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An asymptotically optimal public parking lot location algorithm based on intuitive reasoning

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Abstract: In order to solve the problems of road traffic congestion and the increasing parking time caused by the imbalance of parking lot supply and demand, this paper proposes an asymptotically optimal public parking lot location algorithm based on intuitive reasoning to optimize the parking lot location problem. Guided by the idea of intuitive reasoning, we use walking distance as indicator to measure the variability among location data and build a combinatorial optimization model aimed at guiding search decisions in the solution space of complex problems to find optimal solutions. First, Selective Attention Mechanism (SAM) is introduced to reduce the search space by adaptively focusing on the important information in the features. Then, Quantum Annealing (QA) algorithm with quantum tunneling effect is used to jump out of the local extremum in the search space with high probability and further approach the global optimal solution. Experiments on the parking lot location dataset in Luohu District, Shenzhen, show that the proposed method has improved the accuracy and running speed of the solution, and the asymptotic optimality of the algorithm and its effectiveness in solving the public parking lot location problem are verified.

Key words: intuitive reasoning; selective attention mechanism; quantum annealing algorithm; Quadratic Unconstrained Binary Optimization (QUBO) model; parking lot location

1 Introduction

The rapid increase of private cars and the unbalanced development of the city have led to traffic congestion, difficult parking, and parking chaos. Therefore, the rational planning and construction of parking lots has become an urgent problem to be solved. The facility location problem is one of the classic problems in operations research, which aims to determine the location and number of facilities in the target area and to satisfy certain constraints so that the target is optimal. There are many factors that affect the location of the parking lot, such as walking distance and site area. Considered from the perspective of operations research, this is a multi-objective multi-constraint combinatorial optimization problem of the NP-hard type, which aims to minimize or maximize the objective in order to determine the specific site location[1].

With the development of technology, more and more intelligent algorithms are used to solve such problems. However, neither intelligent algorithms nor Machine Learning (ML) algorithms can well solve the situation of weak common sense cognitive ability, poor robustness, high dimensionality of solution space, diverse objectives, and incomplete data samples[2]. In order to build strong Artificial Intelligence (AI) with human thinking level, the method of building intuitive reasoning ability becomes an important research direction of future AI. AlphaGo is a current case of successful application of intuitive reasoning[3, 4].

Ding et al.[3] and Zheng et al.[5] mentioned that the human brain's understanding of non-cognitive factors

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comes more from intuition and is influenced by experience and long-term knowledge accumulation, which has an extremely important role in human understanding of the physical environment and behavioral interactions. Humans with intuition can make quick and efficient decisions in complex environments, and intuition can largely reduce the search space in the process of problem solving and make the human cognitive process more effective. Therefore, this paper introduces the Selective Attention Mechanism (SAM) inspired by intuition. The selective attention mechanism[6] shows that successful selection of relevant information not only requires effective activation of target information, but also includes active suppression of invalid information to facilitate efficient decision making. It follows that it is feasible to make reasonable use of SAM to reduce the search space and provide search directions for the algorithm. In this paper, guided by the concept of intuitive reasoning, SAM is used to focus on core data and ignore non-important data to narrow the search scope and give the system attention.

During the process of human growth, through learning, common sense, and experience, a decision space is formed in the brain when observing things. The brain then makes random search decisions in the decision space and reacts intuitively once it matches with the current cognitive model. The role of intuition in this process can be considered as guiding the search decision and for the construction of the cost space in the computational process[7]. When the solution space of a solved problem is complex and non-convex[8], traditional intelligent algorithms are likely to fall into local minimums. Constructing brain-inspired intuitive reasoning methods will avoid the local minimal value problem and improve the generalization ability of artificial intelligence systems. The process of human brain reasoning is to obtain the global optimal solution under various constraints, and the intuitive response made by the brain is considered as a search for the global optimal solution in a complex search space. Then the intuition can be considered as the initial position of the solution, which determines whether the final result is a globally optimal solution or not[9].

In order to achieve this performance, Quantum Annealing (QA) algorithm is used in this paper as a method to search for the global optimal solution by exploiting the quantum tunneling effect[10], which can penetrate the energy barrier to reach the lower energy ground state, so that it has the ability to approximate the global optimal solution beyond the local suboptimal solution[11]. From the perspective of solution space search, QA can overcome the poor robustness and sensitivity to initial points of traditional ML compared to traditional ML algorithms. A large number of applications have been realized using the advantages of quantum annealing, such as traffic optimization[12–15], quantum chemistry[16, 17], and resource scheduling[18].

