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Optimized Public Parking Location Modelling for Green Intelligent Transportation System Using Genetic Algorithms

TONG SHEN[1], KUN HUA[2], AND JIAPING LIU[3]

[1]School of Architecture, Chang'an University, Xi'an 710064, China
[2]Department of Electrical and Computer Engineering, Lawrence Technological University, Southfield, MI 48075, USA
[3]School of Architecture, Xi'an University of Architecture and Technology (XAUAT), Xi'an 710065, China

Corresponding author: Jiaping Liu (liujp_chd@126.com)

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ABSTRACT This paper proposes an optimal parking site selection scheme to alleviate CO_2 emissions of the traffic flows for green urban road networks. Through the creative dynamic traffic zone programming, a constrained optimization model is set up to assess the impact of potential public parking locations on road traffic emissions. In each scenario, Thiessen Polygon based zoning method is applied to investigate the distributions of road traffics. The main contribution of this study is as follows. Firstly, this proposed model takes the CO_2 emission of the whole traffic network of sustainable city development as the optimization goal, instead of the traditionally discussed travel distance or cost efficiency. Secondly, a Thiessen polygon based public parking zoning method is developed and implemented realistically. This zoning method provides a precise approach to traffic distribution and parking demand estimation. Rather than the quadrilateral or radial zoning, this method pays more attention to the parking supply demand and its impact on parking congestion. Thirdly, the genetic algorithm (GA) is used to find the optimal public parking location (PPL) sets. GA has a great application value in speeding up stochastic search for global optimization. It is especially suitable to simulate complex and large capacity problems concerning the realistic solutions. By implementing the dynamic zoning and modelling method into intelligent transportation system (ITS), the efficiency of parking induction and dynamic optimization of traffic distribution could be ensured for the future smart mobility. Therefore, this model not only serves as a novel method for public parking allocations, but hold potential to support intelligent parking guidance, as a part of the intelligent traffic system for smart city development.

INDEX TERMS Parking allocation model, congestion management, green intelligent transportation system, genetic algorithm, optimization.

I. INTRODUCTION

Public parking space is normally viewed as a scarce resource in heavy traffic areas, and its limited capacity is one of the crucial factors in intensifying traffic congestion [1]–[4]. Taking Xi'an, China as an example, the parking garage shortages had been accumulated to near 100,000 from 2012 to 2015, as shown in Fig. 1. Parking cruising and illegal parking caused by the limited parking availability, lead to congestion and make the concurrent carbon emissions to their highest levels [5]–[7]. According to [8], vehicles will spend 3.5 to 14 minutes looking for an available public parking space, which result in extra carbon emissions and the traffic flow increases by 20-45% [9]. Paper [10] verified that an 18-minute illegal on-road parking will increase carbon emissions by 26.5% on a lane with traffic capacity of 1200 vehicles per hour. Therefore, with the limited amount of affiliated parking resources, public parking plays an even more important role in mitigating this ever-growing parking demand and alleviating traffic congestion. Efficient management of stationary traffic through public parking space allocation would be critical in speeding up and smoothing traffics [11].

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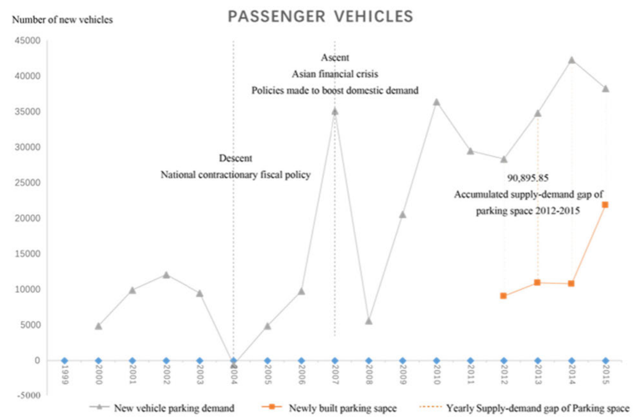

FIGURE 1. The gap between parking supply demand and available parking spaces in Xi'an, China. The broken line with triangle markers describes the annually added new vehicles, and the broken line with square markers represents the amount of newly built parking spaces. From 2012 to 2015, the average gap is as high as 90,895. 85.

In this regard, it would be a major task for urban and traffic planners to provide an effective way of allocating eligible public parking space in limited developable construction area.

In response to this issue, several location models were proposed for public parking allocation [8], [12]–[14]. For instance, the optimization model focuses on improving traffic efficiency of individual or special feeder system to minimize walking time, or parking cost, etc. [3], [13], [15]; The constraint model aims to insure the group traffic efficiency with the sets of parking locations under limited conditions [16]–[18]; The gravity model and traffic assignment model define the assignment of urban vehicles through a matrix of origin-destination determined by land use intensity, in order to find the best available parking location with the shortest travel time or walking distance, etc. [19], [20]. By considering travel distance, time, or walking distance etc., these models are pursuing effective ways to improve traffic performances. However, it is difficult to ensure the ideal speed of the entire road network with lowest carbon emissions. It is well established that, there is a sixth-order curve relationship between the carbon emission rate and the vehicle speed [21]. The general trend of vehicle emissions in congested traffic is about 50% higher than the normal speed [22]. That is to say, a vehicle may emit less CO_2 driving on a longer but unrestricted route, rather than a congested but shorter one. In this context, the traditional model method cannot guarantee the optimal effect of emission reduction. Therefore, a new modeling method is expected to assign locations of public parking facilities on the basis of optimal system carbon emissions and more sensible traffic distributions in resource constrained urban areas.

However, as aforementioned, these conventional models are only static zoning based, in which street blocks or function zones are calculated for parking demand estimation and travel distribution. With these fixed calculation results of traffics, such modeling process can hardly react to the dynamic traffic changing in the real world. For example, if there are no available parking lots in one public garage, the parking demand would be resolved by nearby available parking places [12]. However, such behavioral response to these excessive public parking demand has rarely been applied into modeling yet [12]. Therefore, a dynamic partitioning and traffic assignment approach needs to be considered. Under the time-varying parking availability and traffic environment, the pre-determined traffic allocation schedule would be revised accordingly. Especially for the future development of smart parking, which is an important part of green intelligent transportation system (ITS), the real-time navigation would help to guarantee the parking route in the real world. The development of green ITS will provide an opportunity to reduce the impact of temporary individual public parking decision based on emission reduction, meanwhile, satisfying dynamic scheduling of traffic guidance.

In this work, we propose an optimized public parking location model with the goal of minimizing carbon emissions of traffic flow over urban networks. We apply an adaptive traffic zoning method through dynamic Thiessen Polygon generation. This method allows the simultaneous calculation of both traffic distribution and parking demand in each polygon. Genetic algorithm (GA) is used to find the optimal locations of parking garages among all possibilities. The implicit parallelism of GA makes it possible to search for multiple solutions of the public parking schemes, in order to obtain the optimal solution aggregately. These processes could provide a real-time feedback to dynamic parking demands effectively and ensure the minimum amount of carbon emission as public parking demand is satisfied. Using this proposed model, we take the real traffic and parking demand data of Xi'an city, China as a study case to testify the effect of public parking locating in congestion management. We analyze the variation of carbon emission amount from the original condition to the final optimal result. By doing that, the feasibility of the proposed model is verified. This model proposes a brand new idea for the utilization of public parking in green ITS. The management of public parking location is no longer just a way to passively meet traffic demands, but becomes an active management tool for vehicle emission reduction in real-time.

The remainder of the paper is organized as follows: Section 2 discusses related work about public parking solutions in dealing with traffic congestion; Section 3 presents the modelling method for the dynamic zoning via Thiessen polygons and Genetic Algorithm based optimization process; Section 4 discusses a practical case study and experimental results, and Section 5 concludes the paper.

