Optimization of Location Selection for Fengchao Cabinets in Beijing Based on Deep Reinforcement Learning

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ABSTRACT

With the rapid development of e-commerce today, how to optimize logistics distribution is a challenge for every city. To address the "last mile" delivery problem, Fengchao cabinets have emerged. However, the number and spatial layout of Fengchao cabinets are unreasonable and other problems need to be solved urgently. This study employs various analytical methods and tools, including kernel density analysis, standard deviational ellipse analysis, and average nearest neighbor analysis, to examine the spatial distribution of existing Fengchao cabinets in Beijing. The study also uses Geodetector to explore the impact of GDP, transportation accessibility, population density, and POI on the distribution of Fengchao cabinets. Additionally, a maximal covering location model for Fengchao cabinets in Haidian District, Beijing, is established. Finally, GA, Gurobi, and SpoNet are used to solve the model and determine the optimal distribution, and SpoNet can improve the time and robustness of solving the model to a certain extent. This study provides an effective reference for related research and provides unique insights into the research on the layout of Fengchao cabinets in Beijing.

KEYWORDS

Location Problems, Fengchao Cabinets, Spatial Optimization, SpoNet, Deep Reinforcement Learning

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1 INTRODUCTION

In recent years, with the rapid development of the e-commerce industry, online shopping has increasingly become a part of daily life. Consequently, the express delivery industry has also grown rapidly. The traditional logistics distribution model gradually fails to meet the growing demand, making delivery issues a major challenge for the express delivery industry[1]. High delivery costs and low door-to-door delivery efficiency during the logistics process have caused numerous problems and inconveniences for both delivery stations and their customers[2]. The service model of intelligent parcel lockers standardizes the delivery process, significantly improving delivery efficiency. When selecting locations for parcel lockers, factors such as population distribution, locker capacity, and target audience need to be fully considered. Only by reasonably selecting the installation locations of parcel lockers, considering these factors comprehensively, can we maximize the efficiency of parcel lockers in improving delivery efficiency and service quality[3].

The research conducted by domestic and international scholars on solution models and algorithms for classic location problems has laid an important theoretical foundation for exploring the location models and solutions for express delivery lockers. Yu et al. used the Analytic Hierarchy Process (AHP) to analyze the weight of indicators affecting the location of logistics distribution centers and constructed an evaluation model for distribution centers based on the Fuzzy Comprehensive Evaluation Method [4]. Li and Shi used a genetic algorithm to propose the idea of "hybrid parallel coding" for optimizing the location of logistics distribution centers [5]. Chen et al. analyzed three location models, established location selection evaluation criteria, and achieved efficiency and fairness in facility location [6]. Liu et al. provided an ideal decision-making process of "search first, decide later" and applied the model to the optimization of public facility locations in Shenzhen, achieving good results[7]. The siting of intelligent express delivery lockers is essentially a site selection problem, but research in this area is relatively scarce both domestically and internationally. Huang et al. developed a multi-objective location model for intelligent express delivery lockers in the context of e-commerce, taking into account the impact of distance on consumer satisfaction with the pickup service by constructing a customer satisfaction function[8]. This model aims to minimize economic costs while maximizing customer satisfaction. Zheng et al. proposed a multi-objective optimization mathematical model to study the service area planning for intelligent express delivery locker facilities. They solved the optimization model using a combination of the Taguchi method (TA) and the Non-dominated Sorting Genetic Algorithm II (NSGA-II)[9].

With the rapid development of artificial intelligence technology[10], using deep learning techniques to solve location optimization problems has become an inevitable trend[11]. Rohilla et al. used deep learning for feature extraction and employed a bidirectional optimization hybrid model for optimizing billboard locations[12]. Zhong et al. used reinforcement learning with coverage information to solve the maximum coverage billboard location problem[13]. Wang et al. applied deep learning to solve the Maximum Coverage Location Problem (MCLP) in urban spatial computing, offering a new perspective for addressing spatial optimization problems[14-16]. Liang et al. used bipartite graph neural networks and attention mechanisms to solve the multi-traveling salesman problem in urban logistics[17]. Currently, the location selection problem for intelligent parcel lockers still faces many challenges. Although existing research has made some progress in location optimization theory and models, it still falls short in addressing the location selection problem for intelligent parcel lockers. Most current studies focus on traditional algorithms and models, lacking sufficient consideration of complex and variable real-world scenarios. Therefore, this study utilizes reinforcement learning combined with spatial analysis methods to investigate the spatial distribution of Fengchao cabinets in Beijing and optimize their placement.

