ABSTRACT Vehicle cruising for a destination-nearby parking lot has been a problem to drivers in cities. This problem causes drivers to consume unexpected time and resources to compete for a parking lot. Conventional parking schemes are in place to predict or reserve the parking spaces. Some of these schemes optimize the total cost only for locating parking spaces and road traffic condition is usually ignored. In this investigation, key road traffic conditions, such as vehicle queueing at the intersection of roads and parking fee information, are considered since they influence time and cost in the parking process. As such, a new comprehensive parking scheme is needed in place to assist drivers to identify the appropriate parking lot, estimate the transportation time to reach the parking lot, as well as the parking expenses. In essence, the total journey time and the total cost are important factors. However, former research lacked a harmonious consideration of these two factors. In this paper, a new parking model (PM) is developed for a holistic optimization of time and cost. The performance is measured by a newly defined indicator, referred to as a figure of merit, which is a fusion of time and cost. The analysis reveals that the incorporation of PM improves the performance by 24% ~ 43%.

INDEX TERMS Transportation, optimization, car parking, route planning.

I. INTRODUCTION Vehicle cruising for a parking lot in highly developed cities may jeopardize the traffic congestion in a transportation network. When the transportation network is not well-designed or optimized to effectively guide drivers, congestion problem will become worst. It is reported that traffic congestion is commonly found in the urban cities like USA. In the 2015 urban mobility scorecard, it was indicated that total cost due to congestion was about $160 billion along with 6.9 billion hours [1]. It implied that drivers were required to spend extra time and cost than they expected to reach their destination. A survey conducted by Shoup [2] showed that 30% of traffic congestion was caused by vehicles cruising for parking spaces. For some highly urbanized cities such as Hong Kong, a car park is regarded as a valuable asset since the parking lots are very limited and the parking charge is expensive. In such cities, when drivers found difficulty in finding a Destination Nearby Parking Lot (DNPL), the traffic condition is even more severely jeopardized. Therefore, the demand for a vehicle cruising prevention scheme to alleviate the traffic congestion problem is desperately needed. To achieve this goal, it is envisaged that an optimized parking scheme, that considers the holistic journey from the beginning of travel with the inclusion of the road-to-park conditions, should be developed. The road-to-park conditions should include the charging fees of parking lot and vehicle queueing at signalized intersection roads since the conditions will affect the choice of parking lot. Hence, a Parking Cruising Prevention (PCP) scheme, which incorporates a new Parking Model (PM), is developed to help drivers to seek a DNPL. A new indicator, referred as Figure of Merit (FOM), will be developed to evaluate and thus effectively indicate the parking effectiveness.

In 2015, SIEMENS revealed that a vehicle was required to travel 4.5 km until drivers finally found a parking space in Germany [3]. The literature further indicated that on average, 10 minutes were required to find a parking space and during the hunting process, the vehicle burnt 1.3 kg CO$_2$ into air. Numerous schemes have been proposed to simulate the
behavior of traffic conditions over space and time [4], [5]. Relationship between number of vehicle and time required to pass through an intersection road was extensively studied [6]. Intelligent transportation systems were integrated with traffic signal control to help drivers to reach their destination more promptly [7].

As shown in [1] and [3], the time element in traffic congestion or car parking seeking process was one of the key factors. Therefore, time element is considered in this paper. Driving time and walking distance were considered in the model proposed by Fu et al. [8] which was a two-stage model. With the aid of widely-adopted navigation platform, drivers may still find difficulties in identifying parking lots. Occasionally the Global Positioning System (GPS) cannot work properly in highly dense cities and finally drivers cannot reach the parking properly. There are multiple intersection roads that need to pass through while it consumes drivers extra time and this is the missing element in the estimation of arrival time in the current vehicle cruising prevention scheme. Therefore, a smart parking scheme is desperately desired to tackle the parking problem.

For cost estimation, it considers the elements which can be realized as dollars or directly represented in dollars. In this paper, the elements include fuel, electricity for electric vehicles and parking fee. Fuel or electricity are different types of energy which can be finally realized as dollars. From [9], fuel consumption factor was considered in vehicle cruising problem because it was an inevitable element in transportation. However, idling (engine running but vehicle not in motion) on fuel consumption was another element that was ignored in parking model. For example, Rahman et al. [10] indicated that idling of vehicle also contributed to extra fuel consumption. From [1], it was reported that 3.1 billion gallons of fuel was wasted in congestion. Parking problem was also regarded as a serious fuel waste problem and Guo et al. [11] demonstrated that 120 gallons of gasoline was wasted hourly in the parking process. Therefore, it is concluded that a good parking scheme should consider the cost consideration in terms of fuel and charge information.