II. LITERATURE REVIEW

A number of studies have attempted to investigate public parking at economic and social levels in dealing with traffic congestion [8], [23]–[25]. These researches implement spatial equilibrium models and bottleneck models to reveal parking availability as a tool for travel demand control. However, the fact that traffic routing is always impacted by parking locations was often ignored in these modeling methods. As the adjustor of traffic routing, public parking is also seen as a way to help balance out traffic flows and prevent congestion [26]–[28]. Unlike ancillary parking garages which are serving for certain buildings with relatively fixed routes, the public parking garage (PPG) serves multiple buildings within a fixed distance. Drivers are likely to park then walk to their destinations. According to [28], the selection of parking locations could possibly reduce crowded routes and balance traffic routing to mitigate congestion.

According to [29], Congestion Management Process (CMP) is known as a systematic procedure, including identifying congestion and its causes, applying congestion mitigation strategies, and improving transportation system performances. Therefore, from a CMP point of view, the suitability of public parking allocation in congestion management is related to the process of traffic data collection, dynamic traffic assignment and system of performance monitoring. However, as [12] emphasized, although parking location is considered to have a significant impact on the operations of urban transport systems, the establishment of models often focuses on the impact of parking availability on the temporary decision-making of user travel routes, without proper integration with transport systems, land-use systems and other factors. Moreover, the location of public parking model is based on a location-allocation method. That is, with the unknown parking location and facilities amounts, the distribution relationship between parking supply and demand is not determined. Paper [28] conducted a series of parking location studies. It emphasized that changes in parking locations are also desirable for relieving congestion by matching traffic demand and supply within their service areas, and will cause changes in the modal split. Paper [30] used the real-world traffic data in 1969, taking the *4-step transport network model* for the trip assignment phases and modal split. This *4-step model* is a traditional method for traffic generation, trip distribution, modal split and traffic assignment. It has been applied in urban traffic planning prediction for a long time, but rarely used in parking facility demand forecasting. Therefore, this allocation model is related to the land use impacted traffic and parking demand, as well as the traffic allocation method. However, as we introduced before, this dynamic modal split of land use and traffic has not been fully considered in modeling procedure. This incentivizes us to rethink how to establish an iterative trinity modelling method to coordinate land use, dynamic traffic assignment and parking demand changing.

In order to achieve dynamic parking demand prediction and traffic assignment, the traditional zoning methods seem unsatisfactory. As is discussed before, traffic zone is often generated according to the similarity of land use and road conditions. The similar land use parts are classified as one traffic zone or parking functional zone (radius within 300m) for traffic distribution and parking demand estimation [18], [30]. To achieve a more precise parking demand estimation results, paper [31] proposed the concept of ‘‘parking generation cell’’ in Planning and Evaluation of Urban Public Parking Lots Project (PPE_Pro) system. The parking generation cell is smaller than the traffic zone, consisting of several adjacent buildings as parking generation points. However, the meaning of ‘‘similar’’ for zoning seems unclear. More importantly, as we mentioned before, with this static zoning method, traffic assignment and parking demand is not able to represent the rescheduling behavior of land use model and follow changes in parking demand and traffic assignment. Moreover, traditional traffic assignment algorithms, such as the Dijkstra and Noyd are not able to be applied under a constrained model system. Whereas neural network and genetic algorithms have been implemented, and provide technical support to ensure the calculation efficiency and accuracy for the complex dynamic scheduling.

Optimization models can help determine the optimum location of public parking among the observed distributions. The optimization model for parking allocation has been proposed to benefit interested groups. In this sense, parking fee, travel time and cost, walk time, and parking construction cost etc. are considered as the variables of particular importance. However, to the best of our knowledge, none of current parking location modelling methods are taking congestion effect as criteria for carbon emission optimizations. In this regard, it is still unclear how to identify the control effectiveness of public parking location modelling for congestion management process. Therefore, several key issues that need to be addressed for modeling are optimization goals, constrain criteria, data acquisition methods and zoning methods.

Firstly, concerning the optimization goal, paper [18] presented location constrained and non-constrained models through genetic algorithms, to minimize total walking distance for all parkers at the location. Paper [20] took walking time, parking cost and travel distance as the impact factors, and aimed to find the "best possible" location sets for all day parkers. Some modelling methods are usually making decisions based on the traffic and parking demand situation in peak hours. Paper [17] introduced a multi-level and multi-objective location model for on-street parking and the goal is to optimize circuitous length and walking distance with off street parking facilities. Paper [32] developed a multi-index and multi-restriction model to minimize the total parking construction cost. Similar to what [32] have proposed, paper [13] extended the cost into a broader view including walking costs, model costs, construction cost and parking costs. Paper [3] integrated capabilities of the Geographic Information System (GIS) with multi-criteria decision analysis models to find the compromised parking site solution among interests of different groups. They provide a series of evaluation criteria for parking site location like the minimized land cost, distance to the road, average distance to recreation, administrative and commercial centers. In addition, the cost is another important factor in modeling for non-profit organization, like the university [33].

Some constrain criteria settings are based on behaviors of parking operators and resource-limited urban environments. For instance, paper [15] proposed a single-target location planning model with the shortest walking distance to the parking garage. This model selects the location and berth allocation with the maximum allowable walking distance and other conditions, and finds that with the maximum allowable walking distance, the optimal solution set of position and berth allocation. Paper [34] developed a parking model especially for metropolitan area, where historical monuments are identified as constrain factors. Paper [35] took the maximum walking distance as a constraint factor. Similarly, paper [19] used walking time and searching time as constraint factors, concerning the likely individual travel behavior. To sum up, the commonly used constraint factors are as follows: (1) service radius: usually within 5-6 minutes walking distance, or 200-500 meters. (2) accessible areas (3) construction fee.

From paper [36], due to the limited traffic information, it is unlikely that drivers choose their parking routes to optimize the network performance. Even through the precise modeling methods, the effectiveness of the optimization modelling results will also be hardly ensured in the real world. Therefore, scholars have conducted a lot of researches on dynamic traffic induction systems to mitigate congestion [25], [37]–[39]. In particular, intelligent parking system with navigation and ITS capabilities could be applied to enhance the parking location modeling to relief congestion. Therefore, in green intelligent transportation system and smart cities, it is necessary to choose an applicable public parking location modeling and analyzing method with dynamic programming and scheduling to ease congestion [27]. Such system is guiding people via dynamic parking schedules [40]. As paper [41] predicted, CO_2 emission can be ideally reduced by almost 45%, when traffic flow is smoothed in a constant state.

III. METHODOLOGY

A. GENERAL DESCRIPTION

As discussed in the literature review section, CO_2 emission is often used as an indicator to measure the environmental impacts of congestion [42]–[44]. As there is a remarkable negative correlation between CO_2 emission and average traffic speed, the optimization target is to speed up traffic flow and minimize congestion related emissions, as described in Fig. 2. Hence, in this approach, we investigate public parking allocations with iterative zoning schemes for traffic flow distribution and parking demand estimation. Traffic flow that follows Wardrop's second principle is generally considered to be system optimal (SO). The optimum objective of network system emission is therefore formulated by its relation with traffic flow, and mathematically expressed by the average traffic speed of each road. This approach achieves iterative zoning of schemes. The modeling constrains and zoning operations are as follows:

Firstly, we set the goal of emission reduction of the entire network. This 'GOAL' will be achieved through alternative public parking allocation schemes by two optimization approaches, which are the optimized parking garage amounts

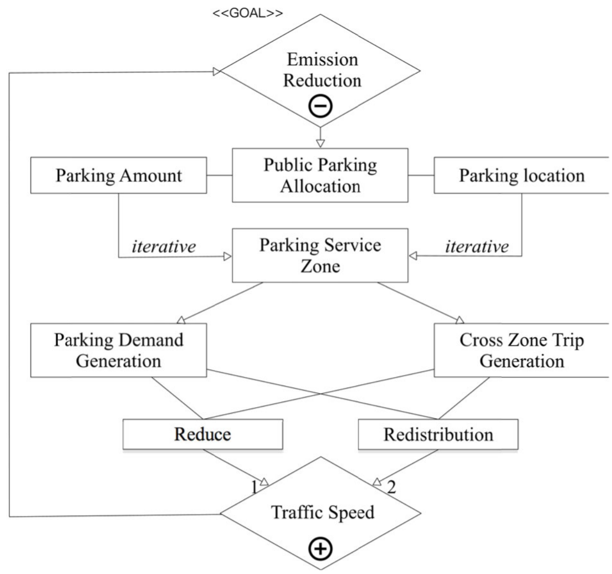

FIGURE 2. Flow Chart: Traffic speed control to reduce emissions.