2 METHOD

2.1 Study Area

Beijing is the capital of the People's Republic of China, serving as the political, cultural, and educational center of the country. Beijing has jurisdiction over 16 districts with a total area of 16,410.54 square kilometers. By the end of 2023, Beijing resident population of 21.858 million people. With such a large population and vast geographical space, the city has high demands for the urban distribution logistics network. Smart Delivery Cabinet, as an integral part of the urban last-mile delivery logistics network, have revolutionized traditional courier delivery models, improving delivery efficiency, enhancing user experience, and promoting the intelligent development of urban last-mile delivery networks. Fengchao cabinets occupy a relatively large share in the smart delivery cabinet market, backed by ample data. This study takes Beijing as the research object, analyzing the distribution of Fengchao cabinets in the city and discussing the optimization of their location selection. Studying the location selection of Fengchao cabinets in Beijing can help better meet the needs of citizens, the government, and enterprises, maximizing the utilization of social resources.

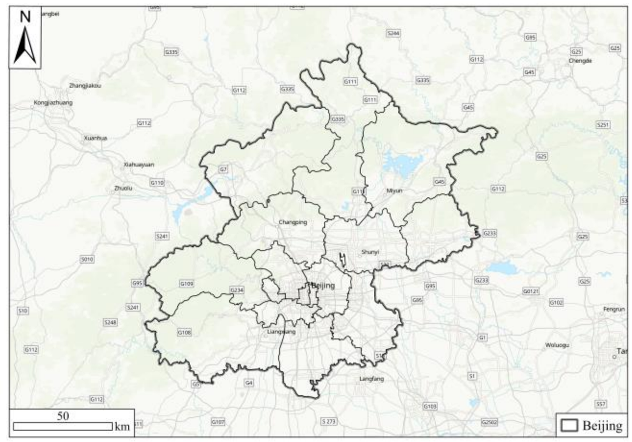

Figure 1: Study Area: Beijing, China

2.2 Data

This study utilizes a dataset encompassing three main categories: geographic, social, and economic. The Points of Interest (POI) data is scraped from the Amap website and includes eight categories: residential areas, shopping centers, research institutions, schools, convenience stores, office buildings, supermarkets, and Fengchao cabinets. The attribute data of POIs includes detailed information such as latitude and longitude, category, and name, providing a foundational dataset for the research. The POI data of Fengchao cabinets reveals their distribution and density across different geographic regions. The traffic network data includes information on road types, road lengths, pavement types, and real-time traffic, which further helps in studying the accessibility and positioning of Fengchao cabinets within the road network. This traffic network data can be obtained from the OSM (OpenStreetMap) website. GDP (Gross Domestic Product), an important indicator that measures the total market value of all final products and services produced in a country or region within a specific period (usually a quarter or a year), is closely related to the distribution and location of Fengchao cabinets. GDP data is sourced from the Beijing Municipal Bureau of Statistics. Population statistics reflect the distribution and activity levels of the population in an area, which is directly related to determining the service radius of Fengchao cabinets. Population data is obtained from the WorldPop website, with a resolution of 100 meters and 1000 meters. By analyzing the aforementioned data, this study examines the spatial distribution of Fengchao cabinets, population distribution characteristics, road network conditions, and the distribution of nearby POIs, thereby providing scientific guidance for optimizing the site selection of Fengchao cabinets.