The objectives of time and cost are important in choosing a parking lot and it is found that there are no vehicle cruising prevention schemes considering both time and cost in the market. Meanwhile, although some parking models were commonly used in analyzing and simulating transportation network [12], [13] and algorithm was developed to help driver to look for parking lot [14], the car park guidance for drivers was ignored since drivers are ignorant of available car parks around the destination. Therefore, it is necessary to design a cruising prevention scheme to guide drivers to reduce the time of vehicle cruising for a parking lot which in turn will alleviate the burden of traffic congestion in cities.

In short, it is noted that the current vehicle cruising prevention scheme has the following three deficiencies:

(a) Vehicle queueing at intersection road is ignored;
(b) No consideration of both time and cost simultaneously in car park hunting process;
(c) Driver’s guidance-to-parking information is ignored.

In this paper, the deficiencies are considered in the PCP scheme.

The contributions of the paper are as follows:
(1) New queueing model and resource model are developed;
(2) A new Parking Model (PM) is developed for a holistic optimization of time and cost;
(3) Performance is measured by a newly defined indicator, referred as Figure of Merit (FOM).

The rest of the paper is organized as follows; section II provides the related work on recent car parking development. Section III describes the PM design in the PCP scheme. Section IV formulates the objectives of total journey time and total cost into a Multi-Objective Optimization (MOO) problem with a set of constraints. Section V shows the performance of our work and the insight of FOM. Section VI gives a conclusion.

II. RELATED WORK

Some of the researches have considered the time element in car parking problem. A Wireless Mobile-based Car Parking System was developed by Khang et al. [14] to help drivers to receive information from car parking space through Short Message Service (SMS). Breadth First Search (BFS) algorithm was implemented and shown that it was able to locate the nearest parking space for drivers. The system allocated the best available parking space to the driver in terms of the distance. iSCAPS was proposed to ensure the availability of parking system for drivers through Near Field Communication (NFC). The system ensured the availability of parking lot for customers, parking reservation availability, payment through NFC and smart phone application [15]. Ji et al. [19] concluded that Parking Guidance and Information (PGI) was a parking scheme that was able to minimize the travel time for some group of drivers. The scheme was implemented in city areas to reduce the time of drivers in locating a parking space. Belloche [21] focused on the modeling to estimate the on-street parking search time. The paper found that the medium search time for a parking lot in surveyed districts was about 20 minutes. The proposed models were related to parking congestion ratio and the models were used to estimate the on-street parking search time. Number of legal and illegal parked vehicles and total space capacity were considered. Zhang et al. [23] developed a fast parking model to help drivers spending minimal time in parking lot seeking. The model was developed based on Timed Petri Nets (TPNs) which considered the time of parking, the time required for an occupied spot, driving time and the time required on road to choose a parking lot. Summary on the choice of a parking lot with least driving and parking time was reported.

Some researchers considered the cost element in car parking problem such as the cost between two positions and revenue of a parking lot. Shao et al. [12] recommended the use of the temporal vacant parking space in residential area when parking space owners were out for work. The proposed
scheme demonstrated that the model can maximize total revenue generated from charging of users. Pham et al. [20] suggested a cost model to be minimized among two positions on map. The cost model included the distance between the two positions and percentage of free parking spaces at each node.

Other researches tried to analyze the parking lot problem from different aspects. Car parking vacancy detection schemes were proposed to help drivers to locate the parking space [16], [17]. The methodologies included neural network based on visual feature extraction from parking space as well as machine learning through sensor captured data. The accuracy of car detection of both proposed schemes reached over 97%. Furthermore, Internet of Things (IoT) was utilized to investigate the practical use of collected real-life IoT data in car parking [18]. A large amount of data was collected from different sensors and some useful features were extracted to find patterns or trends. The author did the first analysis of anomaly detection and clustering on instantaneous car parking data in City of San Francisco. Cao et al. [22] proposed a macroscopic model to analyze the cruising phenomenon. The proposed model considered car park waiting time for drivers and the influence of such waiting time on traffic network. The model needed only 5 sets of input data. The model was validated through empirical data and a case study was carried out within the city of Switzerland. Authors concluded that in future studies, pricing models were expected to incorporate with the developed model. Bischoff and Nagel [24] proposed a model which integrated parking search simulation into the Multi-Agent Transport Simulation (MATSim) which involved the logic simulation of agents through the re-planning method. Results indicated that the model had a great impact on the total traveling time of multiple agents travelling by car. Inci et al. [25] found that existing work on traffic congestion externalities typically ignored the influence of cruising for parking and estimated that an additional parked car will lead drivers to cruise for parking. It means that the cruising is a serious consideration throughout a journey. Guo et al. [26] proposed two types of parking models which were static game theoretic model and dynamic capacity model in order to ease the traffic congestion problem. Both models were used to predict the parking behaviors of drivers. Calibration of dynamic model parameters was carried out through Genetic Algorithm (GA). The study shown that the accuracy of dynamic neo-additive model was higher than the car parking system. Rajabioun and Ioannou [27] proposed a multivariate autoregressive model which considered both the spatial and temporal correlation of parking availability. The model was proved with high accuracy of 95% with a 20 minutes prediction horizon. Privacy-secured system [28] was provided to make a reservation of parking lot for drivers. A payment protocol based on an anonymous e-coin was developed. This system consists of an e-wallet which was used to manage the e-coin for the parking system. Users can pay the e-coin through smart phone. As described in [29], the vehicle parking problem also