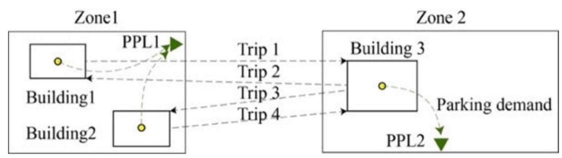

FIGURE 3. Service zone model.

and their locations. Therefore, with iterative dynamic programing, the parking service area will be generated under different parking distribution scenarios. This approach is going to compute and update the amount of parking requirements and travel generation dynamically for each zone. Thus, there are two methods to speed up the traffic, either to redistribute traffic flows or to reduce the parking demand and traffic amount on certain roads.

1) This research assumes that public parking is modeled under statured affiliated parking condition [5], which complies with the parking rule of minimum walking distance. Because for a given destination, parking to the affiliated space is necessarily shorter than that of public parking.
2) We divide the research area in to several parking service zones [31], in each of which there is only one public parking garage, and is used for the parking demand calculation, trip generation and distributions, as shown in Fig. 3.
3) Buildings are considered as individual parking demand generation points in each zone.
4) Buildings included in the PPG service zone, that should have the minimum walking distance to this parking garage.
5) The service radius of public parking garage is no more than 300 meters. For each public parking garage, no more than 300 spaces. Specifically, if there are over 50 spaces in one public garage, its entrance should be at least 100 meters away from road intersections [45].

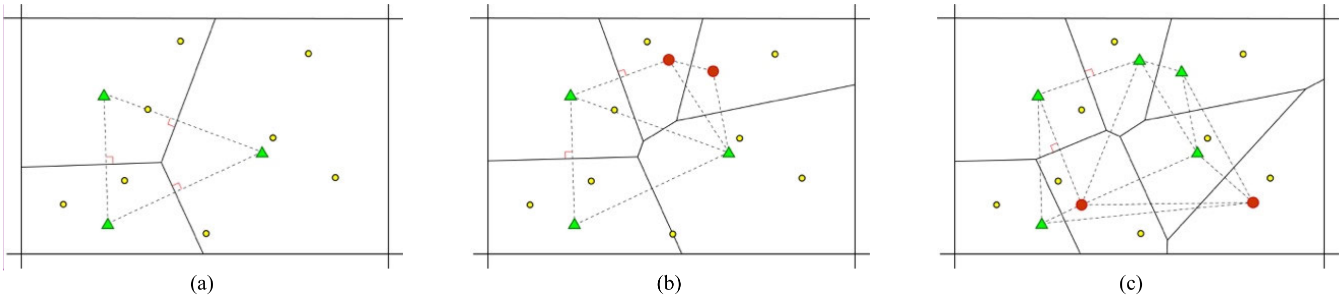

FIGURE 4. (a), (b) and (c) respectively illustrate 3, 5 and 7 Thiessen polygons based dynamic zoning procedure. Small dots represent buildings in each zone. Larger dots represent the added PPG in each procedure, and triangles represent the existing PPG.

B. ZONING APPROACH WITH THIESSEN POLYGONS

In this research, we propose a novel dynamic public parking zoning approach using the Thiessen Polygon method. We take each candidate public parking location as discrete point for polygon generation (see Fig. 4 (a)). The boundary of each zone is the mid-perpendicular of line connecting two adjacent discrete points. Through the Nearest Neighbor principle, this zoning method is performed with the following characteristics:

1) Each building within the polygon has the shortest distance to its public parking garage.
2) The center of each public parking area is the discrete point for Thiessen polygon generation, where the polygon centroid is considered as the feature point for traffic distributions (represented by triangle and circle signs in Fig. 4).
3) The building centroid is the feature point for parking demand generation (represented by small dots in Fig. 4). If the building centroid is coincidently generated on the boundary of polygons (see Fig. 4 (b)), the parking demand of this building could be attributed to either side.
4) Implementing this zoning system for the entire research area, the range of parking demand generation and traffic distribution is defined by each zone.

Taking diagram sequences in Fig. 4 as an example, the sampled area is divided iteratively by Thiessen polygons. By doing this, the polygon covered building area, land use types and trip generations will be revised iteratively. Accordingly, based on this partition method, the zone-to-zone trip distribution will also be revised.

Comparing to the traditional zoning method, our division scheme has two irreplaceable advantages. Firstly, the traffic distribution is usually based on roads between intersections. However, even on one road the traffic flow might differ, resulting from traffic flux changes of incoming and outgoing vehicles (see Fig. 5). In a more precise manner, our zoning method helps to estimate traffic flow on each road, which is divided into several road segments by the boundaries of polygons. More importantly, as shown in Fig. 5, when a vehicle is going to park in Zone ①, its distance to public parking lot of Zone ① should be shorter than any other lots in this area.

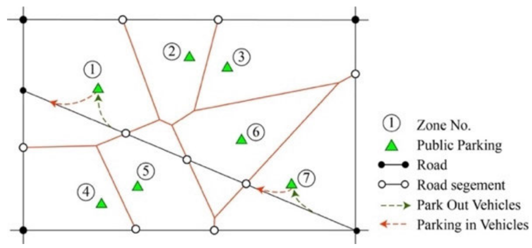

FIGURE 5. Illustration of road segments in calculation of net traffic flows.

The commonly used goal of shortest distance could be guaranteed through fitness functions. Benefited from the geometry character of Thiessen polygon zones, the workload and computational complexity of optimization is therefore dramatically reduced.

C. OPTIMAZATION FORMULATION

The sample research area with the amount of M PPG is considered, including both existing ones and the ones to be built. For simplicity, here each PPG is represented by the centroid point of their construction area and numbered from 1 to m. The coordinates of m^{th} PPG is (x^m, y^m). Individuals are selected from all candidates for the purpose of optimization and based on the selected points, we generate Thiessen polygons analysis zones. There are no more than M' of polygons ($1 \leq M' \leq M$), which are numbered form 1 to m'. Each functional zone takes its centroid as the feature point, and the coordinate of m' th zone is marked as $(x^{m'}, y^{m'})$. The road network model consists of the intersection set $\mathrm{N} = \{1, 2, 3, a \ldots b \ldots n\}$ and road set $\mathrm{R} = \{1, 2, 3 \ldots r\}$.

Most traditional solutions to congestion problems are based on heuristic justification, among which, the most commonly used principle for traffic assignment was enunciated by [46]. As we have discussed before, traffic activities that follow Wardrop's principles can be formulated as mathematical optimization problems. Our goal is to achieve the minimum CO_2 emissions of the whole traffic network. Therefore, a traffic pattern satisfies the second Wardrop principle, which concerns the optimization of system performances, would be the optimal solution to the convex problem as described below:

$$Min\ Z = \sum_r D_r \cdot E_r \cdot L_r \tag{1}$$

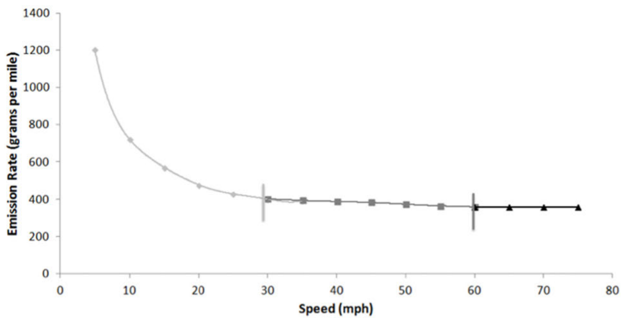

FIGURE 6. Carbon emission rates of Light-duty Vehicles at different average speeds [50].

where, Z represents the network emission level; D_r is the traffic flow on road r (pcu/h)[1]; E_r is the CO_2 emission rate of the average vehicle speed passing through road r; and L_r is the length of road r.