Traditional solutions to parking lot location problems usually first establish different optimization objectives, and then search the solution space using intelligent algorithms[19–22]. In this paper, we take public parking lot location as an example, and based on the currently available public parking lot location data, we consider to build a combinatorial optimization model using parking demand points (Points of Interest (POI)), possible parking locations, and the location relationship between parking lots. SAM and QA are proposed to construct the solution model under the guidance of intuitive reasoning idea. Where, SAM is used to reduce the search space, while QA is used to ensure the search efficiency and search for the optimal solution in the solution space.

2 Asymptotically optimal public parking lot location algorithm based on intuitive reasoning

Theoretical studies and classical simulations have shown that QA algorithms[23] in quantum algorithms can provide significant improvements in terms of algorithm running time and solution quality for some NP-hard problems that cannot be solved well by classical methods. QA, a heuristic technique for finding low-energy configurations of complex Ising models, belongs to a restricted form of adiabatic quantum computing[24] and has received a lot of attention as a new computational paradigm for solving classical optimization problems. In addition, this paper introduces the idea of SAM based on real-world parking experience in the spatial dimension, where selection attention rules are formulated to filter and optimize location data more rationally. It enables us to focus our attention on the data with strong influence relationship with the target point, reduce the solution space, and provide the search direction for QA.

2.1 Model structure

This paper is based on the real latitude and longitude data of Luohu District provided by Shenzhen government data open platform[25]. The input data include parking demand points, possible parking locations, existing parking lot locations, and their parking capacity. Luohu District covers an area of about 80 km^2, and it is impossible to directly calculate all the data in the area with limited computing resources. Therefore, firstly, based on the idea of distributed computing, the whole area is first processed in partitioned blocks. By this way both computational resources can be saved and the relationship between influential data can be better focused. Then the proposed algorithmic model is applied to each partition separately to obtain the new optimal parking location.

The basic structure of the model is shown in Fig. 1. Before modeling each partitioned data, SAM is applied to focus on important data points, which are automatically filtered and optimized by SAM. A multi-objective Quadratic Unconstrained Binary Optimization (QUBO) model is established based on the location relationship between different data points, and the QUBO model is solved using the Qbsolv toolkit, i.e., new location results are obtained by simulating QA's propensity decision for low energy states. Based on the calculation results, the facility location is updated and the selective attention points are updated using the new facility location based on SAM rules. The facility location is updated according to the results. And based on SAM rules, selective attention points are updated by using new facility locations.

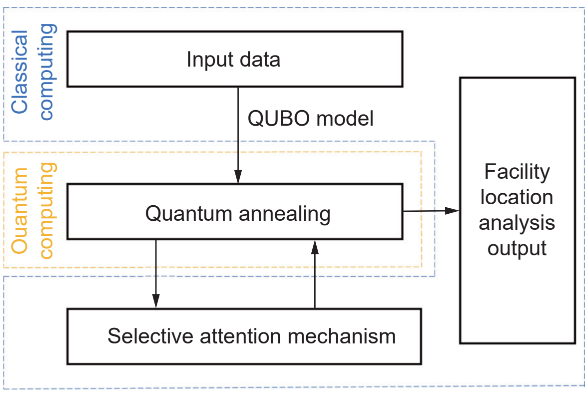


Fig. 1 Basic structure of the model.

The above steps are repeated until the objective function converges, and the final result is the location of the proposed new parking lot in the region.

2.2 Model description

Due to the wide distribution of data areas, regional segmentation of the data is considered. Because each sub-region data are not independent events from each other, which is interrelated and affect each other, it is advisable to use overlapping regions to show the correlation between data from different regions. That is, the whole data area is divided into overlapping circular areas with a radius of 1 km. When dividing the regions, it is necessary to convert meters into latitude and longitude. On the longitude line, the actual distance is about 111 km for each degree difference in latitude; on the latitude line, the actual distance is $111\times\cos\theta$ km for each degree difference in longitude, where θ denotes the latitude. The division scheme of the data area is shown in Fig. 2, where the longitude range: 114.08°–114.19° and the dimensional range: 22.53°–22.59°.

After dividing the experimental data region, the most important aspect of the algorithm is how to build the QUBO model and optimize model combined with QA and SAM. And then the results of each optimization can be obtained by Qbsolv quantum simulation to

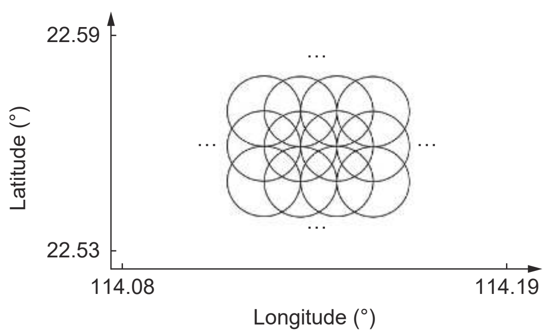


Fig. 2 Data area division scheme.

calculate the location of the facility.