Table 1. Influencing Factors

Dimension of Impact Factor	Data Types	Code Name
Geography	Residential community points dataset	X1
	Office building points dataset	X2
	School points dataset	X3
	Shopping mall points dataset	X4
	Research institute points dataset	X5
	Supermarket points dataset	X6
	Convenience store points dataset	X7
	Road dataset	X8
Economy	GDP dataset	X9
Society	Population dataset	X10

2.3 Methods

The research methods adopted in this study include kernel density analysis, mean nearest neighbor analysis, standard deviation ellipse, geographical detector, and maximum coverage model. In this study, grid units are established based on administrative boundaries, and within each grid unit, the relationship with various influencing factors is analyzed. The weight of each influencing factor is calculated, and the demand intensity of each grid unit is obtained through weighted calculation. The ultimate goal of site selection optimization was to maximize the sum of the demand intensities covered by Fengchao cabinets. Specifically, this study first uses kernel density analysis, mean nearest neighbor analysis, and standard deviation ellipse to analyze the spatial distribution of Fengchao cabinets in Beijing. Then, the research area is divided into small squares with a side length of 500 meters. Next, the geographical detector is employed to investigate the weights of various types of POI, population density, GDP, and road density. Based on the assigned weights, the demand intensity of each grid is calculated, and a corresponding maximum coverage model is established. SpoNet, as a type of DRL (Deep Reinforcement Learning)[18], is widely used for solving spatial optimization problems. Considering the practical situation of the research problem, it is found that SpoNet can also be used as one of the methods for solving models. Therefore, after considering the demand intensity and distribution of demand points in each grid, GA, Gurobi, and SpoNet are used to solve the problem and obtain the final site selection results.

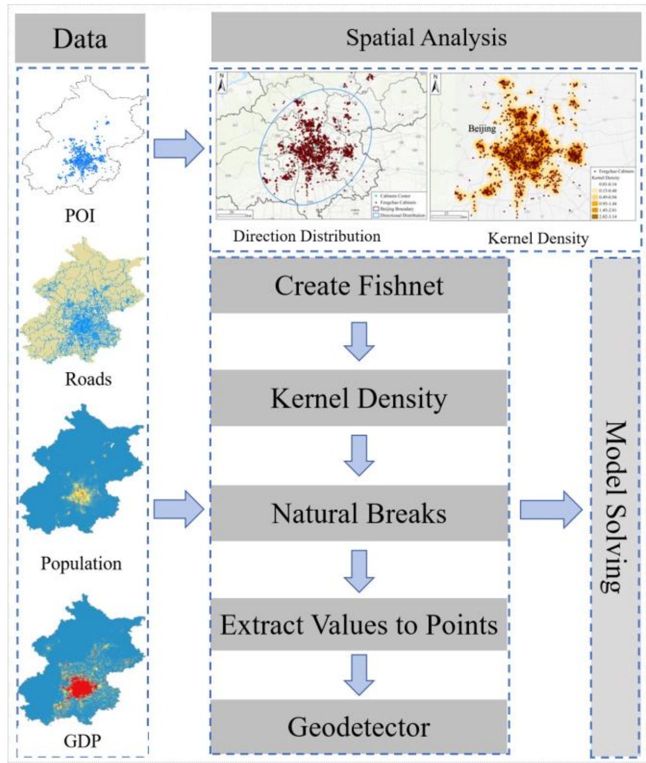

Figure 2: The Process of Fengchao Cabinets Selection Optimization.

3 RESULTS

3.1 Analysis of the Spatial Distribution of Fengchao Cabinets in Beijing

3.1.1 Spatial Distribution

The spatial distribution map of Fengchao cabinets in Beijing shows an uneven layout, characterized by a "dense center and sparse periphery." Specifically, these cabinets are mainly concentrated within the Sixth Ring Road, including Dongcheng District, Xicheng District, Chaoyang District, Shijingshan District, and Haidian District, with relatively fewer cabinets distributed in other areas. The reason is that these districts are the political, economic, and cultural centers of Beijing, where urban infrastructure is well-developed, clustering the city's commercial centers, residential areas, and university districts together. The areas with a high concentration of Fengchao cabinets are also relatively economically developed, leading to a higher demand for express cabinets, whereas the demand is lower in areas outside the Sixth Ring Road.