In (1), E_r is a function of the average traffic speed V_r, described as follows [47]:

$$E_r = f(V_r) \tag{2}$$

where V_r is calculated as follows:

$$V_r = \frac{L_r}{t_r(D_r)} \tag{3}$$

where t_r is a function of t_0 as follows:

$$t_r = t_0\left[1+\alpha\left(\frac{D_r}{C_r}\right)^{\beta}\right] \tag{4}$$

where, $t_r(D_r)$ is the time spent by passing through a road under D_r flow condition. It is a Bureau of Public Roads Function (BPR function) of traffic flows on the road segment with road capacity of C_r (pcu/h[1]) [48]. While t_0 is the road impedance factor, namely the time spent when driving through the road section with the free flow speed. t_0 is the quotient of road length and the road design speed. In (4), α, β are retardation factors calculated in modeling. Here we set the default value $\alpha = 0.15$ and $\beta = 4$ [21], [49].

Thus, (1) can be further reformulated as:

$$Min\ Z = \sum_r D_r \cdot f\left(\frac{L_r}{t_0\left[1+\alpha\left(\frac{D_r}{C_r}\right)^{\beta}\right]}\right)\cdot L_r \tag{5}$$

where, $f\{L_r/(t_0[1+\alpha(D_r/C_r)\wedge\beta])\}$ is the original $f(\mathrm{v})$. The curve function used for $f(\mathrm{v})$ calculation is shown in Fig. 6.

It is obvious that the flow pattern D_r is the only variable needs to be optimized in (5). Therefore, the main issue for system emission optimization is actually to confirm the optimal traffic distribution scheme of the network.

Essentially, our optimal approach for traffic distributions is based all sub-problems such as public parking demand estimations, trip generations and traffic demand calculations, etc.

[1] pcu/h means the traffic volume unit of the passenger car per hour

In the following subsection D, we will illustrate this iterative procedure resulting from the dynamic zoning process.

D. DYNAMIC TRAFFIC DISTRIBUTING SCHEMES

As Thiessen polygon has been introduced as a zoning method, the road between sections are no longer defined as the boundary of service zones. A brand new idea is that the road segments are separated by the boundary of the polygon boundary with the consideration of traffic distributions, where the segments set is K = {1, 2, 3 . . . k}. For each road segment k,

$$D'_k = FD_k - GA_k^w \times OR_w \times TR_w - GP_k^l \times U_{pk} \times T_{pk} \tag{6}$$

where, D'_k is the net traffic flow passing through road segment k; F represents the percentage of the usage of cars over the total of all traffic tools; D_k denotes the total zone-to-zone traffic flow of road k; GP_k^l is the capacity of the public parking garages on road k; GA_k^w is the capacity of affiliated parking garages on road k; TR_m is the turnover rate of the public parking space; TR_w is the turnover rate of the affiliated parking space; OR_m is peak-hour occupancy rate of the public parking garage; OR_w is peak-hour occupancy rate of the affiliated parking garage.

In (6), the capacity of public parking garage is calculated as follows:

$$GP_k^l = \sum_{l=1}^{l} \frac{PD_i - GA_k^w \times TR_w}{OR_m \times TR_m} \tag{7}$$

where, l is the total number of public parking garages on road k; PD_i denotes the parking demand of zone i. And here,

$$PD_i = PG_c \times A_c \tag{8}$$

where c denotes the land use category, ranged from 1-8. For example, $c = 1$ for residential, $c = 2$ for commercial, $c = 3$ for official, $c = 4$ for entertainment, $c = 5$ for education, $c = 6$ for industrial, $c = 7$ for public facility, and $c = 8$ for hospital usages, respectively. PG_c is the parking generation rate of c, and A_c is the size of c.

In (6), D_k represents traffic flow on road k generated by entire interchange trips T_{ij}. Therefore, according to the dynamic zoning method proposed in *section III. B*, the interactive traffic distribution and traffic demand estimation method are applied based on the gravity model:

$$T_{ij} = \frac{\varepsilon TG_i TA_j}{f(I_{ij})} \tag{9}$$

where, ε is the coefficient of the gravity model, which is set to be 0. 8 here as an experience-value [50]; TG_i represents trip generation amount of zone i, TA_j represents trip attraction amount of zone j; $f(I_{ij})$ is the impedance from i to j, defined as the shortest time spent from i to j at free-flow speed.

In (9), TG_i and TA_j could be calculated as follows:

$$TG_i = \sum TG_c \times A_c \tag{10}$$

where, TG_c is the trip generate rate of land use type c at peak-hours;

$$TA_j = \sum TA_{c} \times A_c \tag{11}$$

where, TA_c is the trip attraction rate of c at peak hours.

As introduced by [51], [52], we use the*Inverse Four-stage Land Feedback Model*to measure the dynamic zone-to-zone traffic flow on each road segment.

It needs to be noted that road segment k is not defined as a certain value, but varies according to the division method of polygon boundaries. This dynamic calculation procedure is also applied for the determination of A_c, TG_i, TA_j, PD_i, etc., which are related to the iterative zoning procedure, as shown in Fig. 3 and Fig. 5.

Here take one zoning procedure related trip distribution as an example,

$$\left(T_{ij}\right)_q = \left[\frac{\varepsilon TG_i TA_j}{f\left(I_{ij}\right)}\right]_q \tag{12}$$

where, $\left(T_{ij}\right)_q$ is the q^{th} trip generated from i to j;

$$D_k = \sum_{q=1}^{Q}\left\{\left(T_{ij}\right)_q w_{mk}\right\} = \sum_{q=1}^{Q}\left\{\left[\frac{\varepsilon TG_i TA_j}{f\left(I_{ij}\right)}\right]_q w_{mk}\right\} \tag{13}$$

where, D_k is the traffic flow on road k. The road segment is numbered from 1 to k, particularly according to the dynamic zoning method, the road number is iteratively revised. q is the number of OD pairs, and Q is the total number of OD pairs. w_{mk} is the ratio of the q^{th} OD pair $\left(T_{ij}\right)_q$ allocated traffic flow on road k.

Assuming that from i to j, there are $\tilde{S}$ alternative routes in each OD pair. Therefore, based on the principle of Behavioral Science, general samples of the time spent from i to j should conform to Normal Distribution. Namely, the shorter time of a route duration, the higher probability it would be taken. Therefore, from i to j, the probability of $\forall\tilde{S}$ route to be chosen is estimated as:

$$P_{\tilde{S}} = \frac{e^{-\frac{\left(T_{\tilde{S}}-\mu\right)^2}{2\theta^2}}}{\sum_{\tilde{S}} e^{-\frac{\left(T_S-\mu\right)^2}{2\theta^2}}} \tag{14}$$

where, μ is the expectation value, as the shortest time spent from i to j for most vehicles; θ is the traffic conversion parameter, $\theta = 3\sim3.\ 5$ [53]; T_S is the travel time of each route.

Therefore, the total probability of the q^{th} OD pair allocated on the k^{th} segment isw_{mk}, as follows:

$$w_{mk} = \sum_{s=1}^{H} P_{\tilde{S}} \tag{15}$$

where, H is the number of routes through the k^{th} road segment; In (15), the feasible route $\tilde{S}$ is determined by the following steps:

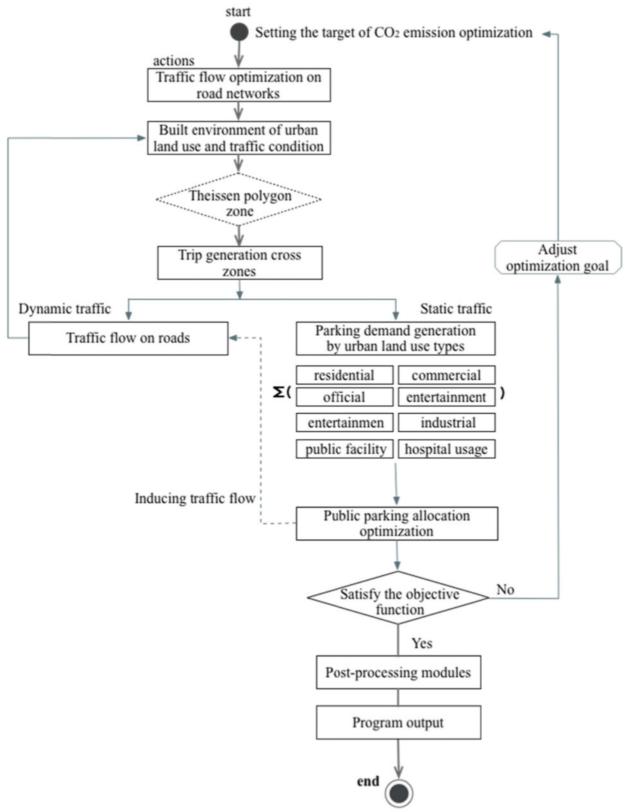

FIGURE 7. Flow chart: Optimization procedure for dynamic programming.