Assume that the set of all possible parking location coordinate points in the test area is $\{v_i\}$, and the number of possible parking locations is $N(i \in \{1, 2, \ldots, N\})$. The binary variable q_i indicates that whether the i-th possible location is a new parking lot location. q_i is 1 when the location is a new parking lot location, otherwise q_i is 0. The set of all new parking locations in the current area is denoted by C_a. Then the following expression Eq. (1) is given.

$$q_i = \begin{cases} 1, \ v_i \in C_a; \\ 0, \ v_i \notin C_a, i \in \{1, 2, \ldots, N\} \end{cases} \tag{1}$$

Figure 3 specifically gives a schematic diagram of some of the variables used in some formulations in this paper. And two overlapping circles C_a and C_a' represent two overlapping test regions with radius approximately equal to 1 km. $\{v_i\}$ is the set of all possible parking lot location points, $d_{ii'}$ is the walking distance between two new parking lots v_i and v_i', d_{it} is the walking distance between new parking lot location v_i and POI v_t, d_{ie} is the walking distance between new parking lot location v_i and existing parking lot location v_e, T is the number of locations of POIs, and E is the number of existing parking lot locations, and

$$\begin{aligned} & t \in \{1, 2, \ldots, T\}, \\ & e, e' \in \{1, 2, \ldots, E\}, \\ & i, i' \in \{1, 2, \ldots, N\} \end{aligned} \tag{2}$$

It should be noted that all distances used in this article are walking distances unless otherwise specified. Typically, walking or driving distances are more effective and realistic in characterizing the distribution of latitude and longitude coordinate points, and match urban roads compared to Euclidean distances. In addition, in the context of parking location, drivers find the location of the parking lot and then reach the area of interest generally by walking. Therefore, the paper calculates the walking distance by the OSMnx software package.

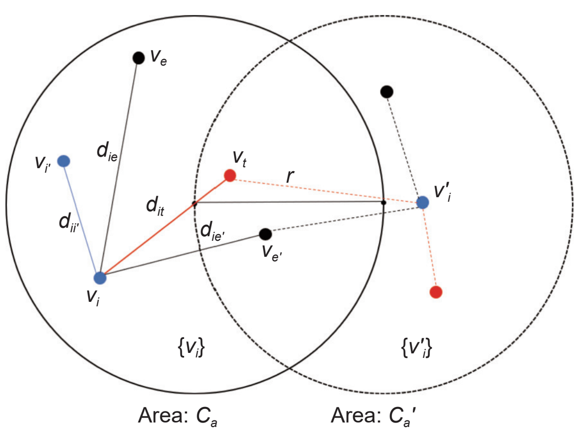


Fig. 3 Diagram of variables.

2.2.1 Selective attention rules

Selective attention rules are developed based on people's real-life experience to filter the data that need to be paid attention to in each step of the algorithm's solution. First, from the perspective of walking distance, by observing people's travel experience, it may be assumed that people's willingness to travel decreases when the walking distance from the parking lot to the area of interest is more than 1 km. That is, if there is no new parking location within 1 km of any POI location, that POI location will not be selected as the selective attention point, otherwise it will affect the constraint relationship between the new parking location and other POI locations. In addition, one of the optimization objectives in this paper is to make the planned parking location as far away from the existing parking location as possible, so that the parking lot covers a larger area. However, if the location is far enough away, it needs not be considered, thus allowing computing resources to be focused on the primary data. Therefore, existing parking lots 1 km away are not considered as selective attention points. The above rules are expressed in Formula (3).

$$\begin{cases} v_i \in \{u_k\}, \ |d_{it}| < 1000 \text{ m}; \\ v_e \in \{u_k\}, \ |d_{ie}| < 1000 \text{ m}; \\ v_i, v_e \notin \{u_k\}, \ \text{others} \end{cases} \tag{3}$$

where $\{u_k\}$ denotes the set of selective attention points, which is a subset of $\{v_i\}$.

Secondly, it is considered from the perspective of the maximum number of parking lot capacity. Excluding parking lot locations with a capacity of less than 50 and more than 600, and the remaining parking lot locations are used as selective attention points. Because, too many or too few parking spaces are rare and not representative. It can be expressed as shown in Formula (4).

$$\begin{cases} v_e \in \{u_k\}, & 50 < \text{total}_{v_e} < 600; \\ v_e \notin \{u_k\}, & \text{others} \end{cases} \tag{4}$$

where total_{v_e} denotes the maximum number of parking spaces that can be accommodated in parking lot v_e.

