Heliyon 10 (2024) e32928

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Urban drone stations siting optimization based on hybrid algorithm of MILP and machine learning ☆

Weijun Pan, Jianwei Gao *, Xuan Wang, Qinghai Zuo, Shijie Tan

Civil Aviation Flight University of China, No. 46, Section 4, Nanchang Road, Guanghan, 618307, Sichuan, China

ARTICLE INFO

Keywords:
Unmanned aerial vehicles (UAVs)
Emergency service facilities
Mixed-integer linear programming (MILP)
Bayesian optimization

ABSTRACT

Urban environments, characterized by high population density and intricate infrastructures, are susceptible to a range of emergencies such as fires and traffic accidents. Optimal placement and distribution of fire stations and ambulance centers are thus imperative for safeguarding both life and property. An investigation into the distribution inefficiencies of emergency service facilities in selected districts of Chengdu reveals that imbalanced distribution of these facilities results in suboptimal response times during critical incidents. To address this challenge, a two-stage clustering method, incorporating X-means and K-means algorithms, is employed to identify optimal number and locations for Unmanned Aerial Vehicle (UAV) fire stations and drone ambulance centers. A Mixed-Integer Linear Programming (MILP) model is subsequently constructed and solved using the Gurobi optimization platform. Bayesian optimization—a machine learning technique—is exploited to elucidate the interplay between response speed and service capacity of these UAV-based emergency service stations under an optimized layout. Results affirm that integration of MILP and machine learning provides a robust framework for solving complex problems related to the siting and allocation of emergency service facilities. The proposed hybrid algorithm demonstrates substantial potential for enhancing emergency preparedness and response in urban settings.

1. Introductory

Modern metropolises exhibit high population density and intricate urban structures, making them prone to a wide range of emergencies and disasters, including fires, traffic incidents, and natural calamities. For instance, data from the National Fire and Police Statistics System [1] indicate that in 2022, Chengdu experienced 14,924 fires, peaking in August with 2,234 incidents, and averaging 72 fires per day. Such events led to direct property losses totaling 63.7 million yuan. Consequently, the strategic configuration of fire stations, ambulance centers, and other emergency service facilities directly influences both the quality of life and the safety of the urban populace. Timely and effective emergency and rescue services are crucial for the protection of lives and property.

Nonetheless, the rational siting and deployment of emergency facilities in large urban areas is a multifaceted challenge, impacted by a myriad of variables such as population distribution, transportation networks, and facility capacities. Unmanned Aerial Vehicle fire stations and Emergency Medical Service (EMS) distribution hubs offer a cost-effective and flexible alternative to traditional

☆ This article is supported in part by the Program of China Sichuan Science and Technology under Grant 2021YFS0319 and the Project of Sichuan Provincial Key Laboratory of Civil Aircraft Fire Science and Safety Engineering under Grant MZ2024JB01.

* Corresponding author.
E-mail addresses: wjpan@cafuc.edu.cn (W. Pan), gjw_cafuc@foxmail.com (J. Gao).

https://doi.org/10.1016/j.heliyon.2024.e32928
Received 10 October 2023; Received in revised form 8 June 2024; Accepted 12 June 2024

Available online 17 June 2024

setups. While conventional siting approaches often rely on experiential judgment or predefined rules and lack the integration of comprehensive data and optimization techniques, scholars globally are increasingly focusing on leveraging big data and optimization algorithms. These modern methods aim to improve the siting of diverse emergency facilities, thereby enhancing a city's emergency response capabilities and overall rescue efficiency.

The objective of this research is to advance an optimal facility siting and allocation scheme by amalgamating mathematical planning techniques with machine learning-inspired optimization algorithms from the domain of operations research. This endeavor involves evaluating various types of facilities—including fire stations, ambulance centers, and UAV platforms—and understanding their interactions. Such a holistic approach aims to ensure that emergency services can promptly reach the maximum number of residential areas while also maintaining rapid response times even under the most demanding scenarios, ultimately elevating the efficiency and reactivity of urban emergency and rescue operations.

2. Related research

The advancement in optimizing the siting and deployment of urban emergency service facilities leans heavily on big data analytics and computational algorithms. A pivotal study by Li Xiang et al. [2] sets the stage by minimizing overall travel expenditures and preserving the spatial integrity of service zones through the incorporation of shelters as replacements in facility service area algorithms. Similarly, a multi-objective model developed by Jinze Li and Fan Tang [3] leverages open-source geographical data to formulate siting plans for modular urban hospitals.

Further contributions to the field include Fang Mingmin's [4] introduction of a comprehensive evaluative index system, and Qiao Lianbao's [5]constraint-defined descriptive framework tailored for efficient algorithmic solutions in large-scale implementations. Studies also venture into spatial dimensions; for instance, Wu Wenjie et al. [6] employed Voronoi polygons to address the spatial optimization of emergency shelters, while Zhong Shaoying [7] analyzed medical facility accessibility across six districts in Beijing, revealing a non-linear accessibility trend.

On the international front, Mixed Integer Linear Programming and heuristics like the K-means algorithm have been widely adopted. Samira Fazlollahi [8] used a systematic approach to reduce the number of decision variables by dividing urban areas into "integrated zones." Meng You [9] proposed a dynamic iterative partial optimization algorithm to handle the challenge of large datasets. Jean-Thomas Camino [10] combined K-means clustering with MILP, demonstrating its efficacy for large-scale, realistic problems. Fani Boukouvala [11] reviewed the research progress in global optimization in Mixed-Integer Nonlinear Programming (MINLP); Akshay Malhotra and Ioannis D. Schizas [12] explored unsupervised clustering based on information content; Matteo Zatti [13] proposed a new mixed-integer linear programming clustering model called k-MILP; WEI TANG [14] designed a new iterative clustering algorithm; and KRISTINA P. SINAGA [15] proposed a new unsupervised k-means (U-k-means) clustering algorithm.

In recent years, UAVs have also been the subject of extensive research in emergency medical rescue and fire safety. Fei Shao [16] evaluated out-of-hospital cardiac arrests in Beijing, China. Justin J. Boutilier [17] and Aaron Pulver [18] focused on the use of drones in emergency medical response. Elena Ausonio [19] proposed a conceptual framework for UAVs in firefighting activities. Sharma [20] used drones for more accurate fire prediction and monitoring. Kai Wang [21] specified the application scenarios of UAVs in urban fire rescue.

In summary, while there has been significant research on the application of UAVs in emergency medical rescue and fire safety, there is a gap in the literature concerning the optimal siting of UAV-operated emergency service facilities in urban settings.

3. Mixed-integer linear programming model

3.1. Model assumption

The optimization model employs binary decision variables to allocate each residential area to at least one type of fire emergency facility (either a traditional fire station or a drone fire station) and one type of EMS emergency facility (either an ambulance centre or a drone ambulance centre). Its linear objective function seeks to minimize the total distance between residential areas and their designated fire and ambulance services, with linear constraints ensuring that each area is served by at least one facility, while also considering the service capacity of each. The model is based on fixed and known parameters, such as the locations and capacities of fire stations and ambulance centers. It operates in a static decision environment where all data, except four specific hyperparameters, remain constant. Distances are calculated using Haversine's formula for drone-operated facilities, allowing for direct, obstacle-free paths, and Manhattan distances for traditional facilities that rely on road networks. While the model optimises service capacity parameters, it simplistically assumes that these are only influenced by available resources, such as personnel and equipment. Additionally, it uses K-means clustering to determine the optimal number and initial locations of UAV stations, though it acknowledges that real-world conditions, such as flight range, safety regulations, and geographic factors, could affect these determinations.

3.2. Model building

3.2.1. Variables and parameters

N: Number of residential areas
F: Number of fire stations
M: Number of ambulance centers

D: Number of drone fire stations
E: Number of drone ambulance centers
$d_{i,j}^{\mathcal{F}S}$: Distance from the i^{th} residential areas to the j^{th} traditional or drone fire station
$d_{i,j}^{MS}$: Distance from the i^{th} residential area to the j^{th} ambulance centers or drone ambulance centers
C_j^{FS}: Service capacity of the j^{th} traditional or drone fire station
C_j^{MS}: Service capacity of the j^{th} ambulance centers or drone ambulance centers
f_{fs}: Serviceability factor for drone fire stations or fire stations
n_j^{fs}: Number of residential areas initially served by the j^{th} drone fire stations or fire station on a proximity basis
c_{min}^{fs}: Minimum service capacity of a drone fire station or fire station
f_{ms}: Capacity factor for drone ambulance centers or ambulance centers
n_j^{ms}: Number of residential areas initially served by the j^{th} drone ambulance centers or ambulance centers on a proximity basis
c_{min}^{ms}: Minimum service capacity of a drone ambulance centers or ambulance centers

3.2.2. Decision variables

$x_{i,j}^{\mathcal{F}S}$: Whether the i^{th} residential areas is assigned to the j^{th} fire station (drone fire station) (binary variable), assigned 1, otherwise 0

$x_{i,j}^{\mathcal{M}S}$: Whether the ith residential areas are assigned to the jth ambulance centers (drone ambulance centers) (binary variable), assigned as 1, otherwise 0

z: Continuous variable representing the distance from the largest residential areas to its assigned emergency facility