Step 1: Find the effective road: Based on the road intersection set $N = \{1, 2, 3, a \ldots b \ldots n\}$, we calculate the minimum travel times from each intersection to the starting point, which are marked as $T(1), T(2) \ldots T(n)$. If $T(a) > T(b)$, the road between *a-b* is considered as an effective road.

Step 2: Set up a feasible route with effective roads selected in step 1;

Step 3: Counting how many times *a-b* has been allocated with traffic flows by entire interchange trips T_{ij}, as is marked as H.

To sum up, the optimization procedure for dynamic programming is shown in Fig. 7. Through the optimization of traffic flow in each road segment, the goal of mitigating congested CO_2 emissions for green ITS will be achieved. The locations of public parking garages will determine how the analysis zones are divided. The land use and traffic factors are changing dynamically. Such changing process will in turn affects the traffic flow and parking demand generation across zones, thereby producing dynamic trip distributing schemes.

E. SOLUTION

The proposed model is a dynamic scheduling procedure via multiple criteria optimizations. This dynamic zoning method will impact land use and traffic system revising. Meanwhile, the set of feasible public parking locations is typically defined by complex constrained factors in urban areas, as well as construction limitations. Genetic algorithm (GA), featured in implicit parallelism and global information need, is a powerful way of searching a range of tasks to discover the optimum solution of the system [21]. Therefore, GA is applied in order to efficiently find the best solution among the complicated set of revised parameters. In this paper, the Partheno-Genetic Algorithm (PGA) is used to solve the problem. This method helps to generate solutions for carbon emission optimization through an efficient way by avoiding local equilibrium and decreasing computational complexity.

In general, there are several specific methods of genetic algorithms in solving multi-objective optimization problems, such as, weight coefficient change method, parallel selection method, arrangement selection method, shared function method and mixed method [31]. In order to facilitate programming complexity, meanwhile satisfy the simultaneous reorganization of traffic and parking demands, the parallel selection method is adopted in this research. The specific programming process is as follows:

1) CODING OPERATION

In this study, genes are initialized utilizing the real-number encoding method to encode various candidate parking garages. The coding sequence of parking garages is $1, 2, 3, 4, \ldots m$.

2) GENERATING AN INITIAL POPULATION

Every chromosome consists of various genes, corresponding to possible solutions of public parking garage sets. The initial genes of public parking garage sets are randomly selected. For instance, if there are 30 candidate public parking garages, numbered as 1, 2, 3 . . . 28, 29, 30, the chromosome could be defined as {1,3,7} or {1,2,9,10,30}, etc.

3) DEFINING THE FITNESS FUNCTION

The fitness function is used to evaluate the solution results in GA. As we described in *section 3.1,* the purpose of the optimized public parking location model is to optimize the CO_2 emission amount for the whole traffic network. Such fitness function is expressed as below:

$$\text{Min Z} = \sum_k D_k \cdot f\left(\frac{L_k}{t_0\left[1+\alpha\left(\frac{x_k}{c_k}\right)^{\beta}\right]}\right) \cdot L_k \tag{16}$$

which is subject to the flow constrains and road constrains

$$\text{st.}\ \begin{cases} \sum_k f_k^{ij} = Q_{rs} \\ f_k^{ij} \geq 0 \\ D_k \leq C_k \end{cases}$$

where, f_k^{ij} represents the traffic flow from i to j on road segment k; Q_{ij} represents the total flow from i to j;

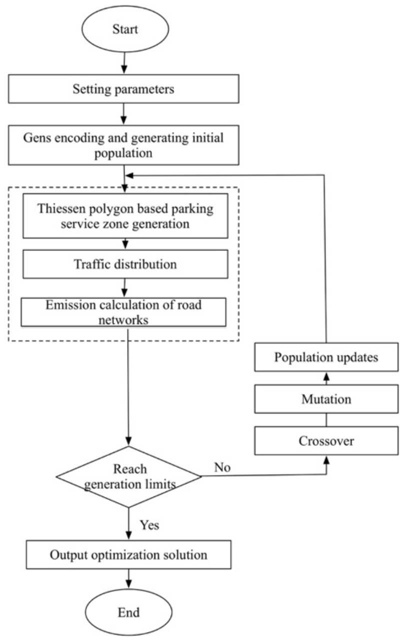

FIGURE 8. **The flow of genetic algorism steps.**

4) POPULATION SELECTION

The purpose of the population selection is to choose a better individual form of initial parking garage coordinates group, and act as a parent for the next generation. The criterion for judging the superiority of the individual is the result of fitness function of each solution set. The better fitness value of an individual, the greater probability of it to be selected for next generation.

5) CROSSOVER

Due to the effect of the replication among generations, the coordinate solution in the mating pool have reduced the average emission amount of the entire system. As the replication process did not produce a new set of coordinates, the fitness of the best individuals in the group will not be decreased. The crossover process is acting on two population groups, which are randomly selected from the mating pool. By selecting parking garages set group with better individuals, the final generation will contain the best legacy of the parent strings.

6) MUTATION

For each public parking garage in a chromosome, mutation will be performed with the same probability. For instance, the current value of one gene is 0 means this parking garage will not be selected in the population group. If mutation happens, the value would be changed to 1, which means it has some opportunity to be selected for the next iteration.

To sum up, as shown in Fig. 8, the steps of using GA to achieve the optimized CO_2 emission of the traffic network are as follows:

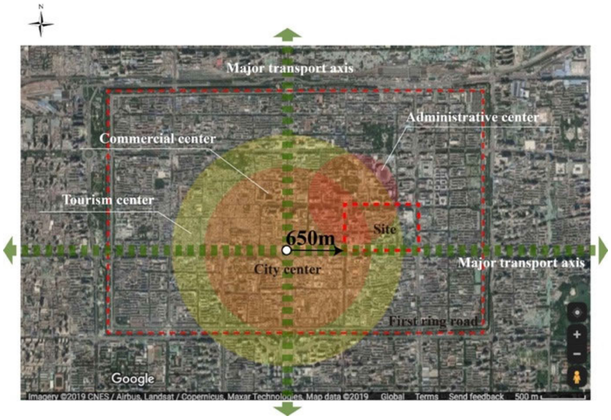

FIGURE 9. Location of the sample site.

Step 1: Initialization. Set population size, chromosome length, number of iterations, crossover probability and mutation probability.

Step 2: Applying binary integers for coding of each public parking garage coordinates and randomly generate the initial population.

Step 3: Calculate the fitness function of each generation with iterative approaches. This approach is separated by three parallel parts, namely Thiessen polygon based zoning, traffic assignment and emission calculation. Sort all individuals from parental generations and select the better individuals and eliminate inferior individuals to produce a new population of public parking sets.

Step 4: Based on the crossover probability, perform a crossover between individuals with random connections. Perform mutation on individual parking garage based on sited probability of mutation.

Step 5: Confirm whether achieved the maximum iteration number or not. if Yes, output the optimal solution of public parking garage locations. Otherwise, return to step 3 for the next round of iterative calculations.

IV. CASE STUDY

Fig. 9 shows a sample site near the Bell Tower center and Jiefang commercial center, downtown of Xi'an, Shaanxi, China, which is a popular historical site of the Ming Dynasty, with high-intensity of land use and obvious public parking shortage. In such areas, the traffic flows are significantly exceeded their parking and road capabilities, and make it prone to heavy congestion with slower or fluctuated traffic speeds, which results in higher CO_2 emissions. The limited constructible space makes the available new public parking locations vital to relief congestion.

