is monitored by one officer.

Figure 2 reveals the distribution of parking violations within one month. More violations happened in the darker colour areas for that month. The sensors on those streets recorded over 500 parking violations within a month while other street segments (e.g. the street segment on Flinders Street from

Fig. 2. The monthly parking violation map

Williams Street to King Street) recorded much less parking violations. Figure 3 shows the distribution of cars in violation is unbalanced. Most violation events are located in some specific positions.

The local transportation council arranges parking officers to take responsibility for each region separately. As shown in Figure 3. We denote parking spaces in each region with different colours.

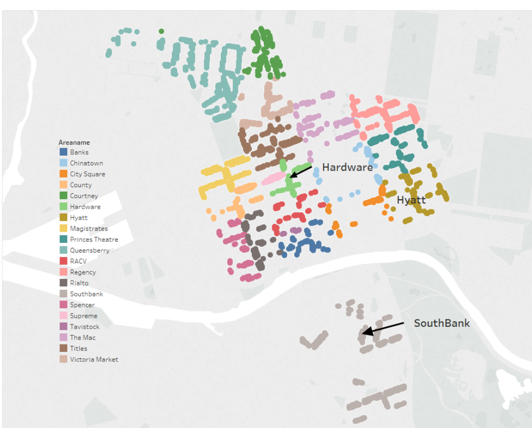

Fig. 3. The parking regions in the CBD area

In real scenario, officers have to patrol along the road and it is impossible to get across the block. Therefore, road network information must be taken into account as well.

C. Distribution of Violation Period

Figure 4 shows the numbers of cars with the length of time in violation. The horizontal axis denotes the length of time from the beginning of the violation to the car leaving time, and the vertical axis means the total violation numbers within a month. The figure 4 reveals that there is no car in violation beyond 100 minutes, and the violation period is mainly between 5 to 60 minutes. This is the key observation that we take account spatio-temporal information in our optimization approach. We take advantage of such observation and build a probabilistic model that can estimate the likelihood of a car in violation leaving which allows us to optimise the strategy that officers use to catch cars in violation.

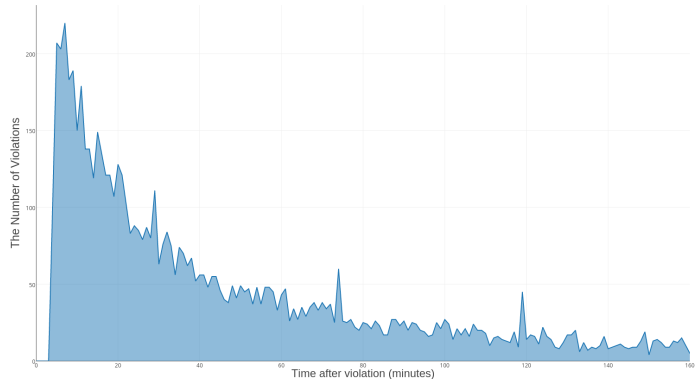

Fig. 4. The numbers of violation with total violation time

IV. Travelling Officer Problem

We describe the Travelling Officer Problem as follows. We have a set of parking spaces in a region, and there are M parking officers. We present each parking space by a node. Parking nodes with cars can be divided into two classes– in violation or in the legal state. Each parking officer takes responsibility for one area. Each officer starts at a random fix point in the area and collect fines from parking nodes in violation state. In this paper, we assume they collect fines with a reasonable walking speed during working hours. They can also take bicycles or other vehicles. The violation state of cars in the graph can be changed with the time. Our objective is to find a path that maximizes infringing cars caught on this route with limited travelling cost. The cost metric is defined in terms of working hours or distance.

A. Prime Model Formulation

We define the map of car parking bays as a weighted completed directed graph $G = (V, E)$, where V is the set of n nodes (vertices) and E is the set of edges. Let $C = (c_{ij})$ be the cost matrix associated with E. The cost in the travelling problem can be the travelling time. Another matrix associated with V is $B(v_i) = B(f_{v_i}(t_i))$, which defines the amount of cars in violation collected from node i at time t.