In short, based on the above literature, it is concluded that objective of time and cost are distinct aspects and there is no former vehicle cruising prevention scheme that considers the followings:

(a) vehicle queueing at intersection road;
(b) both the objectives of time and cost simultaneously and
(c) driver’s guidance-to-parking information;

The deficiencies (a)-(c) are considered in this investigation since they affect the choice of parking lot. Therefore, in this paper, the deficiencies are considered through the PCP scheme. The performance of the developed PCP scheme will be evaluated by using a newly defined FOM which considers the dependence of time and cost. FOM, comprising of composite factors described in Section II (a)-(c), will be evaluated to show the effectiveness of the optimized parking scheme. The FOM evaluation will be shown in Section V.

III. TRAFFIC MODEL DESIGN

To avoid drivers spending unexpected time roaming on streets for a parking lot and hence to reduce the emission of CO₂ as well as resources saving, a new car parking scheme for drivers is designed. To illustrate the problem that drivers encountered, Fig. 1 shows the process of parking lot seeking process.

It is assumed that a driver is going to a destination from starting point or current location and would like to seek a DNPL. There are multiple DNPLs as shown in Fig. 1. After the driver set his/her destination, it is assumed that there are Pᵢ DNPLs detected. The driver would like to choose an optimized DNPL among Pᵢ from the perspective of cost and time.

The driver is now considering two objectives (i) total journey time required to reach the destination; (ii) total cost including fuel and parking charge to be spent for DNPLs.
To understand the underlying process during parking lot seeking, the process in Fig. 1 is divided into three scenes.

The PCP scheme realizes the parking lot seeking process into three scenes and this is shown in Fig. 2.

Queueing Model (scene I): Driver is waiting at intersection road where vehicle queueing and idling consumption are considered. Fig. 1 shows an illustrative example of parking lot seeking process. The signalized intersection will stops/allows vehicle to pass depending on the cycling of the traffic light [30]. Investigation [10] further indicated that idling of vehicle also contributed to extra fuel cost. This queueing model considered the cycle of traffic light and vehicle stream from starting point/current location to DNPL. Apart from the physical travelling time, the queueing at traffic light or intersection road is another key element to be considered. Fuel cost due to idling is also considered.

Resource Model (scene II): Physical travelling distance from staring point/current location to DNPLs. It involves travelling time and fuel consumption. The relationship between vehicle’s speed and fuel consumption was non-linear [31]. This scene contained the modeling of two main objectives. After scene I, the objective of total journey time including travelling time to DNPL will be formulated. Fuel consumption during travelling is also considered which is a part of the total cost.

Parking Model (PM) (scene III): Charge of the parking lot and walking distance from DNPL to destination are considered. It is indicated that walking distance is considered from DNPL to destination [8]. Charge of parking lot and walking distance from the DNPL to destination are also contributed to total cost and journey time respectively. Formulated models in scene I and scene II will be considered in this scenario.

After the PM, the MOO is carried out with Non-dominated Sorting Genetic Algorithm (NSGA) where the output of the NSGA is a set of Pareto Front (PF). Section IV will elaborate in detail. The results of the formulated MOO problem indicate that which DNPL is the fastest or the most economical to reach. Moreover, it also indicated which DNPL is optimized to reach based on FOM considering both the total journey time and total cost.

In the following sub-section A, queueing model (scene I) at intersection of roads is considered first. In sub-section B, resource model (scene II) is built and PM (scene III) is presented in sub-section C.

A. QUEUEING MODEL (SCENE I)

In transportation problems, traffic light and traffic stream were key elements to be considered [32] which determined the waiting time for each vehicle resulting in the efficiency of transportation system. Therefore, a good traffic model should capture the behavior or parameters of traffic light and vehicles such as the traffic light cycle, traffic stream. To illustrate the problem, it is assumed that there is a vehicle stream travelling at an intersection road referenced to [33]. In order to estimate the time required for a vehicle to pass through a traffic light or intersection road, the following assumptions are made.