Thirdly, the location relationship was analyzed between new parking lots. In the experimental data area, if the number of parking lots already existing within 500 m ($|d_{it}|, |d_{ie}| < 500\,\text{m}$) around any planned new parking lot exceeds the number of the area of interest by more than 10 times, based on the actual scenario, it may be assumed that the number of parking lots in the location's nearby is sufficient to meet the demand, no new parking lots are needed, and the location of the proposed parking lot can be reduced by one on the original basis. In addition, if there is no POI within 500 m of any planned new parking lot, it can be assumed that the location will not be used as a new parking lot, and the number of parking lots to be planned will be reduced by one on the original basis. Similarly, if the number of POI within 500 m of any planned new parking lot exceeds half the number of existing parking lots, a new parking lot location will be added. The formula is shown in Formula (5).

$$\begin{cases} M-1, & 10T < E \text{ and } |d_{it}|, |d_{ie}| < 500\,\text{m}; \\ M-1, & v_i = 0 \text{ and } |d_{it}| < 500\,\text{m}; \\ M+1, & T > E/2 \text{ and } |d_{it}|, |d_{ie}| < 500\,\text{m}; \\ M, & \text{others} \end{cases} \tag{5}$$

where $M\,(M \in (0, N])$ is the number of parking lots to be planned.

It is worth noting that the above rules of selective attention points are all built for the scenario of parking lot location, which is inclined to the judgment rules of human brain in the actual scenario. If the algorithm is applied to other scenarios, we can also build rules of selective attention points for the corresponding scenarios.

2.2.2 QUBO model construction

Problems solved using D-Wave systems generally need to be modeled as Ising models or QUBO models, which represent the energy of the system. In most cases, the lower the energy of the model (the objective function), the better the solution and the closer to the global optimal solution. There is very little difference between them, and the QUBO model is used to build the objective function in this paper. The objective function for the QUBO problem is shown in Eq. (6).

$$E_{qubo}\left(a_i, b_{i,j}; q_i\right) = \sum_i a_i q_i + \sum_{i<j} b_{i,j} q_i q_j \tag{6}$$

The scalar representation is used in the calculations unless otherwise specified, where a_i and b_i are the linear bias and coupling strengths, respectively. Based on Eq. (6), multiple optimization objectives are built according to the distance relationship between different location data.

Firstly, the location relationship between the proposed new parking lot and the POI is considered. In real life, we always want the distance between the parking lot and the POI to be as close as possible to reduce the travel distance between us and the destination point. Therefore, for each new parking lot, the walking distance between that location and all POIs in the area needs to be minimized. At this time, the average distance can be expressed in the form of the function shown in Eq. (7).

$$h_1(q_i) = \frac{1}{T}\left(\sum_{t=1}^{T} d_{it} q_i\right) \tag{7}$$

Secondly, the location of the proposed new parking lot in relation to the existing parking lot is considered. In order to make the construction of the parking lot to cover a wider area range to increase the utilization of the parking lot, we want to make the distance between the existing and new parking lots as far as possible, that is, to maximize the distance. The average distance in this case can be expressed in the form of the function shown in Eq. (8).

$$h_2(q_i) = \frac{1}{E}\left(\sum_{e=1}^{E} d_{ie} q_i\right) \tag{8}$$

Finally, the relationship between the locations of the proposed new parking lots is considered. Similarly, in order to make the parking lot construction cover a wider area, the distance between all new parking lots is also desired to be as far as possible, i.e., it is desired to maximize $d_{ii'}$. The average distance in this case can be expressed in the form of the function shown in Eq. (9).

$$h_3(q_i) = \frac{1}{k}\left(\sum_{i'=1}^{N} d_{ii'} q_i q_{i'}\right) \tag{9}$$

where k is the number of parking lots desired to be planned.

In order to guarantee that k positions are selected from the N possible parking lot positions, we hope to find a function $E(k)$, which guarantees that $E(k)$ can be minimized when $\sum_{i}^{N} q_i = k$. It can be expressed by Eq. (10). The meaning of the expression is that when q_i is 0, the result is $-k$, which is a lower energy state than 0. The solution to avoid this situation is to add the square to Eq. (10), so there is the square expression as in Eq. (11).

$$\sum_{i}^{N} q_i - k = 0 \tag{10}$$

$$E(k) = \left(\sum_{i}^{N} q_i - k\right)^2 = \left(\sum_{i}^{N} q_i\right)^2 + k^2 - 2k\sum_{i}^{N} q_i \tag{11}$$