The state of car park bays can be defined as a binary variable in Eq. 1:

$$v_i = \begin{cases} 1 \text{ the node i is in violation state} \\ 0 \text{ otherwise} \end{cases} \tag{1}$$

The state of v_i varies with time, which is defined as $f_{v_i}(t)$. The solution of the problem, defined as a set of edges $S = \{x_{ij}\}$, where x_{ij} is a binary variable as follows.

$$x_{ij} = \begin{cases} 1 \text{ the path goes from node i to node j} \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

Besides, there exists a subset of V, denoted as V^s. V^s is a set of nodes located on path S. We assume there are m nodes in V^s.

We formulate our model using an assignment based linear programming model. We aim to seek for the best solution S with constraints. The general model is given as follows.

$$Max \quad \sum_{i=1}^{m} B(v_i) \quad = B(f_{v_i}(t_i))$$

$$s.t. \tag{3}$$

$$\sum_{x_{ij} \in S} C(x_{ij}) \leq T \tag{4}$$

$$x_{ij} \in S \tag{5}$$

$$t_i = \sum_{j=1}^{i+1} C(e_{j,j+1}) \tag{6}$$

where T is the maximum travel cost for the solution. In this case, it is the maximum working hours of parking officers in a day, t_i represents the time that an officer arrives at node i, and $B(v_i)$ represents how many infringement notices officers managed to issue on node i.

B. Dynamic Temporal Probability Model

As mentioned previously in Section III, there is a distribution of violation period associated with each area. We denote it as $P_{area}(t)$. Here, we have

$$t = t_{dep} - t_{vio} \tag{7}$$

where t_{dep} denotes the time when a car leaves the parking bay, and t_{vio} denotes the beginning time of the cars in violation.

The car leaving event is a spatio-temporal based event, and it is dynamic and uncertain. Therefore, the model should be a time-based probabilistic model. We generalize the Eq. 7 as following:

$$\begin{aligned} P_{area}(t) &= P(t_{dep} - t_{vio}) \\ &\approx P(F(t_{vio}, \lambda)) \end{aligned} \tag{8}$$

where $(t_{dep} - t_{vio}) \sim F(t_{vio}, \lambda)$. The $F(t_{vio}, \lambda)$ is an exponential distribution as we observed in Figure 4. In Eq. 3, $f_{v_i}(t_i)$ varies with the $P_{area}(t)$. When $t = t_i$, P_{area} is the probability that car in violation is still stay in the parking slot at time t_i.

The probability of violation period in each area is essential to our model. We can estimate the violation period of each parking bay with such model. For example, once a signal sent from a parking bay, our model estimates the probability of car leaving before the officer gets there. If the probability is high (i.e., close to 100%), the officer may choose to go other nodes marked in violation because the car may have left when the officer reach there.

The dynamic temporal probability model is likely to be applied to other cities because the probability density distribution model matches the our assumption: The probability that drivers in violation leave the parking slot is exponentially decreased with time elapse. Most drivers know they are likely to be captured if they stay in violation for longer time. They would like to leave within a short time. Only minority of drivers will stay in violation for a long time.

C. Challenges

1) Model of the Computational Complexity: Given a graph G, an upper bound m, and a possible solution in the form of a cascade path, it is possible to verify or reject that solution with n additions and a single numerical comparison. This can be accomplished in polynomial time. Because a potential solution can be verified or rejected in polynomial time, the Travelling Officer Problem is an NP-problem [14].

As we prove that the fine collection problem is an NP-problem, it is extremely difficult to use a polynomial computational complexity algorithm to solve it. Therefore, intelligent search strategies are needed to solve this problem [15].

2) Unexpected States: The state of each node varies with time. In real world, these changes may be unknown to officers, and difficult to predict. Additionally, the patten is slightly different for each area.

V. Path Finding Algorithm

In this section, we present the existing patrolling regime which is currently in operation by the city council. We propose two solutions — the greedy based algorithm with dynamic temporal probability model, and an ant colony optimization based framework.