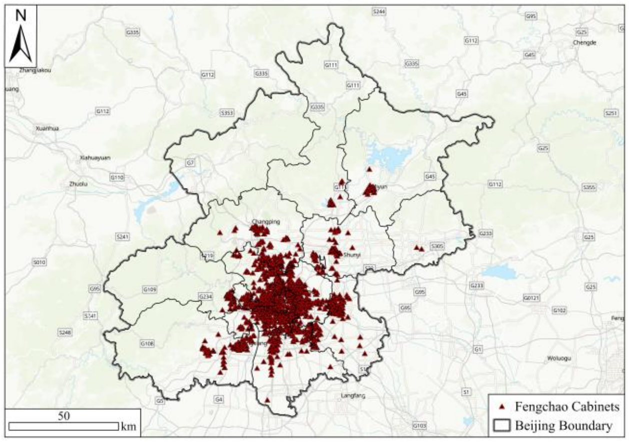

Figure 3: Spatial Distribution of Fengchao Cabinets

3.1.2 Standard Deviation Ellipse

As shown in Figure 4, the areas where Fengchao cabinets are clustered roughly form a "ring" distribution along the northeast-southwest direction. The secondary standard deviation ellipse can cover 88% of Fengchao cabinets locations within Beijing, which corresponds to the city's administrative divisions, regional development levels, and population distribution. The number and density of Fengchao cabinets locations within the ellipse are higher than those outside, reflecting the characteristic of "dense in the center, sparse on the periphery."

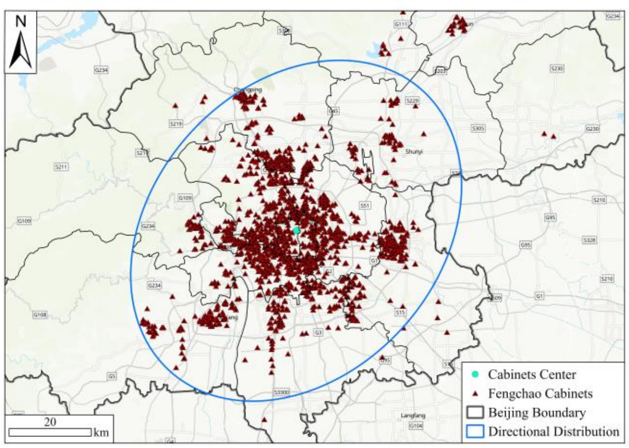

Figure 4: Standard Deviation Ellipse of Fengchao Cabinets

3.1.3 Average Nearest Neighbor Analysis

The Average Nearest Neighbor (ANN) analysis determines the spatial clustering trend of points by calculating the average distance between each point and its nearest neighbor. Based on the results of the ANN analysis (Table 2), the spatial distribution of Fengchao cabinets exhibits a significant clustering pattern. The calculated mean distance is 437.0826 meters, which is substantially lower than the expected mean distance of 679.7547 meters under a completely random distribution. The nearest neighbor ratio of 0.643 clearly indicates the clustered nature of Fengchao cabinets locations. The z-score of -25.499397 demonstrates that this clustering pattern is significantly below the expected value, and the approximate p-value of 0 further supports the non-random nature of this distribution.

This significant clustering distribution indicates that the current spatial distribution pattern of Fengchao cabinets tends to be highly concentrated in certain areas. This high clustering distribution is influenced by various factors, including population density and the intensity of commercial activities. Meanwhile, this high clustering pattern implies that there is an over-concentration of stations in some areas and a lack of stations in others. Through location optimization strategies, potential service blind spots can be identified, and a more scientific and reasonable layout can be applied to improve station coverage and service efficiency.

Table 2. Average Nearest Neighbor Summary

Observed Mean Distance (Meters)	Expected Mean Distance (Meters)	Nearest Neighbor Ratio	z-Score	p-Value
437.0826	679.7547	0.6430	-25.499397	0.000000

3.1.4 Kernel Density Analysis

From the kernel density distribution map, it can be seen that Fengchao cabinets in Beijing exhibit a "multi-core clustering pattern" in the central urban areas and sub-center urban areas, while forming small-scale clustering phenomena in the distant suburban areas. Specifically, four major high-density core areas have formed in Dongcheng District, Xicheng District, Chaoyang District, and Haidian District.