3.2.3. Objective function and constraints

$$\text{Minimize } z = \text{Minimize } \max \sum_{i=1}^{N}\left(\sum_{j=1}^{F+D} x_{i,j}^{\mathcal{F}S}\cdot d_{i,j}^{\mathcal{F}S} + \sum_{j=1}^{M+E} x_{i,j}^{\mathcal{M}S}\cdot d_{i,j}^{\mathcal{M}S}\right) \tag{1}$$

$$s.t. = \begin{cases} \sum_{j=1}^{F+D} x_{i,j}^{\mathcal{F}S} \geq 1, & \forall i \in \{1,2,\dots,N\}, \quad \forall j \in \{1,2,\dots,F+D\}, \\ \sum_{j=1}^{M+E} x_{i,j}^{\mathcal{M}S} \geq 1, & \forall i \in \{1,2,\dots,N\}, \quad \forall j \in \{1,2,\dots,M+E\}, \\ \sum_{i=1}^{N} x_{i,j}^{\mathcal{F}S} \leq C_j^{FS}, & C_j^{FS} = \max(f_{fs}\cdot n_j^{fs}, c_{\min}^{fs}), \quad \forall j \in \{1,2,\dots,F+D\}, \\ \sum_{i=1}^{N} x_{i,j}^{\mathcal{M}S} \leq C_j^{MS}, & C_j^{MS} = \max(f_{ms}\cdot n_j^{ms}, c_{\min}^{ms}), \quad \forall j \in \{1,2,\dots,M+E\}, \\ z \geq x_{i,j}^{\mathcal{F}S}\cdot d_{i,j}^{\mathcal{F}S}, & \forall j \in \{1,2,\dots,F+D\}, \\ z \geq x_{i,j}^{\mathcal{M}S}\cdot d_{i,j}^{\mathcal{M}S}, & \forall j \in \{1,2,\dots,M+E\} \end{cases} \tag{2}$$

3.2.4. Model concepts

(1) The primary aim of the objective function is to minimize the distance from the largest residential areas to its designated drone station, thereby enhancing the efficiency of emergency response.

(2) Each residential area is mandatorily allocated to at least one traditional fire station or drone fire station. This ensures comprehensive fire emergency coverage across all residential areas.

(3) Similarly, each residential area is compulsorily assigned to at least one traditional ambulance centers or drone ambulance centers. This guarantees that medical emergencies can be promptly addressed.

(4) The service capacity of both traditional and drone fire stations must exceed the minimum number of residential areas required to be served. Additionally, it should be less than or equal to the product of the initial number of residential areas to be served based on proximity and the service capacity factor.

(5) For ambulance centers or drone ambulance centers, the service capacity must be greater than the minimum number of residential communities to be served. It should also be less than or equal to the product of the initial number of residential communities served by the proximity principle and the service capacity factor.

(6) The variable z must be greater than or equal to the distance from all residential areas to their assigned traditional or drone fire stations. This ensures that the most distant residential area is within a reasonable range of emergency services.

(7) Similarly, z must be greater than or equal to the distance from all residential areas to their assigned traditional or drone ambulance centers. This constraint ensures that medical services are accessible within a reasonable distance for all residential areas.

Table 1
Data table of residential areas and fire stations and ambulance centers in a district of Chengdu City (keyword search method).

District Name	Number of Residential Areas	Number of Fire Stations	Number of ambulance centers
Area 1	200	31	3

Table 2
Data table of residential areas and fire stations and ambulance centers in a district of Chengdu City (polygonal query method).

District Name	Number of Residential Areas	Number of Fire Stations	Number of ambulance centers
Area 1	1568	31	3

Table 3
Data table of residential areas and fire fighting authorities and ambulance centers in a district of Chengdu City (data preprocessing).

District Name	Number of Residential Areas	Number of Fire Stations	Number of ambulance centers
Area 1	1581	22	8

4. Optimization algorithm

4.1. Data source and processing

The research data utilized in this study is sourced from an open map platform through its Application Programming Interface (API). Specifically, the API is employed to acquire Point of Information (POI) data, which is subsequently stored in files with a .csv suffix for further analysis.

In the initial phase of data collection, only the search service functionalities—namely keyword query and polygon query—are utilized from the web service's basic offerings provided by the open platform. Leveraging the developer documentation supplied by the platform, Python code is written to invoke the API for data retrieval. The keyword query method is specifically employed to collect data on the number of residential areas, fire stations, and ambulance centers, along with their respective latitude and longitude coordinates within a designated district in Chengdu City. Table 1 provides an illustrative example of the data collected for a specific district.

Limited by the API interface call volume limit of 100 times/day, concurrency limit of 30 times/second, so the number of residential areas in the above table does not guarantee the full accuracy, and it is necessary to use the polygon query method to obtain POI data again. The data is shown in Table 2.

In terms of data collection, the keyword query can collect a small range of accurate data, while the polygon query can query a larger range but is not accurate enough. Therefore, these query methods do not fully capture the true number and spatial relationship between residential areas, fire stations and emergency centers.

To address this limitation, we preprocess the data. Specifically, the data obtained from both query methods are subjected to a pre-processing process. This included eliminating duplicate coordinate points and excluding irrelevant location information. For example, an entry such as "First aid knowledge and skills science base of a university" may appear as a result of a keyword query, but is not relevant to urban emergency service facilities. Such entries are therefore filtered out to ensure the relevance and accuracy of the data. The pre-processed accurate and relevant information is then summarised into usable data. For the number of ambulance centers, since three ambulance centers were located closer to the area where the data was collected, but the names were from other areas, they were ignored by both query methods, resulting in a number of ambulance centers of 8, rather than 6 or less than 6. The pre-processed data is shown in Table 3.

4.2. Introduction to Gurobi optimization tool

Gurobi is a state-of-the-art, large-scale optimization solver developed by Gurobi Optimization, Inc., based in the United States. It has gained widespread adoption across various industries, including manufacturing, finance, insurance, transportation, and services. The tool is renowned for its exceptional performance and cost-effectiveness, particularly as real-world optimization problems become increasingly complex and voluminous.

In the seminal work "Decision Tree for Optimization Software" [22], Gurobi is highlighted for its unparalleled computational capabilities in solving Mixed-Integer Linear Programming (MILP) problems. The solver's efficiency makes it an ideal choice for tackling the complex optimization problems modelled in this study. For a detailed comparison of the solution performance, see Fig. 1.

4.3. Model optimization and solution process

The primary objective of the current study is to identify the optimal siting and allocation scheme for both traditional and UAV-equipped urban emergency service facilities, including fire stations and ambulance centers. The optimisation problem is sys-

Unscaled and scaled shifted geometric means of run times

All non-successes are counted as max-time.
The third line lists the number of problems (240 total) solved.

	CBC	Gurobi	COPT	SCIP	SCIPC	HiGHS	Matlab
unscal	1328	81.5	164	888	727	715	2715
scaled	16.3	1	2.01	10.9	8.92	8.77	33.3
solved	107	227	204	137	152	158	72

Fig. 1. Unscaled and scaled shifted geometric means of run times.

tematically broken down into three critical stages. Initially, the model identifies preliminary locations for traditional fire stations and ambulance centers using existing infrastructure and demographic data. The second stage of the study determines the optimal locations for UAV-based fire and EMS stations by employing clustering algorithms, which consider variables such as population density, geographic constraints, and the proximity of existing emergency services. The final stage involves optimising the allocation of both traditional and UAV-based emergency facilities to residential areas using the MILP model, which is solved via the Gurobi optimisation tool. This comprehensive approach to model optimisation and solution is exemplified through a case study focusing on a district in Chengdu City.

4.3.1. *Initial position determination*

The initial stage of the optimisation process involves the identification of the geographical locations of existing emergency service facilities, such as fire stations and ambulance centers, through the extraction of geo-coordinate data from an open platform API. These latitude and longitude coordinates are fundamental in calculating and visualising the distances between each residential area and its nearest emergency facility. In geospatial analysis, two main formulas are employed for distance calculation: the Haversine formula, which assumes the Earth is a perfect sphere and focuses on circular curvature, and the Vincenty formula, which views the Earth as a slightly flattened ellipsoid and involves more complex calculations. For this study, the average distance from residential areas to the nearest fire station and ambulance centers was approximately 1.08 km. Given the short distances and the similarity in results between the two methods, the Haversine formula (3) is selected for its simplicity and faster computational speed. This formula calculates the distance between two points, A and B, with coordinates $(lat_A,\ lon_A),(lat_B,\ lon_B)$, by considering the Earth's curvature.

$$d = 2r \cdot \arcsin(\sqrt{\sin^2\left(\frac{\mathrm{lat}_B - \mathrm{lat}_A}{2}\right) + \cos(\mathrm{lat}_A)\cdot\cos(\mathrm{lat}_B)\cdot\sin^2\left(\frac{\mathrm{lon}_B - \mathrm{lon}_A}{2}\right)}) \tag{3}$$

where d is the distance between two points; r is the radius of the Earth, which is about 6371 kilometers; $(lat_A,\ lon_A),(lat_B,\ lon_B)$ should all be converted to radians, not degrees; $arcsin$ is the arcsin function; sin and cos are the sine and cosine functions, respectively; and square roots are denoted by $sqrt$.

Fig. 2 presents the initial spatial distribution of residential areas and emergency facilities within a specific district. In this map:

Residential Areas: Represented by blue dots, these indicate the locations of various residential areas within the district.

Fire Stations: Denoted by red dots, these markers signify the locations of fire stations strategically positioned within the district.

Ambulance Centers: Illustrated by green dots, these indicate the locations of ambulance centers.

The connecting lines between these dots represent the nearest fire station and emergency center to each residential area, thereby illustrating the initial emergency response network.

Special Consideration for Out-of-District ambulance centers: It is important to note that some ambulance centers, marked with black boxes, are not technically within the boundaries of the District. However, these centers are included in the calculations for the following reason: In real-world emergency scenarios, emergency vehicles may be dispatched from the nearest available center, regardless of district boundaries. Therefore, these out-of-district centers are considered relevant to the study and are included in the optimization calculations.