Assume a vehicle stream is travelling in \( i \)th traffic road of distance and going to pass through the signalized \( ij \)th intersection as shown in Fig. 3. The green light duration which will allow vehicle stream to pass through Line B into the signalized intersection \( ij \)th road is \( g_i \), the cycle for the traffic light system within the signalized intersection is \( c_i \) which means that the probability for the vehicle stream pass through the \( ij \)th intersection without waiting time is represented as

\[
P(green\ light) = \frac{g_i}{c_i}
\]  

On the other hand, the probability for the vehicle stream stops in front of the intersection is represented as

\[
P(red\ light) = 1 - \frac{g_i}{c_i}
\]

Denote \( q'_i(t) \) (vehicle/s) as traffic stream entering from Line A into \( i \)th traffic road as shown in Fig. 3 and \( q_i(t) \) as the leaving traffic stream at Line B into signalized \( ij \)th intersection road , \( \rho_i(t) \) (vehicle/m) is defined as the traffic density at \( i \)th traffic road.

\[
\text{Speed of traffic stream} = \frac{q'_i(t) - q_i(t)}{\rho_i(t)}
\]
The length of platoon waiting at $i^{th}$ traffic road $l_{wi}(t)$ when the traffic light turn from green to red, $q_i(t) = 0$, is now defined as

$$l_{wi}(t) = \frac{q_i(t)}{\rho_i(t)}(c_i - g_i) \quad (4)$$

Length of platoon for vehicle through a single signalized $ij^{th}$ intersection road is further incorporated into (5) where $l_v$ is the averaged vehicle length and $\Delta t$ is the time required for a vehicle from idling to averaged speed.

$$T_{w_{ij}} = \left(1 - \frac{g_i}{c_i}\right)(c_i - g_i) + \frac{l_{wi}(t)}{l_v} \Delta t \quad (5)$$

where $T_{w_{ij}}$ is the queueing delay due to the signalized $ij^{th}$ intersection road. $G$ is defined as the average fuel consumption rate in idling while waiting at the intersection road. The total idling fuel cost due to intersection roads between $j^{th}$ position and $i^{th}$ position is now became:

$$Z_{T_{ij}} = G \sum_{i,j,i\neq j} T_{w_{ij}} \quad (6)$$

**B. RESOURCE MODEL (SCENE II)**

Before travelling to DNPL, the priori information of time of travel to reach the parking lot should be known. Therefore, a transportation network is developed to calculate the physical distance between the starting or current position to parking lot. Graph theory provided a good way to analyze a traffic model [34]. Fig. 4 illustrated a graph with $q$ nodes where $q > p > n > m \geq 1$. Each node represented a position on a traffic network where user can travel from any position to another position through edges. The edge between a pair of node indicated the time delay $T_{w_{ij}}$ due to signalized $ij^{th}$ intersection road and $d_{ij} = d_{ji}$ is defined as the vehicle travelling distance between node $i$ and node $j$. From the network shown in Fig. 4, it is not a fully connected network and it indicated that not all nodes are directly connected and this is the characteristics of the typical transportation network. Within the network, three Node Common Relationships (NCR) between node $i$ and node $j$ NCR($i, j$) are defined to describe such a network. $a_{ij}$ is defined as the total vehicle travelling distance between node $i$ and node $j$.

NCR($i, j$) I: Within this pair of nodes, node $i$ and node $j$ are directly connected. From Fig. 4, examples of directly connected nodes are Node$_{12}$, Node$_{23}$ . . . Node$_{2n}$. For this relationship, the physical distance and time delay encountered are just simply $d_{ij}, T_{wij}$ respectively. In this case, vehicle travelling distance equals to total vehicle travelling distance, i.e. $a_{ij} = d_{ij}$.

NCR($i, j$) II: Within this pair of nodes, node $i$ and $j$ are not directly connected but either of them can reach one another through other node. From Fig. 4, example pairs of NCR($i, j$) II included Node$_{13}$, Node$_{24}$, Node$_{1n}$ . . . Node$_{13}$ For nodes with this relationship, it is necessary to go through other edges in order to reach the final node. Take Node$_{13}$ in Fig. 4 as an example, the vehicle travelling from node 1 to node 2 then node 2 to node 3 are $d_{12}$ and $d_{23}$ respectively. The total vehicle travelling distance from node 1 to node 3 becomes $a_{13}$. $a_{13}$ is the summation of $d_{12}$ and $d_{23}$.