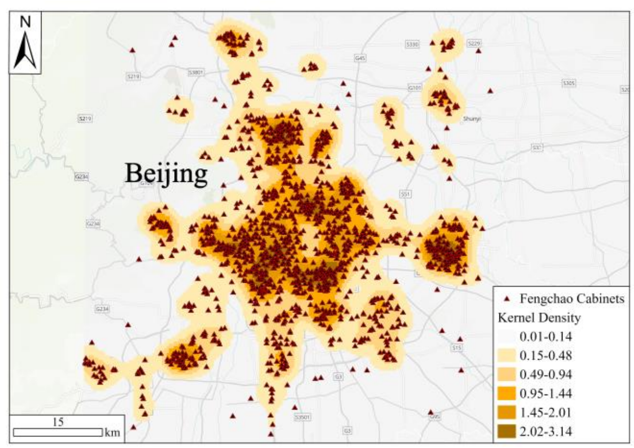

Figure 5: Kernel Density Distribution Map

3.2 Geodetector

Due to equipment limitations, it is not possible to fully solve the location optimization problem for the Fengchao cabinets in Beijing. Only a portion of the data will be selected as an example for solving the problem. Haidian District, being the technology innovation center, education center, economic center, and cultural center of Beijing, makes it an important area both within the city and nationally. Furthermore, according to the above analysis, Fengchao cabinets are relatively concentrated in the Haidian District. Therefore, this study chooses Haidian District in Beijing as the optimization research area. This study utilizes the differentiation and factor detector tools of the geographical detector model to analyze the influence of various factors on the spatial distribution of Fengchao cabinets in Haidian District. The result of the factor detector indicates that these factors can adequately explain the spatial distribution of Fengchao cabinets in Haidian District (Table 3). The factor detector results, ranked by their q-values, are as follows: shopping malls (X4) > GDP (X9) > population density (X10) > supermarkets (X6) > road density (X8) > residential communities (X1) > office buildings (X2) > schools (X3) > research institutions (X5) > convenience stores (X7). It can be observed that the factor shopping mall has the highest explanatory power, indicating that the spatial distribution of Fengchao cabinets in Haidian District is most strongly influenced by the distribution of shopping malls.The secondary factors are GDP and population density, indicating that these are also important factors affecting the spatial distribution of Fengchao cabinets in Haidian District.

Table 3. Factor Detector Results

Independent Variable	Significance Level	q-Value	Explanatory Power Ranking
X1	0.1	0.452	6
X2	0.01	0.388	7
X3	0.01	0.334	8
X4	0.1	0.754	1
X5	0.01	0.049	9
X6	0.1	0.547	4
X7	0.01	0.041	10
X8	0.01	0.473	5
X9	0.1	0.576	2
X10	0.1	0.562	3

The results of the interaction detector are shown in Figure 6, where all pairwise interactions between factors are observed to be enhanced, primarily through nonlinear enhancement. There are no factors acting independently of each other, indicating that the spatial differentiation pattern of Fengchao cabinets in Haidian District is not solely controlled by a single factor but rather by the combined effects of multiple factors. Among the interactions between two factors, the interactions between shopping malls (X4) and population density (X10), shopping malls (X4) and GDP (X9), and shopping malls (X4) and road density (X8) are relatively large. The factor interactions between convenience stores (X7) and research institutions (X5), residential community (X1) and research institutions (X5), and convenience stores (X7) and residential community (X1) are relatively small.