4.3.2. *Drone site locations identified*

The identification of optimal locations for UAV fire stations and drone ambulance centers employs an algorithmic approach utilising an enhanced X-means clustering algorithm, an extension of the traditional K-means. The conventional K-means algorithm requires a pre-specified number of clusters (K), a challenging parameter to determine accurately in practical scenarios due to the potential variability in clustering outcomes based on different K values. X-means overcomes this limitation by automatically determining the optimal number of clusters, enhancing the precision in the location planning for emergency services. Following this, the improved X-means identifies optimal cluster centers, which are then utilised by the K-means algorithm for clustering, designating these centers as future locations for UAV fire stations and drone ambulance centers. Further refining location accuracy, the K-Means++ algorithm, which is known for maximizing the dispersion of initial cluster centers to improve clustering performance, is applied. This algorithm reduces the randomness in cluster centre selection, which is crucial for achieving reliable clustering outcomes. The results, after 1,000

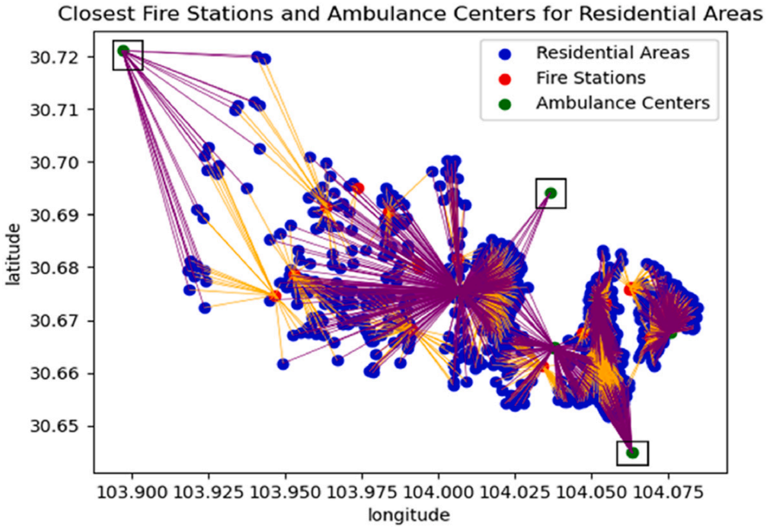


Fig. 2. Closest fire stations and ambulance centers for residential areas.

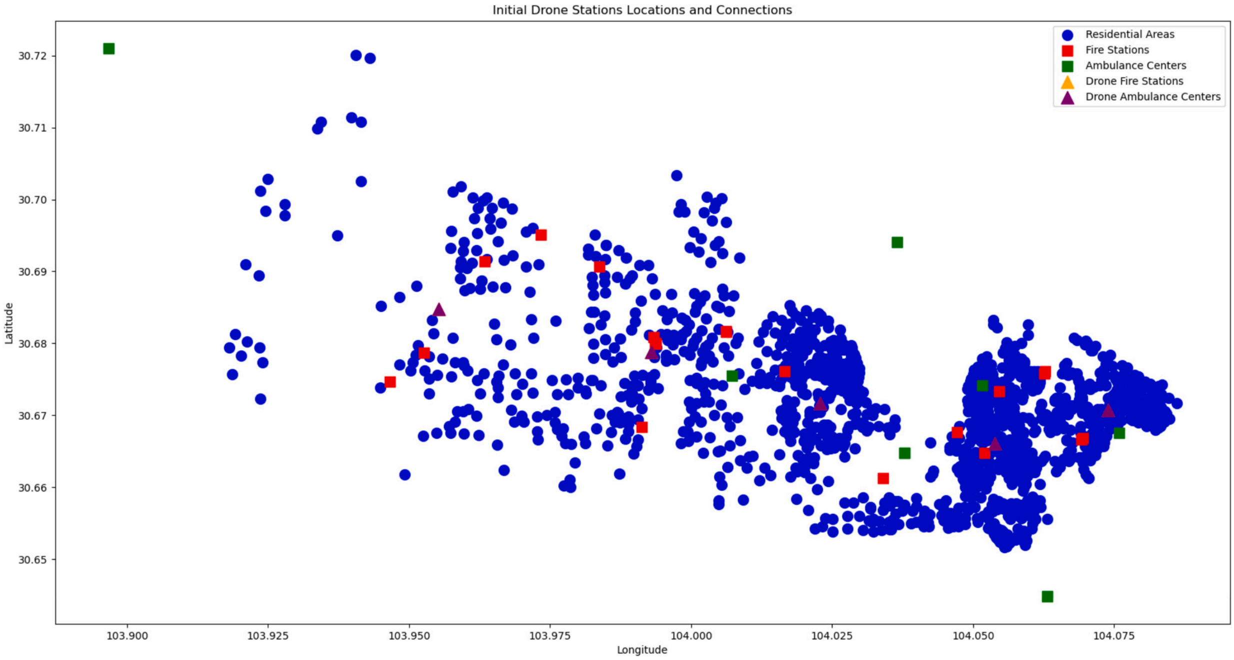


Fig. 3. Initial drone stations locations.

iterations, reveal the optimally determined number of clusters, with the location coordinates of these centers visually represented in Fig. 3, which shows the spatial distribution of the optimized emergency service locations.

The strategic placement of UAV and drone centers has significantly enhanced the efficiency of emergency response by reducing the average distance to emergency facilities from 1.08 km to 0.708 km, thus improving accessibility. These efforts align with the specifications of the Urban Firefighting Planning Specification (GB 51080-2015), ensuring compliance and elevating the operational standards of urban emergency response systems.

According to Provision Note 4.1.3 of the Urban Firefighting Planning Specification (GB 51080-2015) [23], the area of a fire station precinct should range between 3.56 $\text{km}^2 - 6.28\ \text{km}^2$, about $4km^2 - 7km^2$, approximately translating to a straight-line distance of $2km - 2.65km$. Distinctive Distance Calculations for Different Types of Stations It is crucial to note that the distance calculations differ between traditional fire stations and ambulance centers, and their drone counterparts. Traditional facilities use vehicles for emergency response and are thus subject to road limitations, necessitating the use of Manhattan distance for calculations. In contrast, UAVs are not constrained by roadways and only need to consider flight paths to avoid collisions with buildings. This distinction in distance calculation methodologies is visually represented in Fig. 4. Objective of the Study in the Context of Existing Specifications

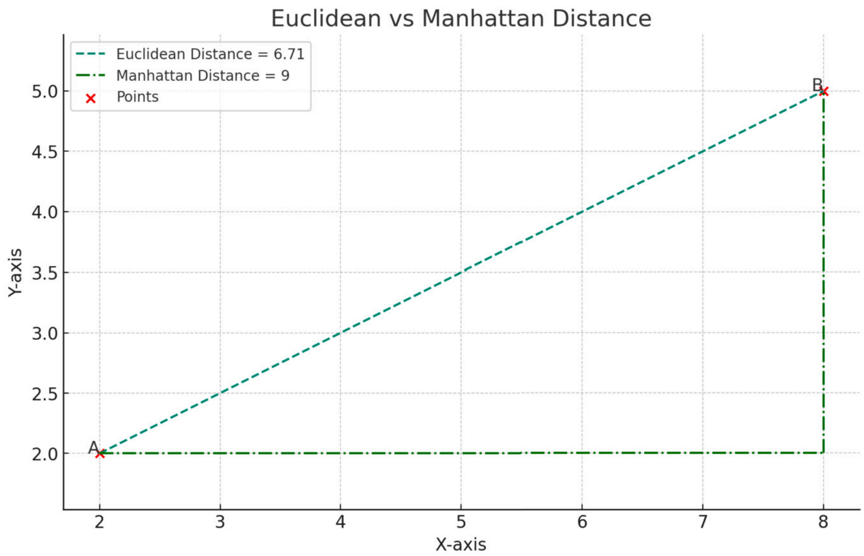


Fig. 4. Euclidean vs Manhattan distance.

Prior to the optimization, the firefighting deployment in the District was already in compliance with the specification requirements. Specifically, there was at least one fire station within a straight-line distance of 2 km to 2.65 km from each residential areason average. However, this study aims to go beyond mere compliance with standards. It seeks to optimize emergency service deployment for extreme emergency scenarios, ensuring the most efficient allocation even in the worst-case situations.

Inclusion of external ambulance centers located outside the district's jurisdiction, while seemingly superfluous, plays an integral role in fortifying the emergency response framework. Despite these centers not being directly assigned to any residential areas within the district, as per the principle of proximity, their strategic incorporation is pivotal. This is particularly pertinent given the spatial distribution of residential areas, which, as depicted in Fig. 4, are densely clustered towards the lower right corner of the district. This clustering risks overloading specific fire stations and ambulance centers, potentially compromising emergency service efficiency and effectiveness. Further analysis into the matching relationships between various emergency facilities—including traditional and drone fire stations and ambulance centers—and residential areas reveals how the proximity rule influences facility distribution, pinpointing potential bottlenecks and inefficiencies. Results presented in Fig. 5 underscore the necessity of including external ambulance centers to alleviate facility overloading, thereby enhancing the overall robustness and resilience of the emergency response system.

Observations from Fig. 6, Fig. 6 provides a compelling visualization of the allocation of residential areas to fire stations and ambulance centers under the proximity rule. A striking feature of this allocation is the uneven distribution of responsibilities among these emergency facilities.