A. Existing Patrolling Regime

Our work is supported by the City Council and we have a couple of discussions on the existing patrolling approach. The existing approach employs a sequential notification of violations, as described by the domain expert and we thereby use it as the baseline method. The existing patrolling regime is simple and straightforward. When parking violation is detected, sensor signals will be sent to the central system, and an in-charge officer will be dispatched [16].

Algorithm 1 captures the regime of existing patrolling method. It works as follows: Once there is a violation occurs, the system will push the event to the in-charge officer's mission queue. The officer always processes the tail event in the queue. Once an event has been processed, it will be removed from the queue. The officer can have a break or rest when the queue is empty.

For the existing approach, we have the following definitions. Q is a queue to store the violation events by time.

Q has some functions associated with it:

- $updateQ(v_i)$: Insert or remove one or more v_i at the tail of the queue.
- $dequeue(v_i)$: Remove the node from the head of the queue and return the node.
- $QisEmpty()$: Check whether Q is empty or not.

This framework is formally described in Algorithm 1.

To explain further, adding a NULL to S means that if there are no cars in violation for time t, the officers will wait until next event.

B. Greedy Algorithm with Probability Estimation

The existing patrolling regime is inefficient. In this section, we apply a greedy based algorithm with proposed probability

Algorithm 1 The Existing Patrolling Regime

Input: a given graph $G = (V, E)$
  a solution $S \leftarrow$ NULL
  a queue Q
  a set Ω of constraints among the variables
Output: a solution S

```
while Cost(S) < T do
    if Q is Empty then
        add a NULL to S
    else
        add dequeue(v_i) to S
    end if
    updateQ()
end while
```

model. The greedy algorithm follows the heuristic of making the locally optimal choice at each stage [17], with the hope that it will end up with a globally optimal answer. The greedy algorithm is one of the best solutions to solving NP-hard problem [18]. The general idea is simple. The patrolling officer chooses the parking space with the highest probability to collect fines as the next destination to go.

To make the question more precise, we extract some operations below.

calProbability (V) Calculate the probability for each potential node $v_i \in V$. The probability of V_i guides parking officers to the next node because it suggests whether the car in violation can be caught or not. Here we use the Eq. 8 to estimate the probability.

updateV$(C(S))$ Update the potential nodes which connects to the current one. V consists of potential points. S is the existing solution needs to be updated. For each iteration, the state of each node in graph should be updated with the latest information from the control center. All information are collected by in-ground sensors.

The complete algorithm is described in Algorithm 2.

Algorithm 2 The Greedy Algorithm with Probability Estimation

Input: a given graph $G = (V, E)$
  a solution $S = \emptyset$
  a set of potential next nodes V
  a set Ω of constraints among the variables
Output: a solution S

```
while Cost(S) < T do
    if V is Empty then
        add a NULL to S
    else
        calProbability (V)
        add v_i with highest probability to S
    end if
    updateV()
end while
```

C. Ant Colony Optimization with Probability Estimation

1) Background and Motivation: Ant colony optimization (ACO) is a highly compatible, probabilistic swarm intelligence methods which is usually used to address meta-heuristic optimizations [19], [20]. ACO can employ heuristic knowledge to find an optimal solution in the search space.

We choose ACO to solve the parking fine collection problem for the following reasons.

- ACO is a swarm intelligence searching algorithm which is mainly used to address NP-hard graph optimization problems such as TSP [21].
- The probability model of the problem matches the meta-heuristic in the ACO framework.
- ACO performs good in the global optimization which is suitable for our purpose—to collect as much fines as possible.
- ACO is a widely accepted optimization algorithm to solve the TSP. TOP is a variant of TSP. [22]

2) ACO-based Algorithm: There are two key factors of ACO algorithm: pheromone and heuristic knowledge, and we define them as τ and η, respectively.

The complete algorithm works as follows. At each iteration, n_a ants construct a solution in the current search space based on previous knowledge (probability model) and a given pheromone model. Then, before the next iteration starts, the pheromone is updated. Finally, we find the best solution and give the next node on this path. Once the search space is changed (i.e., new violation occurs is eliminated, we restart the algorithm to find the new path. The algorithm is explained with more details as follows.