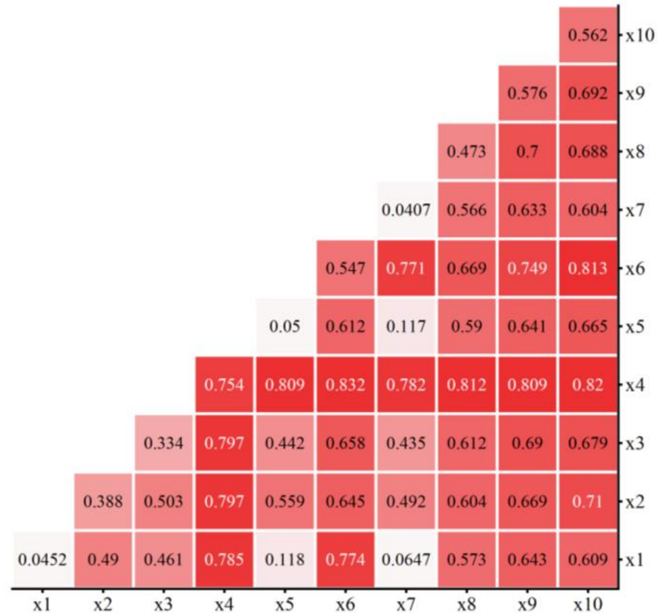

Figure 6: The Results of Interaction Detector

3.3 Location selection

The Maximal Covering Location Problem (MCLP) is a location problem widely used in operations research and geographic information systems [19-22]. Its goal is to select a certain number of facility locations from given service facilities and demand points to maximize the number of covered demand points. In general, this problem involves N requirement points and M candidate facility points, each facility point has a predefined service scope. Within this range, the facility can provide services to nearby demand points, while outside this range, other facilities are needed to provide services. This study establishes a maximum coverage location model for Fengchao cabinets in Haidian District, Beijing and determines 30 deployment points for the Fengchao cabinets, each of which has a service radius of 1000 meters, and then uses SpoNet to solve the model. SpoNet takes 0.24 seconds to solve the problem, and the coverage is 123.867. The result of the solution is shown in Figure 7. The selected locations are predominantly clustered in the southern and southeastern parts of Haidian District. This clustering likely reflects higher demand densities in these regions, suggesting that these areas have a higher concentration of residents or businesses that utilize cabinets services. The distribution also shows a strategic placement to avoid redundant coverage while ensuring that the majority of demand points fall within the service radius of at least one Fengchao cabinet. In the northern and northwestern parts of the district, there are noticeably fewer Fengchao cabinets. This could imply either a lower demand in these areas. The results shown in the map provide valuable insights for the logistical planning and resource allocation of cabinets in urban areas.

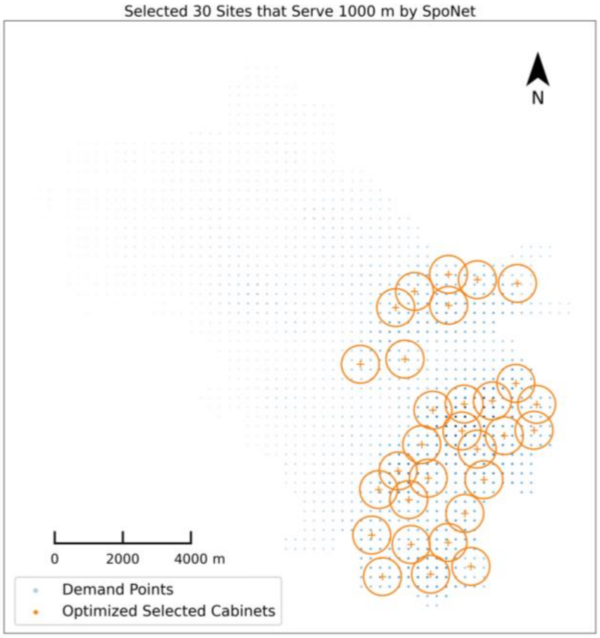

Figure 7: Results of Selecting 30 Fengchao cabinets

4 DISCUSSION

In order to prove that SpoNet is algorithmically superior to heuristic algorithms (genetic algorithms), in this study, with the same size and relevant parameter settings of the model, a comparative analysis is conducted on the results obtained by GA, Gurobi optimizer, and SpoNet, comparing their solving time, demand point coverage rate (Table 4), and spatial distribution of selected locations (Figure 8). The GA solving time is 1.32 seconds with a coverage of 119.109; the Gurobi solver solving time is 6.24 seconds with a coverage of 132.889. The results indicate that in terms of solving time, SpoNet demonstrates a significant advantage, being more than 5 times faster than GA and over 20 times faster than Gurobi, showcasing its rapid solving capability. Regarding demand point coverage quantity, Gurobi's location results are evidently superior to those of SpoNet and GA, likely due to Gurobi's mature solving capabilities. However, the optimal solutions provided by SpoNet outperform those of GA, suggesting that deep reinforcement learning can improve the precision of solving results compared to traditional genetic algorithms. When comparing the spatial distribution of selected locations from the three algorithms, it is observed that the results of SpoNet and Gurobi have a higher degree of similarity, and compared to GA, SpoNet and Gurobi results cover a broader range. Further analysis reveals that the overlapping areas of the solutions from GA and SpoNet are significant, but GA also shows overlaps in regions with lower demand, which is inconsistent with the actual situation. In contrast, SpoNet only shows overlaps in high-demand areas, which aligns with the high-frequency using of Fengchao cabinets in those regions, indicating that SpoNet's algorithm results better matches the actual usage of Fengchao cabinets by users. Overall, this analysis demonstrates that deep reinforcement learning performs well in solving the maximum coverage model compared to traditional algorithms, providing valuable reference and insights for related research.