To build a reliable parking model, we converted Fig. 9 into a simplified road map (as shown in Fig. 10), and conducted a site survey for the existing public parking garage (PPG) from June 1^{st} 0: 00 am to June 30^{th} 23: 59 pm, 2017. Table 1 shows several samples from the total of 11,159 parking data

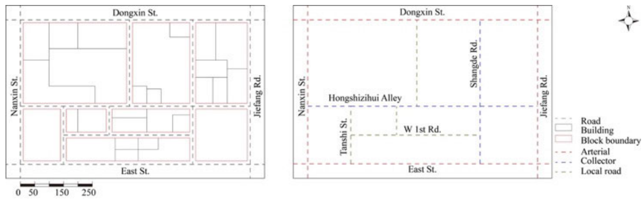

FIGURE 10. Road map of the sample site.

TABLE 1. Occupation of public parking space.

Car License	Space No.	Park in Time	Check Out Time	Parking Duration
SHAAN AT1B6*	1	06/01/2017 08:00:16	06/01/2017 09:23:39	1h 23min 23s
SHAAN AL6B5*	5	06/01/2017 08:01:36	06/01/2017 08:18:48	0h 17min 12s
WAN KH192*	6	06/01/2017 08:09:15	06/01/2017 10:39:13	2h 29min 58s
SHAAN A87ET*	2	06/01/2017 08:14:37	06/01/2017 09:59:34	1h 44min 57s
SHAAN V3928*	3	06/01/2017 08:18:19	06/01/2017 12:33:16	4h 14min 57s
SHAAN AGL65*	7	06/01/2017 08:30:54	06/01/2017 09:09:45	0h 38min 51s
SHAAN A71M2*	11	06/01/2017 08:32:05	06/01/2017 17:10:31	8h 38min 26s
SHAAN AQA29*	12	06/01/2017 08:32:26	06/01/2017 20:43:42	12h 11min 16s
SHAAN H0A00*	4	06/01/2017 08:33:27	06/01/2017 09:29:17	0h 55min 50s
SHAAN A89BY*	8	06/01/2017 08:37:33	06/01/2017 08:46:48	0h 09min 15s

(Note: Here SHAAN and WAN in the car licenses are Chinese province abbreviations. To protect personal privacy, the last number of the car license has been replaced by *.)

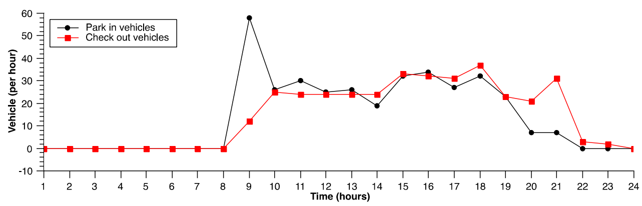

FIGURE 11. Public parking utility information on 1th June.

collected from PPL No. 1-01-0-0148,[2] including parking in time and checking out time of each individual vehicles. Based on these huge amounts of statistical data of public parking behaviors, the turnover rate and parking occupancy rate are determined for the future simulation purpose. As indicated in Fig. 11, we specifically study the impact of public parking location on the parking demand and traffic flow during the challenging morning peak hour (8: 00 a. m. to 9: 00 a. m.).

As clearly shown in Fig. 11, during the morning peak period, most cars are rushing into the public parking spaces, whereas the outgoing flow is relatively negligible. Therefore, without losing generality, during the morning peak hour,

[2]Official ID provided by 54. M. a. G. -i. S. Shaanxi Bureau of Surveying. 2017; Available from: http://www.shasm.gov.cn/; and http://sn.ifeng.com/a/20170712/5813237_0.shtml.

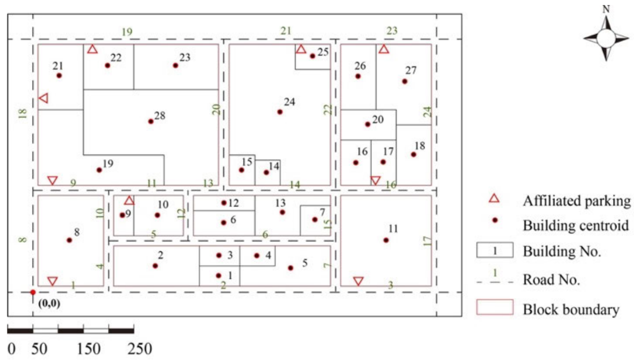

FIGURE 12. Map of building and affiliated parking garage.

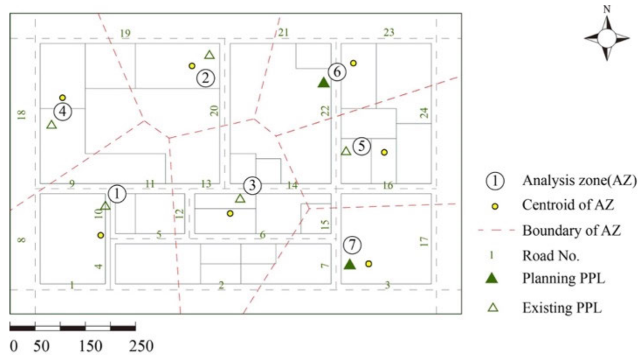

FIGURE 13. Map of buildings and their affiliated parking garages.

TABLE 2. Information of buildings and their affiliated parking space.

Building ID	Land use type	Land use area (m^2)	Affiliated parking lot amount	Parking exist to road No.	Coordinate of centroid X	Y
1	official	3,522			370	30
2	commercial	10,000			245	50
3	residential	4,383			370	70
4	residential	6,153			445	70
5	residential	29,443			513.28	45.17
6	education	24,809			380	135
7	official	12,556			560	140
8	commercial	127,922	639	1	75	100
9	commercial	49,125	245	11	180	150
10	residential	56,407			250	150
11	hospital	97,999	900	3	700	100
12	commercial	29,545			380	175
13	residential	7,953			495.71	154.28
14	official	16,036			465	235
15	commercial	21,889			415	240
16	commercial	21,738			640	255
17	residential	10,878	55	16	695	255
18	commercial	34,638	0		755	270
19	commercial	118,176	590	9	135	240
20	official	10,872			665	330
21	commercial	7,373	37	18	55	425
22	education	9,199	30	19	150	445
23	commercial	64,707			285	445
24	residential	107,925			491.28	354.57
25	commercial	27,152	135	21	555	465
26	commercial	19,459			645	425
27	commercial	122,000	610	23	737.56	414.76
28	residential	95,769			235	335

TABLE 3. Road information.

Road ID	Road Type	Design Speed (km/h)	Capacity (pcu/h)	Length (m)	Time (s)	Start Section	End Section
1	A	50	3,600	150	3	1	2
2	A	50	3,600	450	9	2	3
3	A	50	3,600	200	4	3	4
4	L	20	1,200	100	5	2	5
5	L	20	1,200	160	8	5	6
6	L	20	1,200	290	14.5	6	7
7	C	30	2,400	100	3.3	3	7
8	A	50	3,600	200	4	1	8
9	C	30	2,400	150	5	8	9
10	L	20	1,200	100	5	5	9
11	C	30	2,400	160	5.3	9	10
12	L	20	1,200	100	5	6	10
13	C	30	2,400	70	2.3	10	11
14	C	30	2,400	220	7.3	11	12
15	C	30	2,400	100	3.3	7	12
16	C	30	2,400	200	6.67	12	13
17	A	50	3,600	200	4	4	13
18	A	50	3,600	300	6	8	14
19	A	50	3,600	380	7.6	14	15
20	C	30	2,400	300	10	11	15
21	A	50	3,600	220	4.4	15	16
22	C	30	2,400	300	10	12	16
23	A	50	3,600	200	4	16	17
24	A	50	3,600	300	6	13	17

(Note: In the column of 'Road Type' in Table 3, A, L, and C represent arterials, local roads, and collectors respectively; Here, all roads listed here are two-way road, with two directions.)

we directly use the incoming flow to derive the net flow function as below:

$$D_k' = FD_k - GA_k^w \times OR_w \times TR_w - GP_k^l \times U_{pk} \times T_{pk} \quad (17)$$

according to the previously discussed traffic statistics, the following parameters are chosen as: F = 0. 7, OR_w = 0. 5, TR_w = 2. 0∼3. 0; Here, we assume GP_k^l in saturated condition in Table 2, thereby $U_{pk} = 1$, $T_{pk} = 1$.