NCR($i, j$) III: Within this pair of nodes, node $i$ and $j$ are not directly connected but each of them is not connected to third node. It means that this pair of nodes is isolated from other nodes. From Fig. 4, Node$_{pq}$ is an example of isolated pair of nodes. Since there is no way to reach either node $p$ or node $q$, this relationship will not be considered furthermore.

In brief, the distance matrix $D$ for Fig. 4 is now represented as

$$D = \begin{cases} a_{11} & a_{12} \ldots & a_{1n} \\ a_{21} & a_{22} \ldots & a_{2n} \\ \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} \ldots & a_{mn} \end{cases}$$

where

$$a_{ij} = \begin{cases} 0, & \text{for } i = j \\ d_{ij}, & \text{for NCR (i, j) I} \\ \sum_{i,j,i\neq j} d_{ij}, & \text{for NCR (i, j) II} \end{cases}$$

Hence, the travelling time $T_{dj}$ between $j^{th}$ position and $i^{th}$ position is calculated as

$$T_{dj} = \frac{a_{ij}}{v} \quad (7)$$

where $v$ is the average speed of vehicle. Furthermore, the fuel consumption per unit distance is calculated as [31]

$$F(v) = \frac{a}{v} + b + cv + dv^2 \quad (8)$$

where $a, b, c$ and $d$ are the model parameters in which each parameter is dependent to the type of vehicles. From the model developed in [31], the fuel consumption parameters $a$ lined within the range of $10^0$ to $10^{-2}$; $b$ lined within the range of $10^{-2}$ to $10^{-3}$; $c$ lined within the range of $10^{-3}$ to $10^{-5}$; $d$ lined within the range of $10^{-5}$ to $10^{-6}$ according from the fuel
consumption level. For bus, the fuel consumption parameter was comparatively higher while electric vehicle was the least.

As shown in (8), the fuel consumption per unit distance was related to the vehicle’s speed and presented in a non-linear relationship. The higher the vehicle’s speed, the lower vehicle travelling time is expected and vice versa. Fuel consumption models have been extensively analyzed and summarized [10], [35]. Fuel cost due to travelled distance from \(j^{th}\) position to \(i^{th}\) position is now represented as

\[
Z_{di} = a_i F(v)
\]

(9)

C. PARKING MODEL (SCENE III)

Before choosing a parking lot, it is necessary to know the parking charge of each parking lot. Since the parking charge for different parking lots varied, it is defined that \(m_i\) as the parking charge of \(i^{th}\) parking lot. Moreover, the expected parking hour of user is defined \(e_i\) and it is represented as

\[
e_i = f(x|a_i, b_i) = \frac{1}{b_i^a_i \Gamma(a_i)} x^{a_i-1} e^{-\frac{x}{b_i}}
\]

(10)

which is a gamma Probability Density Function (PDF) and \(a_i\) is the shape parameter and \(b_i\) is the scale parameter. The gamma PDF has been applied in [11] for parking hour estimation. In simply words, the parking charge \(Z_{pi}\) at \(i^{th}\) parking lot is calculated as

\[
Z_{pi} = e_i m_i
\]

(11)

Cost of fuel per gallon is defined as \(C_{C_f}\). Hence, the total cost from \(j^{th}\) position to \(i^{th}\) parking lot is calculated as

\[
Z_{ij} = (Z_{dj} + Z_{Te}) C + Z_{pi}
\]

(12)

On the other hand, the total driving and walking time between any two points are calculated as (13) where \(d_w\) is the walking distance from parking lot to destination and \(v_w\) is the walking speed of user. The total journey time from \(j^{th}\) position to \(i^{th}\) parking lot is calculated as

\[
T_{Dij} = T_{dj} + \sum_{i, i \neq j} T_{wij} + \frac{d_w}{v_w}
\]

(13)

Objectives of total cost and total journey will be formulated into a single MOO problem with a set of constraints which will be discussed in the next section.

IV. MULTI-OBJECTIVE OPTIMIZATION BASED ON NSGA

To determine the performance of the developed PCP scheme, the system requirement is formulated and an optimization is needed. Therefore, an optimization that satisfies all the objective requirements is utilized. It is known that the NSGA is genetically strong and is a powerful seeking skill which imitates the nature of evolution. In many practical engineering problems such as telecommunication network design, global optimum does not exist. Moreover, most of the problems in engineering desired the consideration co-existence of multiple conflicting objectives to provide a comprehensive and better result. Compared to single objective optimization, MOO has outstanding advantages as follows: The diversity of multi-objective optimization was much wider than single-objective optimization [36]. Therefore, the MOO problems rendered the launch of Multi-Objective Evolutionary Algorithms (MOEAs). The MOEA was a kind of GA that always seeking for a set of non-dominated optimal solution which is regarded as PF [37].