When the gap between the ground state and the excited state is smaller, it is easier to reach the excited state from the ground state. Therefore, the hyper-parameters ω_0, ω_1, ω_2, and ω_3 need to be added to adjust the bias and coupling weights of the QUBO model. The hyper-parameters are adjusted based on the number of total variables and the ratio of different input data, which are not generic. According to the three objectives proposed in this paper, the three QUBO models to be optimized can be obtained, as shown in Eqs. (12)–(14). Finally, the solution is performed by the solver, and the locations where q_i is 1 among the possible parking locations are the locations of the parking lots planned by algorithm.

$$\mathrm{Obj}_1(k) = \omega_0 E(k) + \omega_1 \sum_{i}^{N} h_1(q_i) \tag{12}$$

$$\mathrm{Obj}_2(k) = \omega_0 E(k) - \omega_2 \sum_{i}^{N} h_2(q_i) \tag{13}$$

$$\mathrm{Obj}_3(q_i) = \omega_0 E(k) - \omega_3 \sum_{i}^{N} h_3(q_i) \tag{14}$$

3 Experiment and discussion

3.1 Experimental results

In this section of the paper, a regional dataset is used as an example to analyze the asymptotic optimality, effectiveness, and feasibility of the proposed algorithm from specific experimental results. To visualize the data, QGIS software was used to obtain the actual map and map the latitude and longitude location points onto the map. The test area is about 4 km^2, and according to the actual scenario, it may be assumed that the same size of the area can be satisfied by planning 0–3 parking lots. The exact number of parking lots to be planned is determined by the algorithm.

The SAM in the proposed algorithm in this paper is constrained by the planned parking lot location. Therefore, the initialized location using QA for the original input data is required first. Here, the location results of the 3 proposed planning locations are shown in Fig. 4, where blue dots represent existing parking locations, green dots represent POIs, and red pentagrams represent new parking locations.

After obtaining the initialized location results, SAM is applied to provide the search direction for the algorithm and reduce the search space. Until the algorithm converges, the desired parking lot location is obtained. The final result is shown in Fig. 5. It can be found that the number of planned locations is changed from three to two, because the SAM rule in the algorithm judges that two facility locations are sufficient for the planning of the area.

The role of SAM is to select the data points that are more desirable to focus on during the continuous

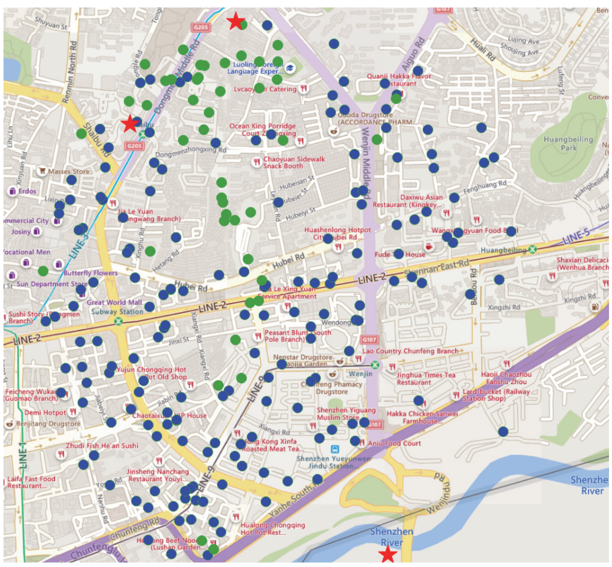


Fig. 4 Results of initial locations selected for parking lot location.

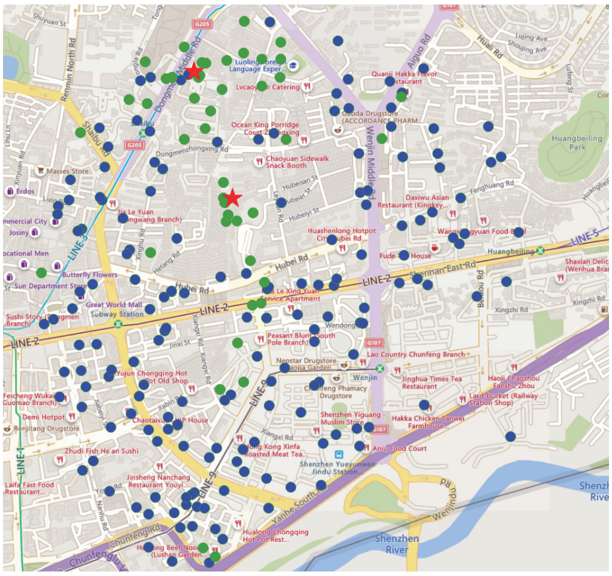


Fig. 5 Location results based on SAM.