The parking demand function is:

$$GP_k^l = \sum_{l=1}^{l} \frac{PD_i - GA_k^w \times TR_w}{OR_m \times TR_m} \quad (18)$$

where $PD_i = PG_c \times A_c$. When $c = 1$, $PG_1 = 0.3$; $c = 2$, $PG_2 = 2.3$; $c = 3$ $PG_3 = 1.2$; $c = 4$, $PG_4 = 0.7$; $c = 5$, $PG_5 = 0.5$; $c = 6$ $PG_6 = 0.8$; $c = 7$, $PG_7 = 0.6$, $c = 8$, $PG_8 = 0.6$, *per* $1000m^2$ area at the peak- hour [45]. Taking $c = 8$ as an example, PG_8 will generate 0.6 vehicle parking demand within a $1000m^2$' hospital building at the peak hour.

Next, we would like to introduce the mathematical modelling for trip generation, parking allocation and traffic distribution in dynamic zoning. Fig. 12 shows the building information of the sample district. In this district, there are 28 buildings, 10 of which have affiliated parking garages.

The lower left corner of the road section is defined as the coordinate origin. Based on this point, the coordination of each centroid is marked, as shown in Table 2. By implementing building information into modeling, the centroid point of each building is considered as the feature point.

Fig. 13 shows the candidate public parking garages. In this example, we assume that there are in total of 5 existing

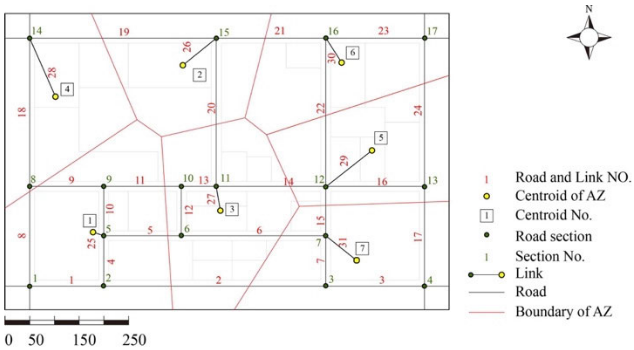

FIGURE 14. Connecting analysis zones to the road networks.

TABLE 4. Road sections information.

Road section NO.	Coordination of section	
	X	Y
1	0	0
2	150	0
3	600	0
4	800	0
5	150	100
6	310	100
7	600	100
8	0	200
9	150	200
10	310	200
11	380	200
12	600	200
13	800	200
14	0	500
15	380	500
16	600	500
17	800	500

public parking garages and 2 awaiting for construction can be selected for the best traffic performance in the network. In this case study, we take the maximum sites of 7 for the optimized performance. Based on the locations of these green triangles, 7 separate Thiessen Polygons are created as parking analysis zones. The information of each polygon is represented by their centroid, the yellow dot. More details of the roads' information of Fig. 13 is listed in Table 3.

Furthermore, the information of road sections of Fig. 14 is also listed in Table 4.

Table 5 provides basic information of these 7 public parking garages and their polygons.

The link is created from the centroid of AZ to the nearest road section, as shown in Fig. 14. All the traffic flows generated within AZ are distributed through links to the road networks. Based on the generated links, their length and locations of centroids are measured, as shown in Table 6.

In this example, a total of 7 centroids of polygons are considered as feature points for the traffic assignment and are connected via different links. The feature of 7 links among 7 public parking and 24 roads scenarios are shown in Fig. 15.

TABLE 5. Information of public parking garages and road networks.

PPL /Poly gon ID	Max Capa city	Coordination Centroid of PPL		Exit on Road NO.	Coordination Centroid of Polygon	
		X	Y		X	Y
1	20	140	166.12	10	129.67	106.72
2	30	346.44	468.15	19	314.54	445.32
3	30	408.42	183.81	14	388.62	149.57
4	30	31.44	328.88	18	53.93	381.47
5	20	619.52	278.67	22 S to N	694.72	271.89
6	20	576.87	407.73	22 N to S	634.00	449.65
7	40	626.00	47.23	7	664.17	50.99

TABLE 6. Link information for traffic distributing.

Link ID	Length (m)	Cent roid ID	Coordination		Sect ion ID	Coordinatio n	
			X	Y		X	Y
25	21.42	1	129.67	106.72	5	150	100
26	85.28	2	314.54	445.32	15	380	500
27	51.16	3	388.62	149.57	11	380	200
28	130.22	4	53.93	381.47	14	0	500
29	118.92	5	694.72	271.89	12	600	200
30	60.75	6	634.00	449.65	16	600	500
31	80.74	7	664.17	50.99	7	600	100

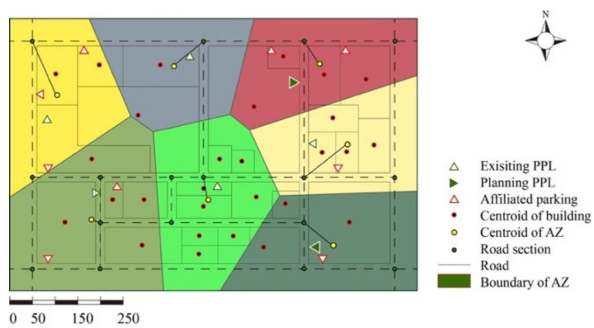

FIGURE 15. Dynamic zoning and modeling.

Although a downtown area is chosen in this case study, but it will be easily expanded to other constrained optimization models. As shown in Fig. 15, the basic approach of our research is to divide the study area into Thiessen polygon formed parking analysis zones. Based on these zones, the traffic distributions and parking demands will be achieved to further alleviate the congestion and carbon emissions.

In this study, according to the previous calculation process, if there are more than 7 parking candidates, the computing complexity will be a way too high. This will, in effect, result in a poor search efficiency because of the large amount of potential calculations.

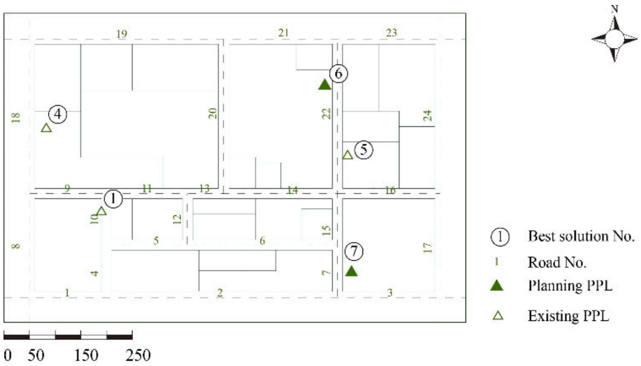

FIGURE 16. Optimal parking garage selection result.

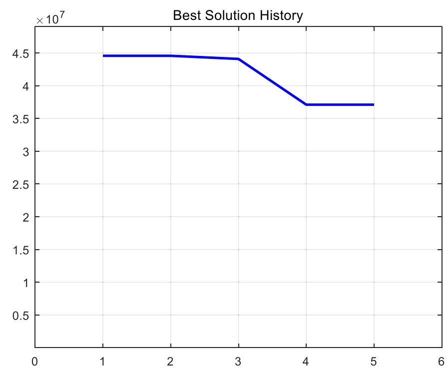

FIGURE 17. Carbon Emission Reduction through various PGA iterations.

We conducted the dynamic zoning process and traffic distributions through MATLAB (MATrix LABoratory) programming (MATLAB 2016a). The computing environment is the Microsoft Windows 7, with 2.6 GHz Intel Core i7 central processing unit (CPU), and the graphics processing unit (GPU) is Intel HD Graphics 4000 (1536 Mb). The optimal public parking allocations are achieved via the Partheno-Genetic Algorithm (PGA) that was discussed in section 3, as shown in Fig. 16. From the total 1-7 available parking sites, [4,1,6,5,7] are finally chosen as the best 5 parking locations.