IniPheromoneModel() At the beginning of each step, the pheromone values are all initialized to a constant value $c > 0$.

MoveToNextNode() The ant walks to the next node depends on heuristic knowledge and pheromone distribution. The probability for the choice should be proportional to $[\tau(x_{ij})]^{\alpha} \bullet [\eta(x_{ij})]^{\beta}$, where η is a probability that a car leaves its parking bay. The values of parameters α and β determine the relative importance of pheromone, and the car leaving probability model. Therefore, in this case, the probabilities for choosing the next node (i.e., transition probabilities) [21] are defined as follows.

$$
\begin{aligned}
P(x_{ij}|s^p) &= \frac{[\tau(x_{ij})]^{\alpha} \cdot [\eta(x_{ij})^{\beta}]}{\sum_{x_{kl} \in E} [\tau(x_{kl})]^{\alpha} \cdot [\eta(x_{kl})^{\beta}]} \\
&= \frac{[\tau(x_{ij})]^{\alpha} \cdot [P(v_j)^{\beta}]}{\sum_{x_{kl} \in E, v_p \in V} [\tau(x_{kl})]^{\alpha} \cdot [P(v_p)^{\beta}]} \\
&= \frac{[\tau(x_{ij})]^{\alpha} \cdot [P_{v_j}(t_{dep} - t_{vio})^{\beta}]}{\sum_{x_{kl} \in E, v_p \in V} [\tau(x_{kl})]^{\alpha} \cdot [P_{v_p}(t_{dep} - t_{vio})^{\beta}]}
\end{aligned}
\tag{9}
$$

where $P_{v_p}(t_{dep} - t_{vio})$ is the probability model mentioned above and s^p is the constructed path in the map.

PheromoneUpdate() The aim of the pheromone value updating rule is to increase the pheromone values on solution components that have been found in high quality solutions [23]. In this case, we define it as follows.

$$\tau(x_{ij}) = (1-\rho)\cdot\tau(x_{ij}) + \frac{\sum\limits_{v_i \in S_p} B(v_i)}{\sum\limits_{v_i \in V} B(v_i)} \tag{10}$$

where $\rho \in (0, 1]$ is called evaporation rate [23]. It has the function of uniformly decreasing all the pheromone values. From a practical point of view, pheromone evaporation is needed to avoid a rapid convergence of the algorithm towards a local optimized region.

The completed algorithm is given in Algorithm 3

Algorithm 3 The ACO based Fine Collection Algorithm with Probability Estimation

Input: a given graph $G = (V, E)$
a best solution $S_{bs} = \emptyset$
IniPheromoneModel()
Probability model η
Output: The best solution so far S_{bs}

while $Cost(S) < \text{T}$ **do**
  while Iteration < nIteration **do**
    if V is Empty **then**
      add a NULL to S
    else
      for $i = 1; i < n; i++$ **do**
        calProbability (V_i)
        Constrctred Solution S^p
        if $B(S^p) < B(S_{bs})$ **then**
          $S_{bs} \leftarrow S^p$
        end if
      end for
    end if
    PheromoneUpdate()
  end while
  MoveToNextNode()
end while

VI. EVALUATION

We evaluate the greedy and ACO based approaches in this section. We use the parking sensor dataset provided by the local city council [5]. At the beginning, We present some rules and assumptions made in association with this dataset, which are summarized as follows.

- The violation sensor data only be sent to one officer. Other parking officers are not able to receive them.
- The officer does not know whether a car has left until they arrive at the spot.
- All officers start working from 7am to 7pm in a day.
- We assume a normal walking speed of 70 meters per minute.
- The system updates the parking space states in real-time. However, the algorithm calculate the solution only when the officer is available due to the limited computational resources.
- We select the nearest public transport stops or stations near to each political area as the starting point of officers every day.