In the analysis of emergency service distribution, it is evident that certain fire stations and ambulance centers, including those outside the district's jurisdiction, remain unassigned to any residential areas. This highlights a significant issue of resource inefficiency. Conversely, other facilities face the challenge of being overloaded with a disproportionately high number of residential assignments, which corroborates earlier concerns about potential facility overload suggested by the density distribution of residential areas. This situation gives rise to a number of adverse implications for emergency response. The unassigned facilities result in the underutilisation of resources, while the overloaded facilities may suffer from increased response times, which are detrimental in emergency scenarios and can also negatively impact the quality of service. In light of these findings, it is imperative to reassess the allocation strategy. While proximity remains a critical factor, it should not be the sole criterion for assigning facilities. In order to mitigate inefficiencies and improve the emergency response system, it is necessary to integrate other factors, such as facility capacity, road conditions, and historical data on emergency incidents, into a more comprehensive and balanced allocation model.

4.3.3. MILP + Bayesian allocation optimization algorithm

The data analysis conducted earlier revealed that while the introduction of drone fire stations and drone ambulance centers alleviates some pressure on traditional emergency facilities, it also results in an imbalanced load distribution. Specifically, some facilities remain underutilized due to their distance from residential communities, while others operate under overload conditions. This imbalance could exacerbate the outcomes of emergency events if they occur in a more concentrated timeframe.

To address the allocation of emergency facilities to residential communities, a two-pronged algorithmic approach is employed. An MILP model (see equations (1), (2)) is constructed to optimize facility allocation with the objective of minimizing the worst-case scenario distance between residential communities and their assigned emergency facilities. Additionally, Bayesian Optimization is utilized to dynamically adjust the hyperparameters(c_{min}^{fs}, f_{ms}, c_{min}^{ms}, f_{fs}) during the MILP solving process. This optimization technique builds a probabilistic model of the objective function and strategically selects promising hyperparameters for evaluation. Computational efforts were executed using Gurobi Optimizer version 10.0.2 on an 8th generation Intel Core i7-8700 CPU, where the MILP model consisted of 69,606 constraints, 66,403 variables, and 265,608 non-zero elements, including one continuous and 66,402

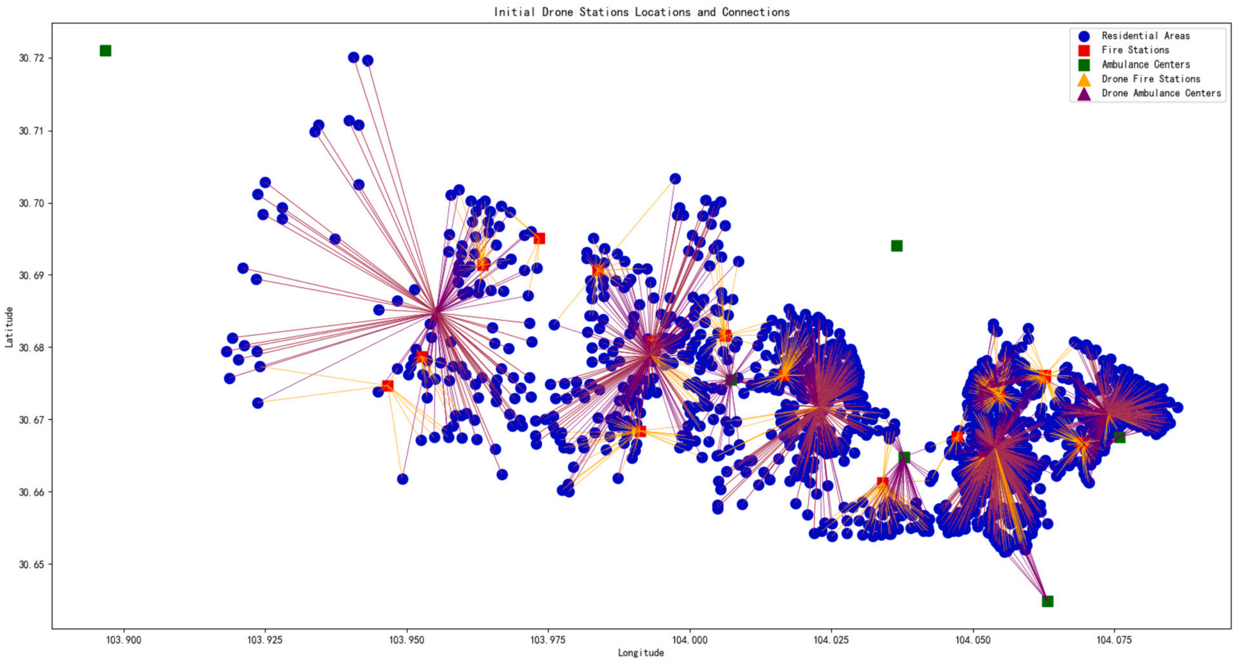
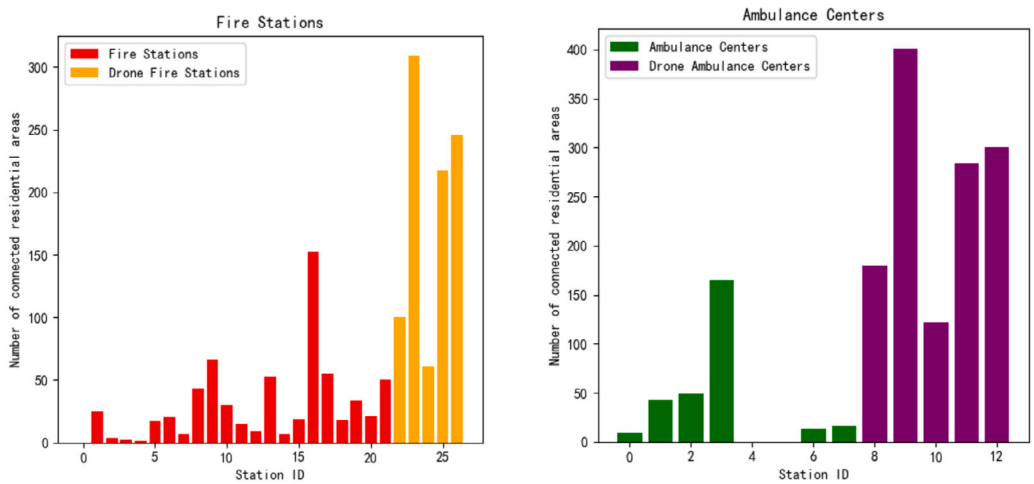


Fig. 5. Initial drone stations locations and connections.



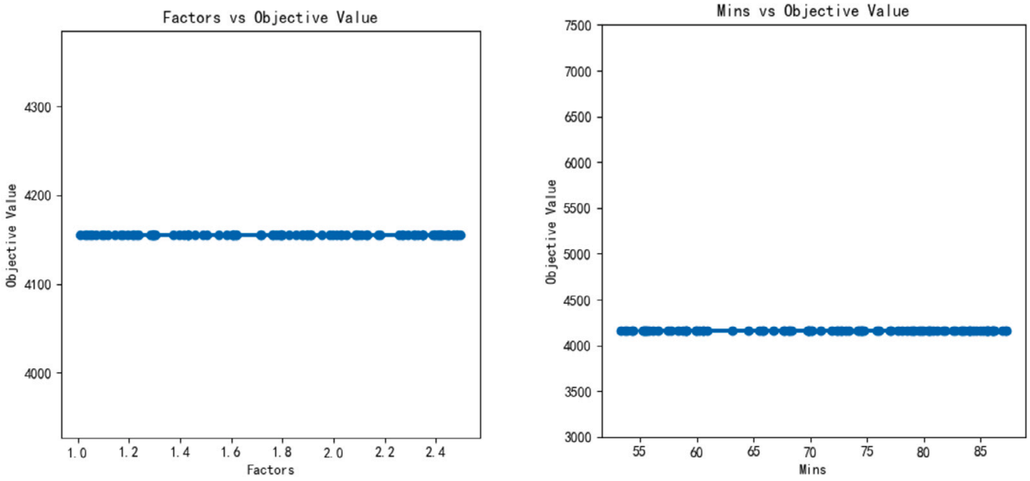
(a) Distribution of Services at Fire Stations	(b) Distribution of Services at Ambulance centers

Fig. 6. Distribution of services at fire stations and ambulance centers.

binary variables. Initially, the heuristic solution registered an objective function value of 644.9989, with the optimal solution reaching 4155.793754252. Gurobi's optimization involved a parallel linear programming optimizer and the generation of multiple cutting planes, specifically 736 MIR, 95 RLT, and 2 Relax-and-lift. After 100 iterations, the Bayesian optimization tuned the hyperparameters within stable ranges, indicating robust experimental data as represented in Fig. 7.

The combined MILP and Bayesian optimization approach not only addresses the limitations of each individual method but also provides a robust and dynamic optimization framework. It successfully balances the load among emergency facilities while considering worst-case scenarios, thereby enhancing the efficiency and effectiveness of urban emergency response systems. In this section, we delve into the statistical representation of the impact factors and their relationship with the objective function. This is visualized in Fig. 8, which shows a three-dimensional distribution of the two types of impact factors: the minimum service capacity of emergency facilities and the objective function.

The Bayesian optimisation algorithm has a significant impact on the selection of hyperparameters, which are crucial for achieving the optimal objective function as depicted in Fig. 9. The algorithm's capacity to uniformly distribute the selected hyperparameters



(a) Factors vs Objective Value (b) Mins vs Objective Value

Fig. 7. Factors and mins vs objective value.