A. INITIALIZATION

During the initialization stage, the number of generation, population size, objective functions and constraints were determined. The averaged distance of two nearest solution points represented the optimal solution. The main point to solve a MOO through GA is to generate a new population for further optimization in order to reach optimal solutions. Process of selection, crossover and mutation simulated the process of natural evolution [37]. Such an iteration process will be stopped when either the maximal number of generation is reached or the output solutions converge and the final PF is obtained. Each solution point on PF is an optimal solution and does not dominate each other.

B. DESIGN CONSTRAINTS

To enhance the rate of convergence during the optimization, it is necessary to assign upper and lower boundaries of the parameters which fulfilled to the unique design of the transportation network. During the operation, the quality of undesirable individuals can be effectively reduced by assigning reasonable boundaries and hence fasten the computation.

C. DEFINITION OF FITNESS FUNCTION

In general, in MOO, the objective functions are expressed as [38]

Minimize \(F(x) = (f_1(x), \ldots, f_m(x))^T\)

subject to \(x \in \Omega \) \(x \in \Omega\)

(14)

where \(f_m(x)\) is the objective values for each individual in the whole population, and \(\Omega\) is the variable range.

A binary variable is defined to indicate whether parking lot \(i\) is chose from position \(j\):

\[x_{ij} = \begin{cases} 1, & \text{if parking lot } i \text{ is chose from position } j \\ 0, & \text{otherwise} \end{cases}\]

(15)

Let \(S_j\) be the fuel level of the vehicle at position \(j\) and the vehicle is going to \(i^{th}\) parking lot. Now the MOO is designed to 1) minimize the total cost \(Z_{di}\) and 2) minimize the total journey time \(T_{Dij}\) during car park process. The two objectives are formulated as

Minimize \(F_1 = \sum_{i} \sum_{j} x_{ij} Z_{ij}\)

Minimize \(F_2 = \sum_{i} \sum_{j} x_{ij} T_{Dij}\)

(16)

(17)
subject to

1) typical travelling speed range for vehicle in weekday busy hours

\[ v \in [10 - 80] \text{ km/hour} \] (18)

2) only one parking lot will be reserved for one vehicle at position \( j \).

\[ \sum_i x_{ij} = 1, \quad \forall j \] (19)

3) current fuel level \( S_{ij} \) can support the vehicle to reach parking lot \( i \) from current position \( j \)

\[ \sum_i \sum_j x_{ij} (Z_{dij} + Z_{Tij}) \leq S_{ij} \] (20)

4) there is a maximal acceptable walking distance \( d_{\text{max}} \) from parking lot to destination [8]

\[ d_w \leq d_{\text{max}} \] (21)

V. RESULT AND ANALYSIS

To validate the performance of the developed PCP scheme, it is appropriate to design a route for testing. The University of Hong Kong was designed as the starting point and City University of Hong Kong was chosen as the destination point and the route is shown in Fig. 5. The scenario became a driver driving his vehicle from starting point to destination point and an optimized DNPL is sought for. There are seven DNPLs detected, namely parking lots A to G.

It is worth to emphasize that after the driver has parked his car, say, in parking lot A, he still is required to walk from parking lot A to destination. Parking lot A was 9 km from starting point of user while parking lot G was 10.6 km which is the longest distance among the seven DNPLs from the starting point.

During the whole process from starting point to destination point, two main objectives were considered, namely total cost and total journey time. For total cost represented in (12), it consisted of the fuel consumption during vehicle idling, driving as well as car parking charge. For total journey time in (13), it consisted of queueing at the intersection of road, vehicle travelling time and walking time from DNPL to destination.

For validation purpose, range of 250 meters, 500 meters and \( d_w \leq 1000 \) meters were investigated as well. As a prior validation, the area of interest was confined where the walking distance \( d_w \) was less than 250 meters centered at the City University of Hong Kong. However, within such an area of interest, only two DNPLs (parking lots A & B in Fig. 6) were found. One of them has a parking charge of 111% to a typical parking company. Hence, the area of interest of 250 meters was not a feasible way to evaluate the developed scheme since such the area only focus on the travelling distance while the total cost \( Z_{ij} \) was ignored. Fig. 6 showed the positions of DNPLs.

The area of interest was then extended to walking distance of \( d_w \leq 500 \) meters. Within this area, total four DNPLs (parking lots A to D in Fig. 6) were found. Among the four DNPLs, the range of parking fee lined between 38% ~ 167% to that of a typical parking company provided.