TABLE I
ATTRIBUTE LIST FOR PARKING EVENTS

Attribute name	Description
Street Marker	The signs placed on the side of parking bays
Area Name	City area - used for administrative purposes
Arrive Time	Time that the sensor detected a vehicle over it
Departure Time	Time that the sensor detected a vehicle is leaving
In violation	Indicates that the Parking event exceeded the legally permissible
Sign	Parking sign in effect at the time of the parking event.

TABLE II
OTHER ATTRIBUTES USED IN EXPERIMENTS

Attribute name	Description
Location	The longitude and latitude of parking slot
Violation time	The violation time based on signs
Violation period	The length of time that car overstays

We conduct an experiment involving car parking violations on 23 areas for a complete week in first week of September 2011. These areas are defined by the local city council. Each parking officer takes responsibility for issuing parking tickets to cars in violation within his zone. We use the default setting of the ACO. The $\alpha = 1.0$, the $\beta = 2.0$ and the $\rho = 0.3$. Although the performance can be boosted with parameters tuning, we only conduct a couple of experiments to test our model because we aim to propose a general solution which can be applied to most cities.

A. System Implementation

We implemented and tested the system (including the TOP model) in C++. The route information is acquired through web service calls to Google Maps APIs. The code runs on a Quad-cores laptop running Windows operating system. We do not use any external code or libraries.

B. Dataset

1) Parking Dataset from the CBD: As mentioned in Section III, the dataset consists of all parking events in the CBD's on-street car parking bays over a year.

To apply our model to the dataset, we show a list of 6 attributes extracted from the dataset (as shown in Table I), and a list of attributes we defined from that dataset (as shown in Table II).

2) Google Maps: Distance is the most important attributes that we use to calculate the cost, and find the solution in our model. Since we conduct experiments in real scenarios, it is important to measure the distance between two points on the map. Therefore, we extract records that reflect accurate positions and driving distance (the distance calculated on street path) between car parking bays from Google Maps.

C. Evaluation Methodology

We propose two criteria to measure the solutions we propose. One is the fines that can be collected, and the other is the length of time that officers can have a rest between events. The main purpose of our solutions is to collect as many fines as possible. Hence, the benefits index is the most important criteria, and it is defined in Eq.11.

$$Benefit = \sum_{t=T_s}^{T_e} B(S) \tag{11}$$

where T_s is the start time of working in a day, T_e is the end of working hours.

The other important criteria is the rest or break time, it is defined in Eq.12.

$$Rest = \sum_{t=T_s}^{T_e} t(S = \emptyset) \tag{12}$$

$S = \emptyset$ means that there is no any violation during such time period. If an area has low violation density on that day, the higher performance algorithm is able to help officers to spend less time on patrolling but have more break or rest time. This is because algorithms with higher efficiency take less time on the useless path, and find the shortest path to reach car parking bays in violation.

D. Performance Results

We conduct two main experiments to evaluate our models and algorithms. In the first experiment, we evaluates the performance of weekly fine collection. The other one is to explore the relationship between the walking speed of parking officers and the performance of algorithm. Actually, the algorithm performs differently in different areas due to a large variety of distribution of car parking bays and violations. Therefore, we also conduct experiments on each area, and show results for some typical areas.

1) Comparison Studies: In this section, we compare three solutions with two proposed criteria for one week.

The left diagram of Figure 5 shows the overall weekly fine collection results. Compared to the benefits from a fine collection using the existing patrolling regime, both ACO and Greedy with probability estimation significantly improve the gains in benefit. The greedy algorithm and ACO performs similar in general. Compared with the greedy algorithm, ACO performs more stable in gaining benefits on the weekdays. The ACO-based algorithm performs better in the weekend. We analyse the difference between the parking data during the weekdays and weekends. We find that the distribution of violation in weekends is significant different from distribution in weekdays. The cars in violation on the weekdays usually are located in more specific time such as after lunch or after work. We plan to explore more temporal information in the future.

The right diagram of Figure 5 shows the average weekly break time for all areas. Both ACO and Greedy outperform the existing patrolling regime. However, the greedy algorithm performs better in terms of break or rest time. It is because the greedy algorithm focuses on local optimal. It prefer choose the closer parking nodes, which leads to less time consumption on the way. But for the ACO algorithm, the path computation takes account on both probability of car leaving the bay, and maximizing the points that can be collected. ACO covers more car parking bays than the greedy algorithm. However, it also spend more time on the travelling.