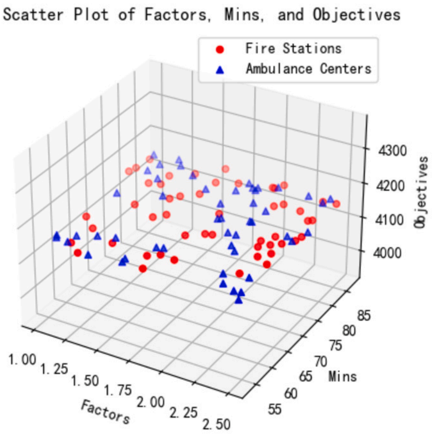


Fig. 8. 3D scatter plot of factors, mins, and objectives.

across their respective parameter spaces enhances the optimization process in several ways. Firstly, the uniform distribution serves to reinforce the robustness of the process, as it implies a comprehensive exploration of the parameter space. Secondly, this distribution pattern enhances the generalisability of the model, indicating that it is not overly sensitive to specific hyperparameter values. Consequently, the model is applicable to a variety of scenarios. Finally, the presence of hyperparameters within specific ranges indicates that the algorithm has identified areas within the parameter space that are likely to optimise the objective function. The three-dimensional distribution of these parameters provides insight into the intricate relationship between the minimum service capacity of emergency facilities and the objective function, further validating the effectiveness and uniform distribution achieved by the Bayesian optimization. This indicates that the optimization process is well-balanced and robust, which is essential for the practical application of the model in urban emergency management.

5. Interpretation and analysis of results

In the final analysis, Fig. 10(b) elucidates the efficacy of the optimized allocation strategy in mitigating the operational burden on emergency service facilities, particularly those situated in the densely populated residential sectors delineated in the lower right quadrant of Fig. 10(a). By judiciously reallocating EMS facilities from the upper right sector to proximate residential communities, the strategy achieves a more equitable distribution of service capabilities. A comparative analysis with Fig. 10(a) reveals a marked attenuation in the density of connective lines between emergency service facilities and their designated residential communities. This is especially salient for facilities that were previously subjected to disproportionate operational demands owing to their geographical proximity to high-density residential areas. Conversely, Fig. 10(b) exhibits a more uniform dispersion of these connective lines, thereby signifying a more balanced and efficient allocation of emergency service resources.

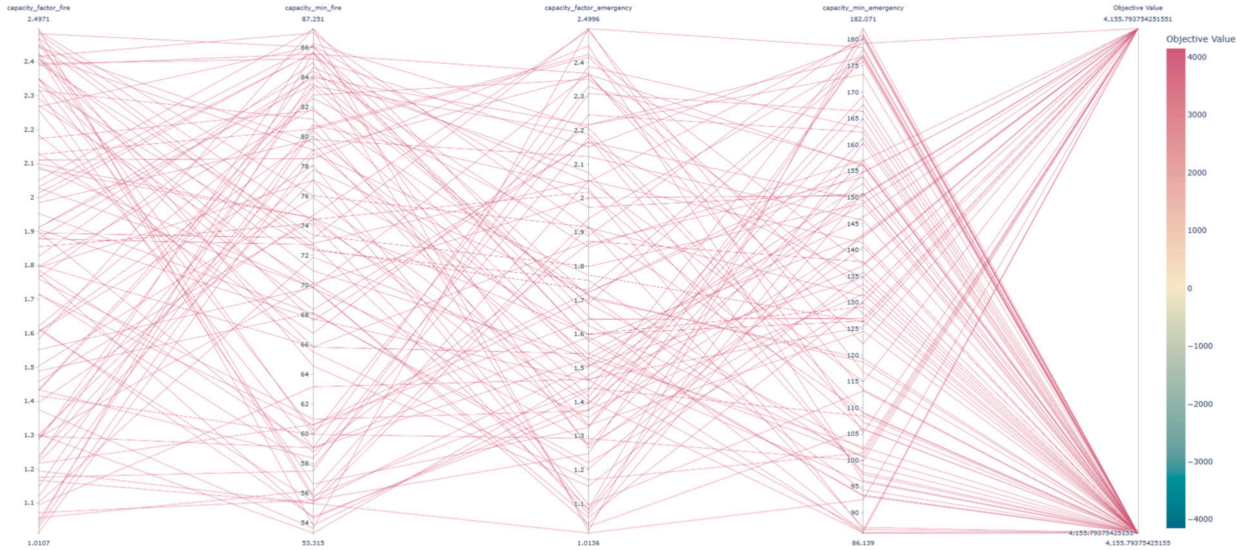
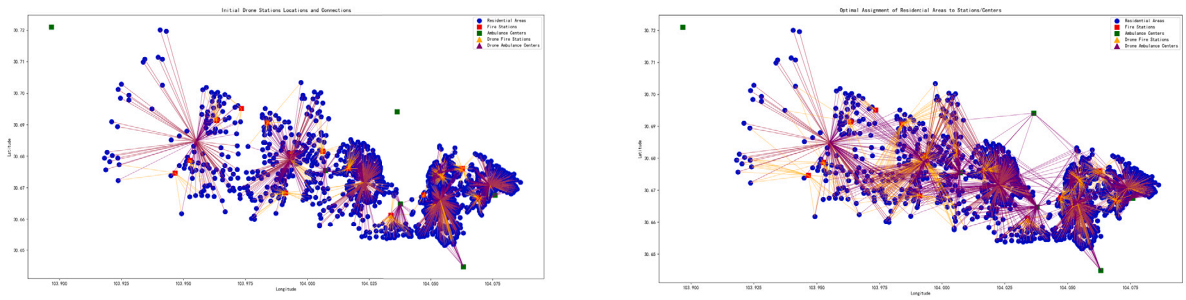


Fig. 9. Network diagram of impact factors.



(a) Figure 5. Initial Drone Stations Locations and Connections

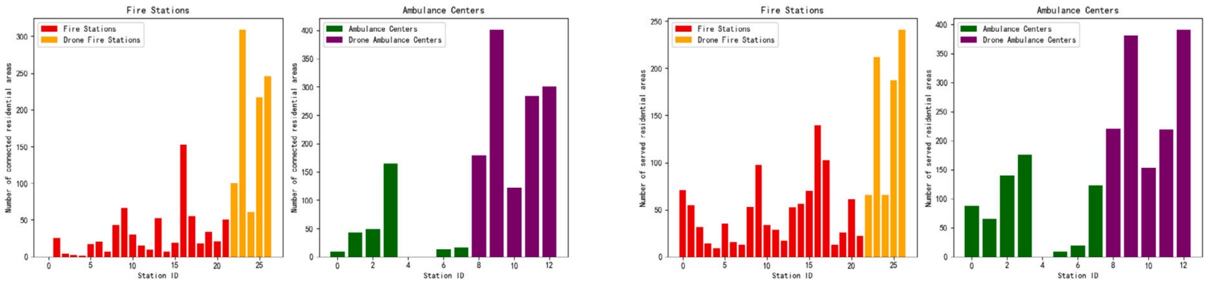
(b) Optimal Assignment of Residential Areas to Stations/Centers

Fig. 10. Comparison of service concentration of each emergency service facility under different optimization methods.

The intricate interplay between emergency service facilities and residential areas is vividly depicted in Fig. 11. Statistical analysis reveals a notable uptick in the number of residential Areas served by previously underutilized emergency facilities. For instance, Fire Station 0, which initially had no assigned residential areas based on the principle of proximity-based rescue (see Fig. 11(a)), now serves approximately 71 subdivisions post-optimization (see Fig. 11(b)). Concurrently, facilities that were previously overburdened have experienced a reduction in operational pressure. A case in point is Drone Fire Station 1, which saw its service area decrease from 309 to 212 residential areas after optimization. Such transformations, from zero to average service levels and from overburdened to balanced service levels, are readily observable in the comparative graphs. The optimization yields an optimal objective function value of 4.155 km, with hyperparameters set at $c_{min}^{fs} = 1.19$, $f_{ms} = 55$, $c_{min}^{ms} = 1.91$, and $f_{fs} = 87$. The average distance for all residential areas to their furthest assigned emergency facility is reduced to 1.516 km. This implies that, under the current residential layout and employing the MILP+Bayesian optimization algorithm, the service capacity of emergency facilities can be enhanced to 1.19 and 1.91 times their pre-optimization levels. The minimum number of residential Areas covered increases to 55 and 87, effectively reducing the average distance to emergency facilities in the district to a range of 0.708 to 1.516 km.

However, Fig. 7, Fig. 8 and Fig. 9 indicate that the optimal objective function values exhibit minimal fluctuation within the experimentally verified hyperparameter range. Thus, employing the MILP+Bayesian optimization algorithm ensures effective coverage for 52 to 87 residential areas at 1.0 to 2.5 times the existing firefighting facility capacity, and 85 to 182 residential areas at 1.0 to 2.5 times the current EMS capacity.

It is, however, important to note that the southeastern region of the district, being in close proximity to the densely populated centre of Chengdu City, presents unique challenges for emergency response. The strategic location of some emergency service facilities, situated at the epicentre of numerous residential areas, has the unintended consequence of diminishing their effective emergency response capacity. The spatial distribution of residential areas exerts additional pressure on these facilities, thereby potentially compromising their ability to respond optimally during emergency situations (see Table 4).



(a) Figure 6. Distribution of Services at Fire Stations and ambulance centers

(b) MILP+Bayesian Optimized Emergency Facility Location Information and Allocated Quantity Statistics

Fig. 11. Comparison of the number of service cells for each emergency service facility under different optimization methods.

Table 4
Experimental results of optimizing the deployment of emergency service facilities in other jurisdictions in selected Chengdu cities.

Initial Mean Distance[1]	Optimized Mean Distance[2]	Rate of Change	Initial Gini Coefficient[3]	Optimized Gini Coefficient	Rate of Change
821	1516	+0.85	0.21	0.18	-0.14

[1] Average distance to the nearest two types of emergency service facilities for each residential community.
[2] Average distance from each residential areas to the two types of emergency service facilities assigned to it.
[3] The Gini coefficient is an indicator for judging the degree of equality of distribution based on the Lorenz curve; the smaller the data, the more evenly distributed. $G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left|x_i - x_j\right|}{2\sum_{i=1}^{n}\sum_{j=1}^{n} x_i}$.