To further understand the performance of the developed parking scheme, \( d_w \leq 1000 \) meters was adopted in this investigation. It is observed that when \( d_w \) was further extended but less than 1000 meters; three extra DNPLs (parking lots E to G in Fig. 6) were found while the range of parking charge kept unchanged from 38% ~ 167%. It is assumed that users have obtained the real-time parking space information and can make parking space reservation before using this parking scheme.

In the case implementation, within the area of interest in Fig. 6, there were seven DNPLs detected. The designed parking hours of each parking lot was set to three [11]. Each DNPL was analyzed by the developed PCP scheme in terms of total cost and total journey time which included both the travelling time and walking time. Take parking lot A as an example, from Fig. 6, it has the shortest journey distance 9 km among other DNPLs from current position while the parking...
TABLE 1. Measured data for scheme validation.

<table>
<thead>
<tr>
<th>Description</th>
<th>Measured data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of DNPL</td>
<td>7</td>
</tr>
<tr>
<td>Total vehicle travelling distances $d_{ij}$ from start point to parking lot A to G (destination is surrounded by the parking lot A to G)</td>
<td>9.0 ~ 10.6 kilometers</td>
</tr>
<tr>
<td>Walking distance $d_{wp}$ between destinations to parking lot A to G</td>
<td>40 ~ 950 meters</td>
</tr>
<tr>
<td>Maximum number of signalized intersections</td>
<td>13</td>
</tr>
<tr>
<td>Parking charge benchmarked to a parking company in Hong Kong</td>
<td>38% ~ 167%</td>
</tr>
</tbody>
</table>

TABLE 2. Parameters setting of NSGA.

<table>
<thead>
<tr>
<th>Description</th>
<th>Measured data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>100</td>
</tr>
<tr>
<td>Maximum number of generation</td>
<td>200</td>
</tr>
<tr>
<td>Crossover fraction</td>
<td>0.8</td>
</tr>
<tr>
<td>Mutation rate</td>
<td>0.2</td>
</tr>
</tbody>
</table>

TABLE 3. Characteristics of literature work and the developed PCP scheme.

<table>
<thead>
<tr>
<th>Research</th>
<th>Region (if applicable)</th>
<th>Objective - time</th>
<th>Objective - cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>[12]</td>
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The formulated MOO problem was then solved by NSGA. The key measured data for the scheme validation is listed in Table 1. Parameters setting of NSGA is listed in Table 2.

Table 3 is presented to summarize the characteristics of literature work and the developed PCP scheme. As discussed, a good parking scheme should consider both objectives of time and cost and finally provide an optimized DNPL which is a faster and more economical route for drivers to reach. In the remaining parts of this section, the importance of the two objectives will be explained.

As shown in Fig. 7, the PCP scheme was applied to parking lot A for explanation purpose. It is observed that there are multiple points on the curve and each point represented a solution for the problem described in (16) and (17). It is observed that the relationship between the time and cost in parking scheme is contradictory implying that time is saved when extra cost is spent and vice versa. This phenomenon corresponded to (8) which indicated that the fuel consumption per unit distance and vehicle’s speed was in non-linear relationship. In Fig. 7, two extreme points are defined which are referred as cost dominance point and time dominance point.

Cost dominance point: It indicated that the objective of cost is emphasized, it means that this point has the lowest cost which is $96.69 corresponding to 23.65 minutes using optimized vehicle’s speed of 27.66 km/hour.

Time dominance point: It indicated that the objective of time is emphasized, it means that this point has the lowest time required which is 10.86 minutes corresponding to $100.8 using optimized vehicle’s speed of 79.95 km/hour.

For the same DNPL, different optimized vehicle’s speed will be adopted to reach the minimal cost or minimal time respectively. Let’s take Fig. 7 as an example. For cost consideration, the optimized vehicle’s speed is 27.66 km/hour while for time consideration, the optimized vehicle’s speed is 79.95 km/hour. The difference of the two optimized vehicle’s speeds will finally lead to significant change of total journey time.
Similarly, the PCP scheme was applied to rest of six parking lots B to G and their results were shown in Fig. 8(a) and Fig. 8(b) respectively.

For Fig. 8(a), cost dominance point is considered for the seven DNPLs. It showed the total cost required to reach for each of the DNPL. When total cost is considered, parking lot D is favorable for drivers.

For Fig. 8(b), time dominance point is considered for the seven DNPLs. Since the objective of total journey time is emphasized, different optimized vehicle’s speed will significantly vary the total journey time. When time is considered, parking lot A is favorable for drivers.