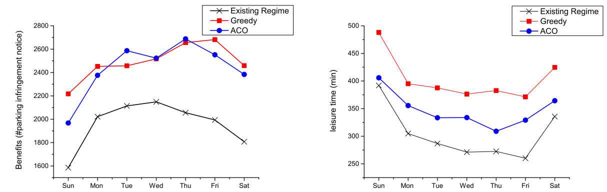

Fig. 5. Left figure is the weekly fine collections in the CBD through three algorithms. Right figure shows the weekly break/rest time in the CBD through three algorithms

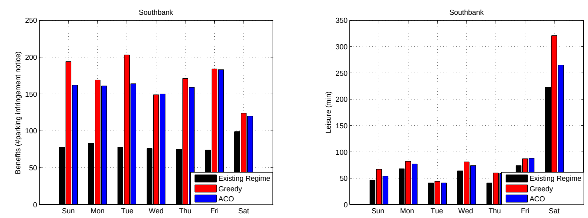

Fig. 6. The weekly benefits and break time in Southbank

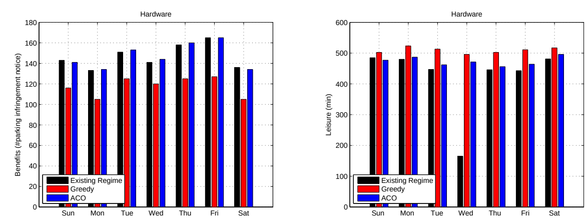

Fig. 7. The weekly benefits and break time in Hardware

2) Weekly Fine Collection in Main Areas: There are many areas in the CBD. We apply three algorithms to all areas, and compute the gains in benefit and break measurement. We observe that these three algorithms perform differently in different areas. We classify areas into three categories: greedy algorithm domain, ACO-domain, and areas that both of them having similar performance. In each class, we would present some representative areas to show the results of benefit and break time by applying three different algorithms. **greedy domain areas** Figure 6 illustrates the weekly benefits and break time in the region Southbank with a small number of violations. The graph shows that greedy algorithm with probability estimation performs better than both ACO and existing regime. The performance of ACO is slight lower than the greedy algorithm, and performs much better than the existing regime. Most of greedy domain areas show a similar trend. However, in term of break time, the greedy algorithm looks more promising. It has an enormous advantage in spending less time on navigating to car parking bays in violation. Such areas occupy around 30% of total areas.

ACO domain areas Figure 7 illustrates the weekly benefits and break time in Hardware. The graph shows that ACO algorithm outperforms others in these areas. The ratio of this class is about 20%.

Balanced areas Figure 8 illustrates the weekly benefits and

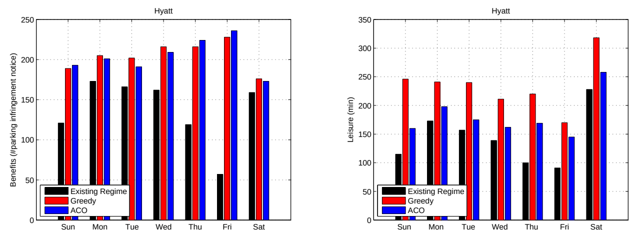

Fig. 8. The weekly benefits and break time in Hyatt area

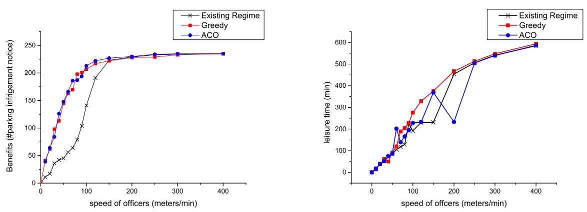

Fig. 9. Left figure shows the benefits in relation to the speed of parking officers, Right figure shows the relationship between break time and speed of parking officers

break time in region Hyatt. ACO and the greedy algorithm have similar performance in benefits for more than half of the areas. In terms of achieving longer break time, the greedy algorithm performs much better than the other two algorithms.