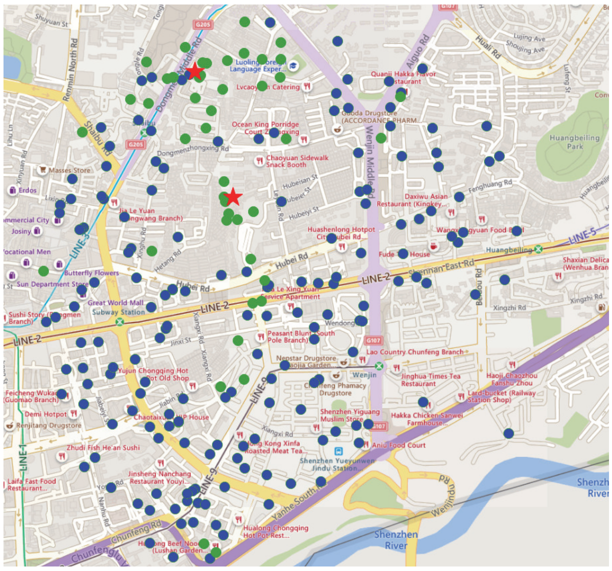


Fig. 6 Location results without SAM.

optimization of the algorithm, and to determine how many locations need to be planned for a given area based on the given rules. In other words, SAM can adaptively determine the number of locations that should be selected, assuming that the rules developed match the real-world scenario. On the contrary, without SAM, it is not possible to determine the number of locations to be selected except artificially, and it is not possible to focus attention on important data to match people's parking travel experience in reality. The final location result can only be given to the algorithm and the initial input data, and the result may be optimal for the algorithm, but it does not necessarily satisfy the perceived results of people in real-life scenarios. The location selected results for the case without the introduction of SAM are shown in Fig. 6. It is worth noting that for the purpose of observing the comparison results, two locations are chosen for planning instead of three in the case without SAM.

3.2 Algorithm evaluation

The study of performance evaluation criteria of multi-objective optimization algorithms is also a current hot topic. It differs from single-objective optimization which the performance of the algorithm can be evaluated by simply finding the minimum or maximum value in the solution set. But the optimal solution of multi-objective optimization is a set consisting of a non-dominated set of solutions due to the contradictory nature between multiple objectives. Reference [26] reviewed the multi-objective evaluation criteria in recent years, and the performance evaluation criteria of the solution set mainly include convergence evaluation, uniformity evaluation, and extensiveness evaluation, where the convergence evaluation is used to evaluate the accuracy of the solution. The classical convergence indicator Generational Distance (GD) was first proposed in Ref. [27] to evaluate the accuracy of the solution set. In Ref. [28], a new multi-objective evolutionary algorithm "Generation Distance Multi-Objective Evolutionary Algorithm (GD-MOEA)" is proposed based on GD indicator, and the results show that it is a better choice for solving multi-objective optimization problems if both the quality of the solution and the running time required to generate the solution are considered. Therefore, in this paper, GD indicator is chosen to evaluate the asymptotic optimality of the proposed algorithm. The calculation of the GD is directly given here as shown in Eq. (15).

$$\mathrm{GD}(P,P^*)=\frac{\sqrt{\sum_{y\in P}\min\limits_{x\in P^*}\mathrm{dis}(x,y)^2}}{|P|} \tag{15}$$

where GD is the generational distance, P is the solution set obtained by the algorithm, P^* is a set of uniformly distributed reference points sampled from the Pareto Front (PF), and $\mathrm{dis}(x,y)$ denotes the approximation between position x in the solution set P and position y in the reference set P^*.

The disadvantage of GD is that it requires a reference set, which can easily lead to a less objective measurement, and it is not realistic to find the complete Pareto optimal set. For this disadvantage, we find the corresponding PF as reference points set by randomly generating 10 000 sets of solutions each time. Based on the dataset used in the previous section, the obtained target space is shown in Fig. 7, where the three dimensions represent the average distance between the new planned parking lot locations and the average distance to the existing parking lots and the POIs, respectively. The red data points set P^* is one of the reference points sets. The corresponding GD is obtained according to each group of reference points, and the average of multiple GDs is calculated as the final result.

3.3 Experimental comparison analysis

The algorithm's performance results and solutions' accuracy on different types of datasets are discussed from the perspectives of whether the regional data are dense and uniform, respectively, and the average of the five sets of GDs solved is taken as the final evaluation result.