Fig. 17 shows the effect of Carbon emission reduction through various PGA iterations. It can be clearly observed that several rounds of PGA optimizations are needed to achieve the best traffic and carbon emission alleviation result. In this simulation, the carbon emission amount has been slightly dropped after the first several rounds of optimization, and reached the best rest after the 4th round iteration and no further improvement after that. Through this case study, it seems that an appropriate number of iterations for the best overall performance is expected and will be a very interesting and realistic topic for future studies.

V. CONCLUSION

This paper proposes an optimal parking site selection scheme to alleviate CO_2 emission of the traffic flows in green urban road networks. Through the dynamic traffic zone programming, a constrained optimization model has been set up to assess the impact of alternative public parking locations on road traffic emissions. In each scenario, Thiessen Polygon-based zoning method has been applied to investigate the distributions of road traffics. A case study example is then discussed to verify the proposed public parking location (PPL) assignment is an optimizedrealistic solution for green intelligent transportation systems (ITS).

The main contribution of this study is as follows. Firstly, this proposed model takes the CO_2 emission of the whole traffic network as the optimization goal instead of the traditionally discussed distance or cost efficiency. Hence, a better PPL solution could be provided for congestion relief in sustainable smart city development. Secondly, a Thiessen polygon based public parking zoning method is developed and implemented realistically. This zoning method provides a precise approach to traffic distribution and parking demand estimation. Rather than the quadrilateral or radial zoning, this method pays more attention to the parking supply demand and its impact on parking congestion. More importantly, the nearest neighbor principle of Thiessen polygon is used for optimization. The commonly used goal of shortest distance could be achieved through fitness functions. This amelioration is vital to improve calculation efficiency for the complicated optimization research. Thirdly, the genetic algorithm (GA) is used to find the optimal PPL sets. GA has a great application value in speeding up stochastic search for global optimization. It is especially suitable to simulate complex and large capacity problems concerning the realistic solutions. Last but not least, this research also shines a new light on an evidence for static traffic with a strong ability to influence the dynamic traffic flow. Especially in terms of congestion control, this dynamic zoning method could be explored to a wider scale for real-time traffic inducement. With the real-time traffic information provided by the roadside sensors of ITS, the dynamic zoning based parking guidance would have potential to promote traffic system performances under the support of smart city infrastructures. By implementing the dynamic zoning and modelling method into intelligent transportation system, the efficiency of parking induction and dynamic optimization of traffic distribution could be ensured for the future smart mobility.

APPENDIX

Abbreviations	Full name
α, β	retardation factors
μ	expected value
θ	traffic conversion parameter
ω_q	ratio of the q^{th} OD pair allocated flow on k
ς	coefficient of gravity model
A_c	area of land use type c
a, b	intersection number

c	land use category (c∈1=residential, 2=commercial, 3=official, 4=entertainment, 5= education, 6=industrial, 7=public facility, 8=hospital usages)
C_r	road capacity of r
C_k	road capacity of k
D_k^{ij}	flow form i to j assigned on k(pcu/h)
D_k	total flow assigned on k flow of zone to zone trips allocated on road k in total
D'_k	net flow on k
D_k^q	flow of q^{th} OD pair allocated on the k^{th} segment
E	CO_2 emission rate of the average speed
$f(I_{ij})$	impedance form *i* to *j*
F	percentage of the usage of cars over the total of all traffic tools
GP^l_k	capacity of public parking lot *l* with an entrance on k
GA^w_k	capacity of the affiliated parking lot *w* with an entrance on road k
H_k	number of routes through the k^{th} road segment
H_{ab}	total number of road a-b has been allocated with flow by total cross zone trips
i	i^{th} Thiessen polygon defined analyzing zone
j	j^{th} Thiessen polygon defined analyzing zone
K	Set of road segments
k	k^{th} road segment cut by the boundary of M'on r
L_r	length (m) of road r
L_k	length (m) of road segment k
m	m^{th} feature point of public parking lots (PPL), m∈M
M	Set of PPL
M'	set of PPL defined Thiessen polygons, M= {1,2, 3...i…j...l...m'}
m'	m'^{th} feature point of Thiessen polygons, m'∈M'
MK_k	number of public parking lots with entrance on road K
N	set of road intersections; N= {1,2,3,a…b…n}
n	n^{th} road intersection, n∈N
O_{ij},	flow form i to j
OA_{ij}	from i to j the probability of ∀SA route to be chosen
OR_m	peak-hour occupancy rate of public parking space
OR_w	peak-hour occupancy rate of affiliated parking space
PG_c	parking generation rate of c
q_{ij}	*q^{th} trip generated from zone i to zone j*
q	q^{th} *OD* pair
Q	total number of OD pairs
R	set of roads
r	r^{th} road defined by intersections, r∈R
r_0	road impedance factor
SA_{ij}	from i to j, the number of alternative routes
$t_k(D_k)$	time spend passing through k of V_k flow
TA_c	trip attraction rate of c at peak hours
TA_j	trip attraction amount of zone j
TG_c	trip generate rate of land use type c at peak-hours
TG_i	trip generation amount of zone i
TR_m	turnover rate of public parking space
TR_w	turnover rate of affiliated parking space
V_r	average traffic speed pass through *r*
V_k	average traffic speed pass through *k*
(x^m, y^m)	coordinates of m^{th} PPL
Z	network emission level

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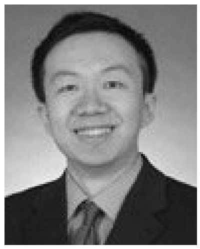
TONG SHEN received the master's degree in architecture from University College London (UCL) in Urban Design. She is currently pursuing the Ph.D. degree with the School of Architecture, Chang'an University, Xi'an, China, under the supervision of Prof. J. Liu. She is currently participating in the research project named "City-Wide Analysis to Propel Cities Towards Resource Efficiency and Better Wellbeing" funded by the National Natural Science Foundation (NSFC), China, and the Engineering and Physical Sciences Research Council (EPSRC), U.K. Her research is mainly focused on the method of integrating transportation, building, landscape activities, as well as reevaluate transportation and its associated urban fabric for sustainable urban planning. She took her internship at the China Academy of Urban Planning and Design (CAUPD), in 2011.



KUN HUA received the B.Sc. (Hons.) and M.Sc. degrees in electrical and computer engineering from the Xi'an Jiaotong University, China, in 1999 and 2004, respectively, and the Ph.D. degree in computer and electronic engineering from the University of Nebraska Lincoln, Nebraska, NE, USA, in 2008. He is currently an Associate Professor with the Electrical and Computer Engineering Department, Lawrence Technological University, Southfield, MI, USA. He continued his research at the University of Nebraska Lincoln as a Postdoctoral Researcher, in 2009. His current research interests are in the areas of wireless communication and multimedia signal processing. He is the chair and also a committee member of several conferences. He is a recipient of the Best Paper Award of the ACM ANSS 2011 and another of his paper is nominated as the Best Paper in the IEEE BCGIN 2011. He has served as a Guest Editor in several special issues for the *International Journal of Distributed Sensor Networks*.

JIAPING LIU received the master's degree in science of building technology from the Xi'an University of Architecture and Technology, in 1986, and the Ph.D. degree in science of architecture technology from Chongqing University, in 1998. He is currently the Director of the Green Building R&D Center, Xi'an University of Architecture and Technology, and the Dean of the School of Architecture, Xi'an University of Architecture and Technology. He is the Academician of the China Academy of Engineering (CAE). His current research interests include city-wide technical analysis to propel environmental resource efficiency and better wellbeing. His laboratory research interests focus on supporting fundamental and applied research related to low carbon cities, smart cities, low carbon transportations for the purpose of promoting a sustainable city, and livable urban environment. His research findings have been applied in urban development in worldwide, and the awards and honor include the National Award for Science and Technology Progress, the World Habitat Awards, and the Prize for Scientific and Technological Progress from The Ho Leung Ho Lee Foundation.