In an effort to validate the robustness and general applicability of the optimization algorithm employed in this study, additional experimental data and results have been included in Appendix A (see Tables A.1 and A.2 and Figs. A.1–A.4). These supplementary experiments, conducted across diverse geographical and infrastructural settings, serve to demonstrate that the algorithm is not unduly influenced by the specific distribution patterns of residential areas and emergency facilities. The outcomes from these auxiliary tests affirm the algorithm's capacity for effective optimization across a broad range of residential and emergency facility configurations, thereby attesting to its generalizability.

6. Conclusions and outlook

This study presents a comprehensive framework for optimizing the location and allocation of emergency service facilities, incorporating machine learning algorithms and operations research techniques. Specifically, the X-means and K-means algorithms effectively address the location problem, balancing the trade-offs between construction costs and operational pressures. Further refinement is achieved through a hybrid optimization algorithm that combines MILP with Bayesian optimization. This approach allows for dynamic adjustment of hyperparameters, thereby providing a more nuanced evaluation of service capacity constraints. The objective function, designed to minimize the farthest distance to available emergency services in worst-case scenarios, serves as a robust metric for assessing the efficacy of deploying UAV fire stations and EMS distribution centers. Experimental results validate the algorithm's capability to enhance emergency response times and operational efficiency.

However, several avenues for future research remain. These include evaluating the comparative emergency response capabilities of traditional and UAV-based facilities, devising strategies for their coordinated deployment during emergencies, and incorporating more granular data on residential demographics and infrastructure into the model.

In summary, this paper introduces an innovative optimization algorithm that amalgamates machine learning techniques with operations research methodologies. The proposed framework not only addresses the inefficiencies arising from imbalanced distribution and allocation of emergency services but also establishes the feasibility and effectiveness of incorporating UAV-based facilities into existing emergency response infrastructures.

CRediT authorship contribution statement

Weijun Pan: Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Jianwei Gao:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Xuan Wang:** Writing – review & editing, Conceptualization. **Qinghai Zuo:** Writing – review & editing. **Shijie Tan:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Weijun Pan reports financial support was provided by Sichuan Province, China Science and Technology Department and Sichuan Provincial Key Laboratory of Civil Aircraft Fire Science and Safety Engineering.

Appendix A. Data and experimental results from other areas of Chengdu city

Table A.1
Data tables of residential areas and firefighting authorities and ambulance centers in other jurisdictions of selected Chengdu Cities (after data processing).

District Name	Number of Residential Areas	Number of Fire Stations	Number of ambulance centers	Number of drone fire stations	Unmanned drone ambulance centers
Area 2	1561	18	3	3	3
Area 3	946	16	2	2	2
Area 4	1067	13	2	4	3
Area 5	1418	20	6	3	4

Table A.2
Experimental results of optimizing the deployment of emergency service facilities in other jurisdictions in selected Chengdu cities.

Initial Average Distance	Optimized Average Distance	Rate of Change	Initial Gini Coefficient	Optimized Gini Coefficient	Rate of Change
1573	1969	+0.25	0.39	0.28	-0.28
1825	2291	+0.25	0.21	0.12	-0.43
1052	1207	+0.15	0.29	0.27	-0.25
1515	1766	+0.17	0.31	0.27	-0.13

References

[1] Ministry of Emergency Management – Fire and Rescue Department, National Fire and Police Statistics System, http://stat.119.gov.cn/. (Accessed April 2022), 2023.

[2] L. Zhong, X. Xianrui, Y. Hong, Optimized organization of service space in capacity-constrained public facilities: the case of Shanghai emergency shelter, Town Plann. (1) (2015) 75–80.

[3] L. Jinze, T. Peng, Research on multi-objective optimal siting model of emergency service facilities based on urban big data, in: Digital Intelligence: Proceedings of the 2020 National Symposium on Teaching and Research of Digital Technology in Architectural Faculties, 2020.

[4] F. Mingmin, Research on evaluation and optimization model of urban emergency service facilities layout, Ph.D. thesis, Jilin University, 2011.

[5] Q. Lianbao, Z. Huagui, Queuing model-based siting of β reliable maximum coverage emergency service vehicles: models and algorithms, Fudan J. Nat. Sci. Ed. 2 (2013) 167–176.

[6] W. Wenjie, Z. Siyuan, Z. Wenzhong, et al., Analysis of the optimized configuration of emergency shelter locations in Beijing, Humanit. Geogr. 25 (4) (2010) 41–44.

[7] Z. Shaoying, Yangxin, Chenrui, et al., Study on the spatial accessibility of hierarchical public service facilities–taking Beijing comprehensive medical facilities as an example, Geogr. Stud. 35 (4) (2016) 731–744.

[8] S. Fazlollahi, L. Girardin, F. Maréchal, Clustering Urban Areas for Optimizing the Design and the Operation of District Energy Systems, Computer Aided Chemical Engineering, vol. 33, Elsevier, 2014, pp. 1291–1296.

[9] M. You, Y. Xiao, S. Zhang, P. Yang, S. Zhou, Optimal mathematical programming for the warehouse location problem with euclidean distance linearization, Comput. Ind. Eng. 136 (2019) 70–79.

[10] J.-T. Camino, C. Artigues, L. Houssin, S. Mourgues, Milp formulation improvement with k-means clustering for the beam layout optimization in multibeam satellite systems, Comput. Ind. Eng. 158 (2021) 107228.

[11] F. Boukouvala, R. Misener, C.A. Floudas, Global optimization advances in mixed-integer nonlinear programming, minlp, and constrained derivative-free optimization, cdfo, Eur. J. Oper. Res. 252 (3) (2016) 701–727.

[12] A. Malhotra, I.D. Schizas, Milp-based unsupervised clustering, IEEE Signal Process. Lett. 25 (12) (2018) 1825–1829.

[13] M. Zatti, M. Gabba, M. Freschini, M. Rossi, A. Gambarotta, M. Morini, E. Martelli, k-milp: a novel clustering approach to select typical and extreme days for multi-energy systems design optimization, Energy 181 (2019) 1051–1063.

[14] W. Tang, Y. Yang, L. Zeng, Y. Zhan, Size constrained clustering with milp formulation, IEEE Access 8 (2019) 1587–1599.

[15] K.P. Sinaga, M.-S. Yang, Unsupervised k-means clustering algorithm, IEEE Access 8 (2020) 80716–80727.

[16] F. Shao, C.S. Li, L.R. Liang, D. Li, S.K. Ma, Outcome of out-of-hospital cardiac arrests in Beijing, China, Resuscitation 85 (11) (2014) 1411–1417.

[17] J.J. Boutilier, S.C. Brooks, A. Janmohamed, A. Byers, J.E. Buick, C. Zhan, A.P. Schoellig, S. Cheskes, L.J. Morrison, T.C. Chan, Optimizing a drone network to deliver automated external defibrillators, Circulation 135 (25) (2017) 2454–2465.

[18] A. Pulver, R. Wei, C. Mann, Locating aed enabled medical drones to enhance cardiac arrest response times, Prehosp. Emerg. Care 20 (3) (2016) 378–389.

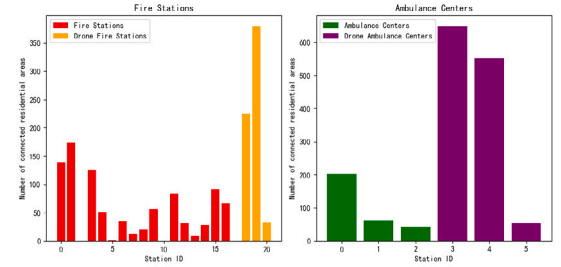
[19] E. Ausonio, P. Bagnerini, M. Ghio, Drone swarms in fire suppression activities: a conceptual framework, Drones 5 (1) (2021) 17.

[20] A. Sharma, P.K. Singh, Y. Kumar, An integrated fire detection system using iot and image processing technique for smart cities, Sustain. Cities Soc. 61 (2020) 102332.

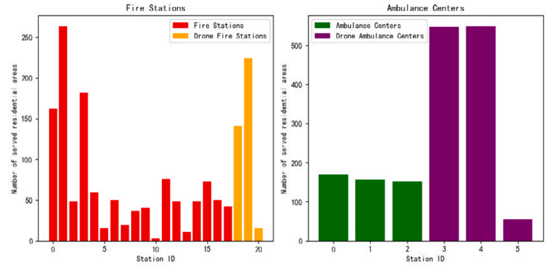
[21] K. Wang, Y. Yuan, M. Chen, Z. Lou, Z. Zhu, R. Li, A study of fire drone extinguishing system in high-rise buildings, Fire 5 (3) (2022) 75.

[22] HansMittelmann, The MIPLIB2017 benchmark instances, https://plato.asu.edu/ftp/milp.html. (Accessed 29 June 2023), 2023.