However, the problem now became which parking lot, A or D, should be chose for drivers since parking lot A has the minimal total journey time while parking lot D has the minimal total cost. The PCP scheme provided a solution to this problem.

From the perspective of drivers, the criteria for choosing a DNPL is to keep both cost and time in a relatively low level. To do so, it is necessary to illustrate the scheme’s result in a more observable way.

In the case study, seven DNPLs are found. When multiple parking lots were considered, it is required to display the results in an more observable way. Therefore, the PCP scheme was applied to the seven DNPLs and result was illustrated in Fig. 9. From Fig. 9, each color represented the performance of the PCP scheme correspondent to a particular DNPL. Since seven DNPLs were found and hence seven different colors were used. Fig. 9 is provided to show how the change of vehicle’s speed affects the performance of the two objectives which are total cost and total journey time. At the initialization process of the NSGA, the value of vehicle’s speed is set from 10 km/hour to 80 km/hour where 80 km/hour was speed limit of most expressways in Hong Kong. It is observed that increasing vehicle’s speed contribute to time saving while bringing higher total cost.

For analysis purpose, Figure of Merit (FOM) is defined. It is calculated as \( \text{FOM} = \frac{\text{total cost}}{\text{total journey time}} \). FOM is an indicator to show the value of total cost  \( \times \) total journey time at a particular vehicle’s speed during the car parking. Parking lot with lower value of FOM is more favorable for drivers.

From Fig. 9, different vehicle’s speed corresponded to different total journey time and total cost respectively. It means that there is a range of FOM for each DNPL. Hence, the maximal and minimal FOM values of a DNPL can be obtained. Fig. 10 showed the maximal and minimal FOM for each DNPL. From Fig. 10, parking lot D provided the lowest FOM where the optimized vehicle’s speed was 79.95 km/hour. The maximal FOM is also provided to illustrate the range of FOM. It is observed that the range of FOM for a DNPL can vary quite significantly. For example, the maximal FOM to minimal FOM of parking lot A and parking D were changed by 109% and 49% respectively. For a single DNPL, say, parking lot A, the reason of causing the change of maximal FOM to minimal FOM by 109% was the value of adopted vehicle’s speed. In this study, parking lot A has the largest percentage change 109% while parking lot D has the lowest percentage change 49%. It was because the total vehicle travelled distance, parking charge and number of intersection roads encountered among the seven DNPLs were different. Hence the percentage changed were different among the DNPLs.

In brief, since parking lot D has the minimal FOM, hence it is the optimized to go from the perspective of total journey time and total cost.

To validate the effectiveness of the queueing model in the developed PCP scheme, the queueing model was removed in (13) and the PCP scheme validation was carried out again. Since one of the time elements was removed from (13), a decrease of minimal FOM for all DNPLs was expected. Fig. 11 showed the difference on minimal FOM with and without the queueing model.
From Fig. 11, it is observed the FOM without queueing model is lower than that of the FOM with queueing model. This is due to the removed queueing model in PCP scheme and hence all the FOM without queueing model is lower. When the queueing model is removed, the minimal FOM of the parking lot G is less than that of parking lot D. Hence, parking lot G now become more favourable.

From Fig. 11, it is observed that there is a decrease on minimal FOM when queueing model is removed. The decreased percentages from parking A to G are 35%, 31%, 28%, 24%, 24%, 25% and 43% respectively. Such a percentage difference is due to the number of signalized intersection roads encountered from starting point to the seven parking lots A to G are different. For the path with more signalized intersection roads such as parking lot G, the path has the maximum number of signalized intersection roads. In means that the queueing model played a significant role in the formulation of total journey time. Once the queueing model is removed from the total journey time formulation for parking lot G, an obvious decrease on the overall minimal FOM is expected. Figure 11 showed the removal of queueing model is able to affect the minimal FOM and finally the preference of parking lot. Hence, the influence of queueing model should not be negligible.

VI. CONCLUSION
It is observed that one of the main reasons causing traffic congestion is vehicle cruising for a DNPL. This will cause drivers to spend unexpected time and cost to find a DNPL and hence it will jeopardize the traffic congestion. Unfortunately, there is no vehicle cruising prevention scheme which alleviated the burden of traffic congestion by guiding drivers to DNPL effectively. The contributions of this paper are (1) New queueing model and resource model are developed for parking lot seeking; (2) A new PM is developed for a holistic optimization of time and cost; (3) Performance is measured by a new indicator referred as FOM. Analysis reveals that the incorporation of PM improves the performance by 24% ~ 43%. Appropriate parking lot can be obtained from the FOM. Hence, drivers can reduce the time of vehicle cruising on roads and this will finally alleviate the burden of traffic congestion.

REFERENCES
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