3) Comparison of Different Walking Speed: The walking speed of parking officers also influences the benefit and break time of our fine collection model. With an increasing speed of parking officers, they are able to cover more nodes during a shorter period. Lower speed suggests that heavier tasks, and raises more challenges to the algorithm because officers need to spend more time on the travelling route.

The left diagram of the Figure 9 shows the result of benefits gain with an increasing walking speed. Both ACO and the greedy algorithm perform much better than the existing regime at any speed. Within 100 meters/minutes, ACO performs better than the greedy algorithm.

The right diagram of the Figure 9 shows the result of longer break time with an increasing walking speed. The rest or break time is likely to be longer if parking officers move faster because officers spend less time on the route. The greedy based algorithm performs the best in this experiment. Both ACO and the existing algorithm have a similar trend with increasing walking speed. Interestingly, the break time of ACO and existing regime decrease between 150 m/min and 250 m/min. This would be explored in the future work.

In summary, both the greedy algorithm and ACO perform much better than the existing regime in increasing benefits and reducing time wasted navigating to destinations. They both perform better than the original algorithm, which suggests that our model and proposed solutions work well for the TOP.

E. Discussion

According to the experimental results, we draw two conclusions. Firstly, both of ACO-based algorithm and Greedy-based algorithm can be used in real application for improving fines collection. The ACO-based algorithm can be applied in the weekends and Greedy-based can be used in the weekdays. Secondly, if we take break time into account, greedy-based algorithm performs better. That is, greedy-based algorithm provides parking officers with lower workloads.

VII. Limitation and Future Work

In this section, we discuss some limitations of the current model and algorithm, along with our ongoing work and potential future directions.

Firstly, the existing parking management system deployed by the local city council which still depends on parking officers to issue infringement notices physically though thousands of in-ground sensor have been installed. It is recommended to design an automatic system to issue electronic infringements using these sensor data that pose more challenges to ensure data integrity. Also, the algorithm design in this paper is based on pre-defined areas that are set by the government. We believe that there is a better way to segment the CBD into new areas for more efficient parking management. We plan to apply clustering methods based on violations, and geographic areas. We also plan to design more efficient algorithms to solve the Travelling Officer Problem.

Secondly, the current design is based on the assumption that only one officer knows the violation occurs nearby. This assumption is a result of one of the limitations of the existing parking system deployed by the local city council, which is a lack of inter-communication between parking officers. In this case, although the proposed algorithms work the best for one officer, it may not achieve the best overall result. In the future, we plan to study multiple officers collaborating each other to solve this problem, aiming to hire fewer officers for saving tax payers money.

Finally, people may concern about the fairness issue in parking management system (i.e. if drivers with parking violation for a longer period should get more penalty). The current design of our algorithms does not distinguish between drivers with longer-period violation or shorter-period violation. Instead, the system offers drivers 5 minutes grace period (i.e., if they leave within 5 minutes, the system does not consider they are in violation). In the future, we may look into the fairness issue.

VIII. Conclusion

In this paper, we propose an accurate and efficient model for Travelling Officer Problem (TOP) and two innovative solutions, a greedy algorithm and an Ant colony optimization based algorithm, to allocate resources for managing parking areas and collecting fines. They both take advantage of heuristic knowledge to improve the efficiency of parking officers in performing patrolling tasks. To verify our model and solutions, we build a system that implements our model and solutions using a real-world parking sensor dataset from on-street parking bays provided by the local city council. We also propose two meaningful criteria to measure and evaluate the performance of the proposed TOP solutions. In the future, we plan to apply clustering methods based on violations and geographic areas, and design more efficient algorithms to solve the Multiple Travelling Officer Problem. Spatio-temporal clustering methods based on the knowledge can solve the region division problem.

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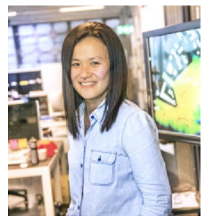

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