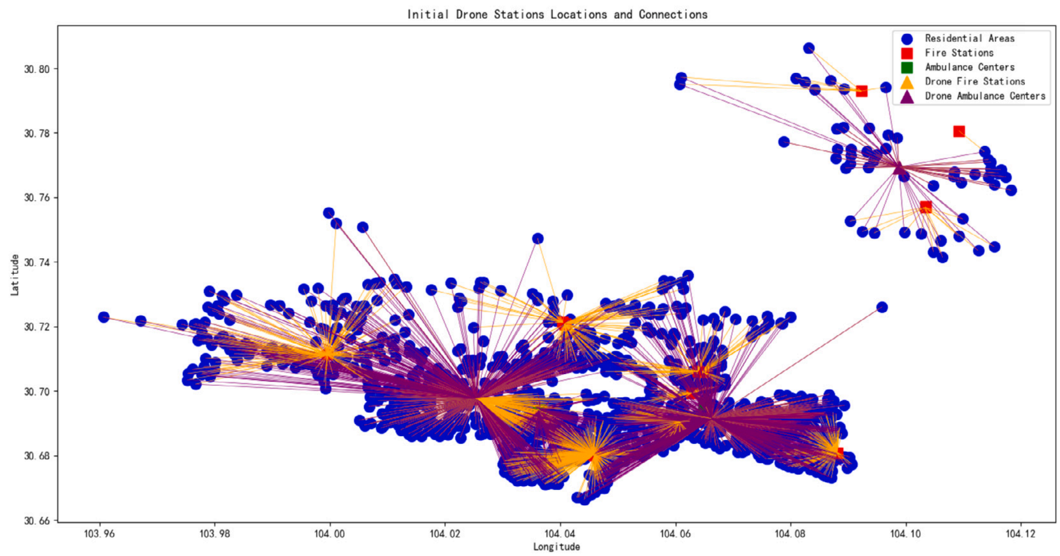
[23] C. Planning, D. Institute, GB 51080-2015 Urban Fire Planning Code, China Construction Industry Press, pp. 2015–7–2015-1.



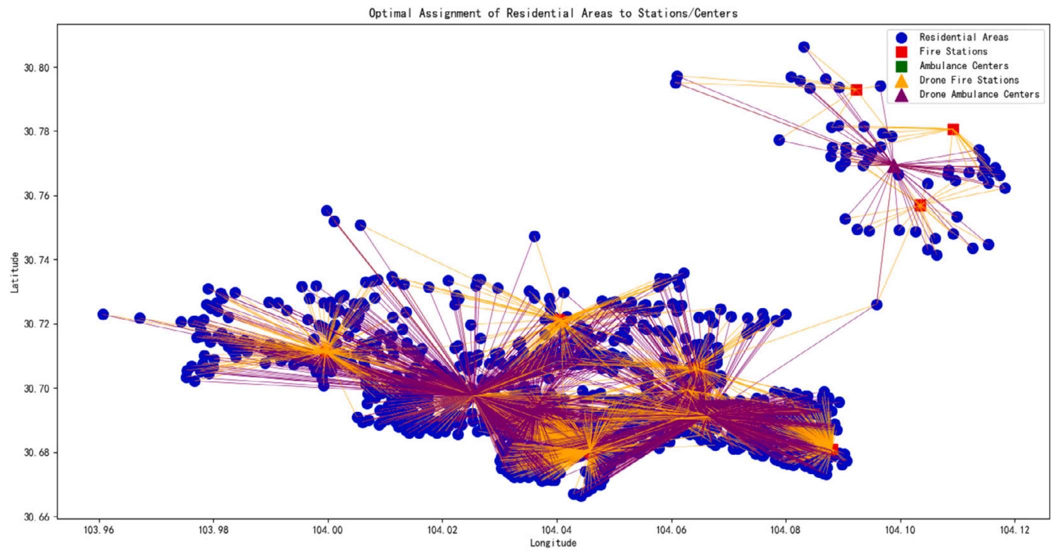
(a) Distribution of Services at Fire Stations and ambulance centers



(b) MILP+Bayesian Optimized Emergency Facility Location Information and Allocated Quantity Statistics

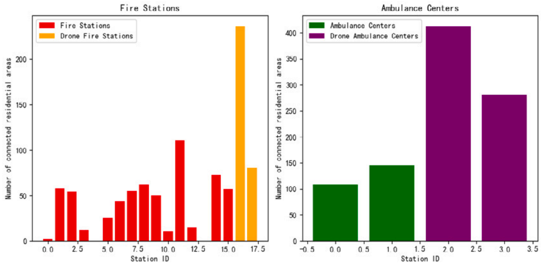


(c) Initial Drone Stations Locations and Connections

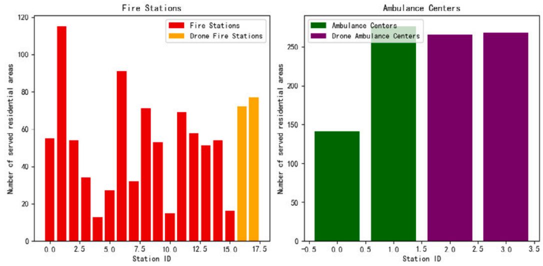


(d) Optimal Assignment of Residential Areas to Stations/Centers

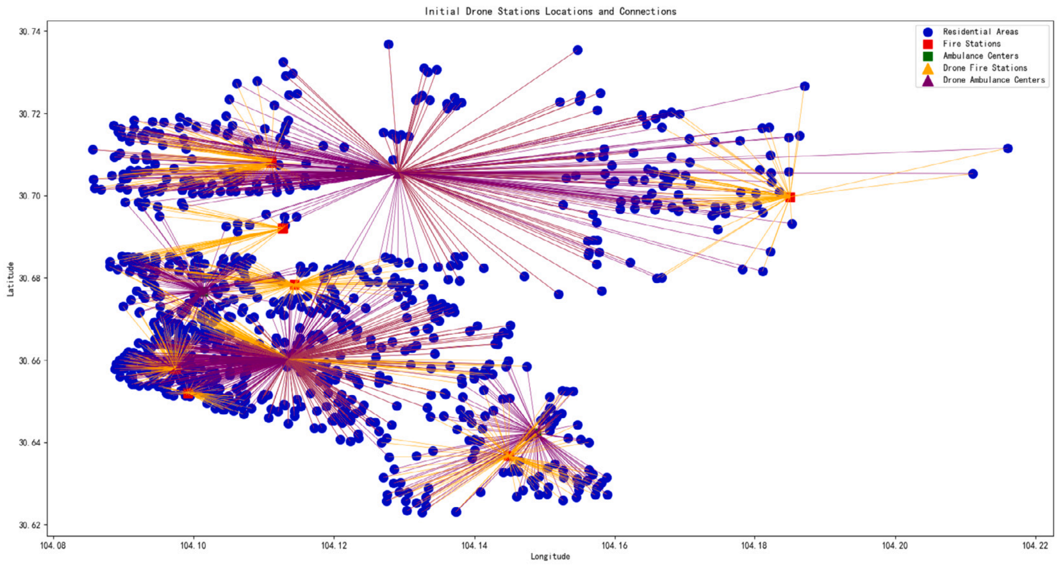
Fig. A.1. Results of experimental data visualization in Area 2.



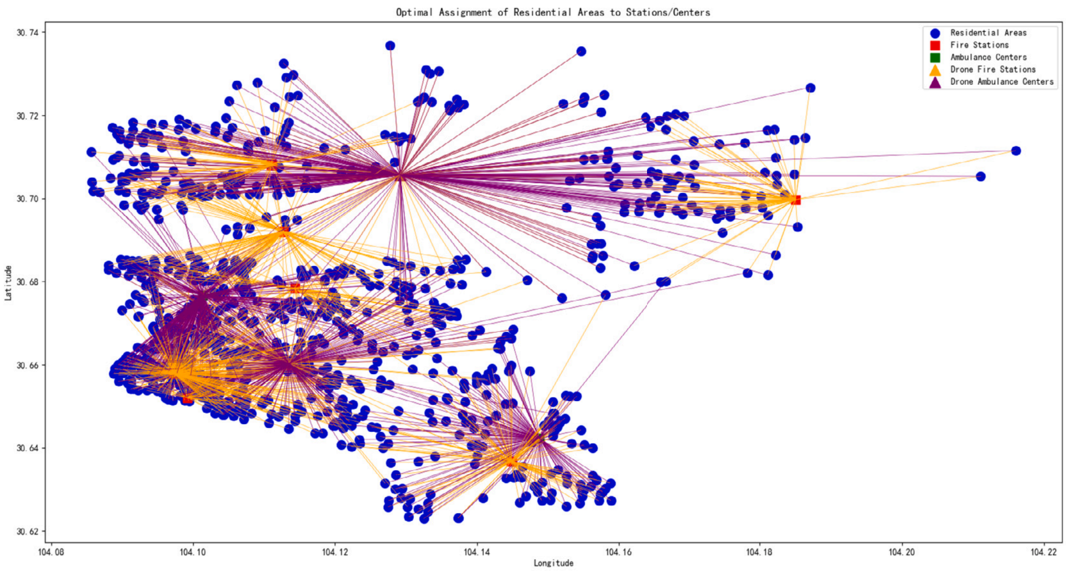
(a) Distribution of Services at Fire Stations and ambulance centers



(b) MILP+Bayesian Optimized Emergency Facility Location Information and Allocated Quantity Statistics