Table 4 Comparison of Results from Different Solving Methods

Solving Method	Solving Time(s)	Coverage Quantity
SpoNet	0.24	123.867
GA	1.32	119.109
Gurobi	6.24	132.889

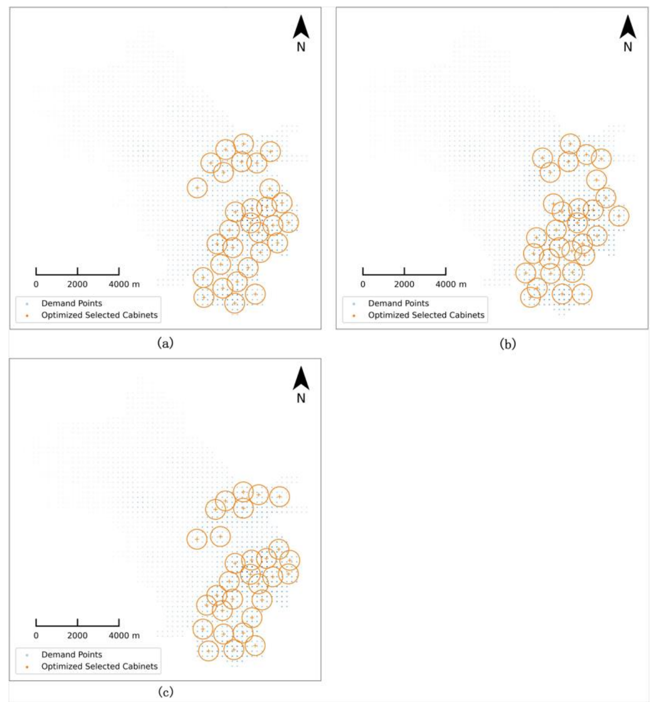

Figure 8: Results of Different Solving Methods: (a) Solution from Gurobi; (b) Solution from GA; (c) Solution from SpoNet

In addition, in this study, the optimal result of coverage can be achieved by selecting 30 Fengchao cabinets through SpoNet. With the increase in the number of Fengchao cabinets, although the coverage will also increase, it will lead to a waste of Fengchao cabinets resources. This means that the same demand area will be redundantly covered by different Fengchao cabinets, as shown in Figure 9. This will lead to an increase in operating and maintenance costs, as each Fengchao cabinet requires investment, including purchase cost, installation cost, and maintenance cost. As the number of Fengchao cabinets increases, operating costs will rise significantly. If these additional Fengchao cabinets cannot be fully utilized, these investments will fail to generate the expected economic benefits and may even result in economic losses. For a company like Fengchao, this is undoubtedly a significant challenge and therefore, it is not advisable. Moreover, when the number of cabinets exceeds actual demand, many cabinets will remain idle. This idle state of resources is not only a waste of physical space but also an indication of inefficient resource allocation. Ideally, the number of cabinets should match user demand to achieve optimal resource allocation. Therefore, this study chooses 30 Fengchao cabinets to achieve the optimal result for site selection.

Figure 9: Results of Selecting 40 Fengchao cabinets

5 CONCLUSION

This study primarily studies the spatial distribution of Fengchao cabinets in Beijing. It utilizes the Geodetector to identify the main factors influencing the layout of Fengchao cabinets. By determining the weights of these factors, defining demand points and facility points, and calculating the demand intensity of each demand point with weighted calculations, a maximal coverage location model for Fengchao cabinets is established. Finally, this model is solved using Genetic Algorithm (GA), Gurobi, and SpoNet. The results demonstrate that the using of deep reinforcement learning in this study can improve the solving time and effectiveness of the maximal coverage location model to some extent. Moreover, the location selection results for Fengchao cabinets in this study are also of great significance for the deployment research of Fengchao cabinets in Beijing. However, there are some limitations to this study, such as not considering the impact of the construction cost of Fengchao cabinets on their location selection, and the model used by SpoNet requires further training. In the future, we will continue to address these issues, improve the efficiency of the model solving, and provide more valuable insights for the location layout of Fengchao cabinets in Beijing.

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