The results of applying the proposed algorithm to solve the location of parking lots in different types of data areas are shown in Fig. 8, where the blue dots indicate the locations of existing parking lots, the green dots indicate the locations of POIs, and the red

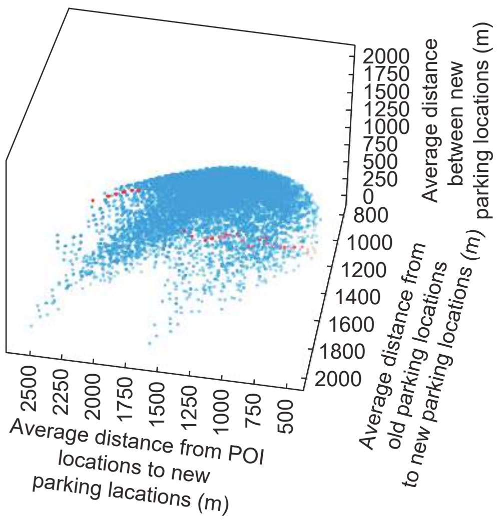
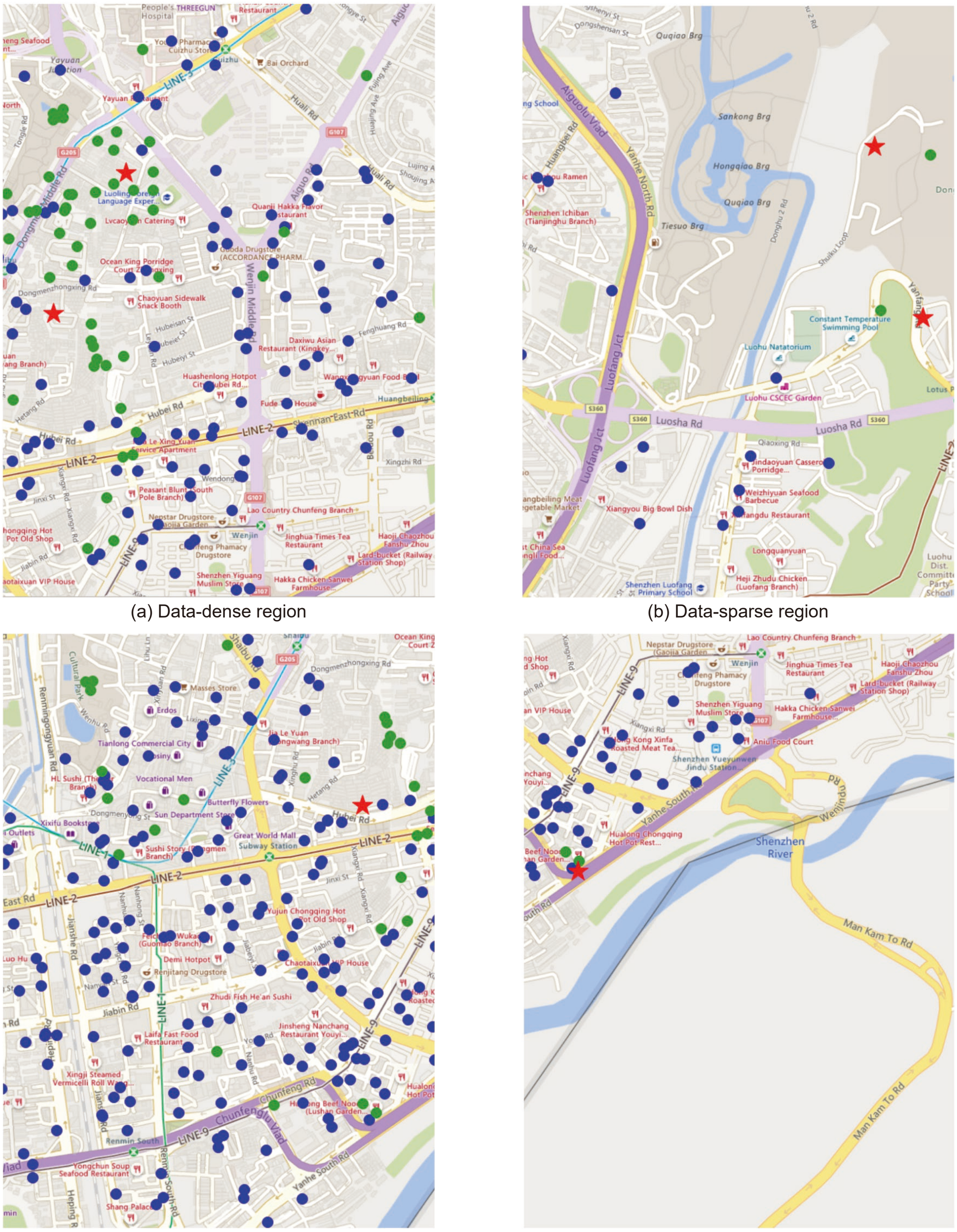


Fig. 7 Target space.