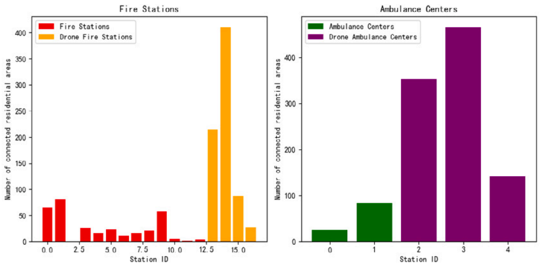


(c) Initial Drone Stations Locations and Connections

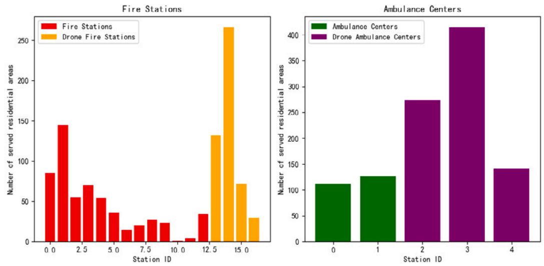


(d) Optimal Assignment of Residential Areas to Stations/Centers

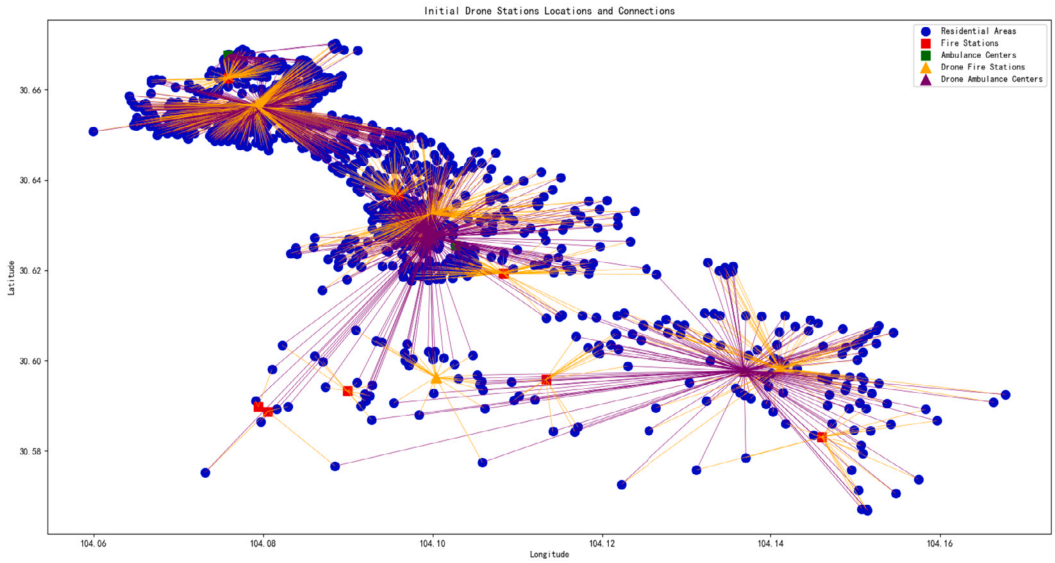
Fig. A.2. Results of experimental data visualization in Area 3.



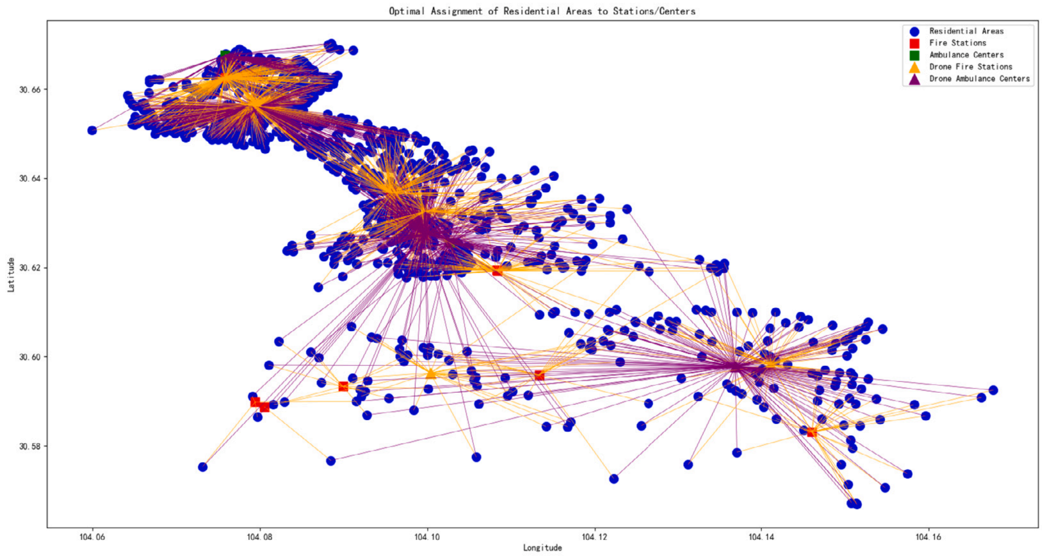
(a) Distribution of Services at Fire Stations and ambulance centers



(b) MILP+Bayesian Optimized Emergency Facility Location Information and Allocated Quantity Statistics

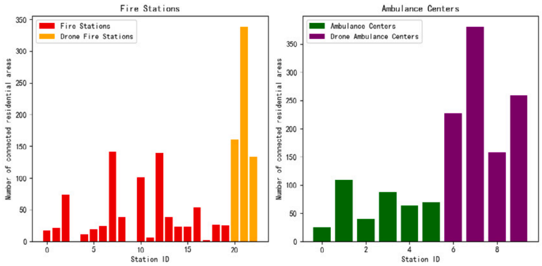


(c) Initial Drone Stations Locations and Connections

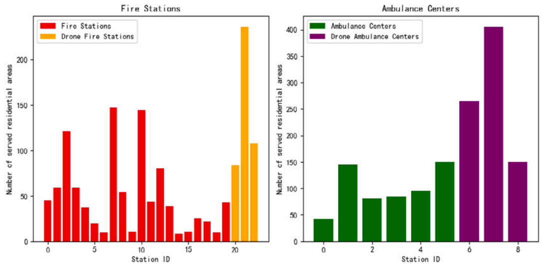


(d) Optimal Assignment of Residential Areas to Stations/Centers

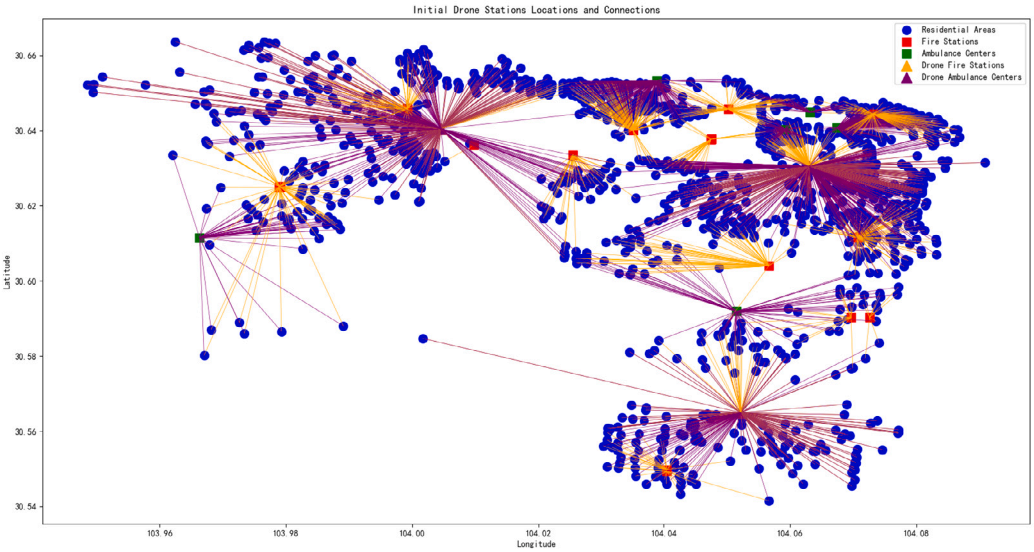
Fig. A.3. Results of experimental data visualization in Area 4.



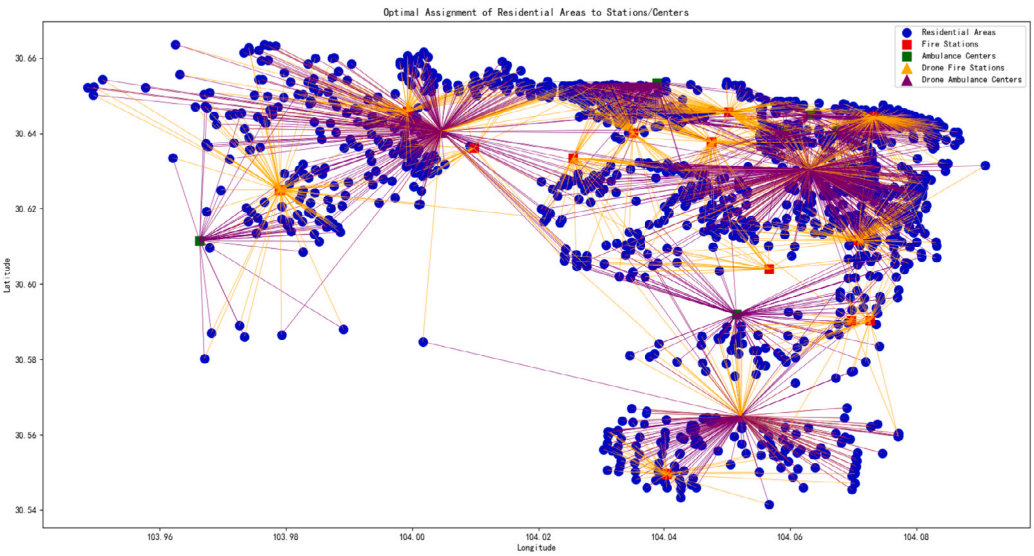
(a) Distribution of Services at Fire Stations and ambulance centers



(b) MILP+Bayesian Optimized Emergency Facility Location Information and Allocated Quantity Statistics



(c) Initial Drone Stations Locations and Connections



(d) Optimal Assignment of Residential Areas to Stations/Centers

Fig. A.4. Results of the experimental data visualization in Area 5.