pentagrams indicate the locations of the planned parking lots. Only one parking location is planned for the uniform data area (Fig. 8c) and two parking locations are planned for the remaining areas (Figs. 8a, 8b, and 8d). The GD values of the corresponding regions solved by applying the proposed algorithm are given in Table 1. To better illustrate the advantages of the proposed algorithm in this paper, it is compared with the Simulated Annealing (SA) algorithm. The GD values for the corresponding regions by SA are given in Table 2. By analyzing Tables 1 and 2, it can be concluded that the asymptotic optimal location algorithm proposed in this paper demonstrates good asymptotic optimality and better solution performance regardless of whether the data points in the experimental region are sparse or uniform. It is worth stating that the proposed algorithm can reach the optimal solution when planning only one parking lot location (Fig. 8c), and in other cases, it can also approximate the optimal solution. In addition, Fig. 9 shows the difference in running time between the proposed algorithm and the simulated annealing algorithm, and the results show that the proposed algorithm in this paper has a shorter running time for a larger amount of data (a larger solution space).

4 Conclusion

The facility location problem has long been a hot topic of academic discussion, but there is no specific solution that can be applied to location planning for different situations in different domains. One of the main reasons is that the facility location problem is essentially a combinatorial optimization problem that belongs to NP-hard type, for which an exact solution cannot be found in polynomial time. So far, the conventional methods used to solve such problems are various types of classical intelligent algorithms, but when the data dimensionality is high, the solution performance of classical intelligent algorithms as well as the accuracy of the solution decrease sharply. In this paper, a combination of QA and SAM is introduced to solve such combinatorial optimization problems with the help of the idea of intuitive reasoning. In which, SAM is used to reduce the search space and provide direction for the next search step, and QA is used to search the discrete solution space and improve the



(a) Data-dense region (b) Data-sparse region

(c) Data-uniform region (d) Data-non-uniform region

Fig. 8 Results of applying the proposed algorithm to solve the location of parking lots in different types of data areas.

Table 1 GD values of different data types solved by applying the proposed algorithm.

Data type	GD_1	GD_2	GD_3	GD_4	GD_5	Average GD
Dense	3.094 753	2.103 046	2.761 769	3.053 735	3.084 275	2.819 516
Sparse	5.749 821	5.617 428	9.164 820	6.184 797	9.164 820	7.176 337
Uniform	0	0	0	0	0	0
Non-uniform	2.961 126	4.125 723	2.805 142	2.167 247	5.642 616	3.540 371

Table 2 GD values of different data types solved by applying the SA algorithm.

Data type	GD_1	GD_2	GD_3	GD_4	GD_5	Average GD
Dense	6.054 494	8.804 771	5.846 120	4.579 409	5.530 251	6.163 009
Sparse	17.557 714	15.060 840	18.812 472	16.007 424	16.170 276	16.721 745
Uniform	0.159 977	0.149 196	0.153 192	0.158 134	0.137 260	0.151 552
Non-uniform	14.661 305	12.963 182	12.300 968	15.645 859	15.074 010	14.129 064

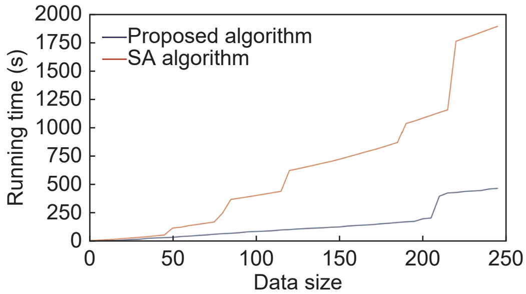


Fig. 9 Relationship between data size and algorithm running time.

search efficiency. This paper conducts experiments based on real parking lot data in Luohu District, Shenzhen City, and explores multi kinds of optimization objectives using walking distance to measure the variability between different location data. To evaluate the convergence of the solution set (solution accuracy) of the proposed scheme in this paper, the accuracy of the solution under different data scenarios is evaluated using the GD indicator. Comparing with the classical SA algorithm, the results show that the proposed scheme in this paper can obtain better solutions with good asymptotic optimality, feasibility, and effectiveness, and shorter solution time, which provides a new direction for achieving robust artificial intelligence. It is also an important reference for other siting problems and provides more references for the application of intuitive reasoning ideas. It is worth mentioning that, thanks to the quantum tunneling effect of quantum annealing algorithm, the proposed scheme performs better in the case of larger solution space, which provides a new idea for solving the problem of facility location in the future. This paper discusses the location of public parking lot from the perspective of intuitive reasoning, but there are still many deficiencies, the lack of more diverse data scenarios, such as traffic flow or economic cost. Considering more influencing factors and objectives to design the algorithm, we will get the location results that are more in line with the real scene.

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