Geospatial Health 2024; volume 19:1310

Dynamic location model for designated COVID-19 hospitals in China

Wang Fei, Yuan Linghong, Zhang Weigang, Zhang Ruihan

School of Economics and Management, Chang'an University, Xi 'an, Shaanxi Province, China

Abstract

In order to effectively cope with the situation caused by the COVID-19 pandemic, cases should be concentrated in designated medical institutions with full capability to deal with patients infected by this virus. We studied the location of such hospitals dividing the patients into two categories: ordinary and severe. Genetic algorithms were constructed to achieve a three-phase dynamic approach for the location of hospitals designated to receive and treat COVID-19 cases based on the goal of minimizing the cost of construction and operation isolation wards as well as the transportation costs involved. A dynamic location model was established with the decision variables of the corresponding 'chromosome' of the genetic algorithms designed so that this goal could be reached. In the static location model, 15 hospitals were required throughout the treatment cycle, whereas the dynamic location model found a requirement of only 11 hospitals. It further showed that hospital construction costs can be reduced by approximately 13.7% and operational costs by approximately 26.7%. A comparison of the genetic algorithm and the Gurobi optimizer gave the genetic algorithm several advantages, such as great convergence and high operational efficiency.

Correspondence: Zhang Ruihan, School of Economics and Management, Chang'an University, Xi 'an, Shaanxi Province, China.
Tel.: +86.187.9247.7296
E-mail: 360563673@qq.com

Key words COVID-19; dynamic set-covering location; genetic algorithms; designated hospital; China.

Funding: this article was supported by the Natural Science Foundation of China "Research on Urban Spatial Structure Reconstruction Based on Modern Logistics" (41371180).

Conflict of interest: the authors declare no conflict of interest.

Availability of data and materials: all data generated or analyzed during this study are included in this published article.

Received: 6 May 2024.
Accepted: 20 September 2024.

Geospatial Health 2024; 19:1310
doi:10.4081/gh.2024.1310

Introduction

Since its first detection in December 2019, the coronavirus disease 2019 (COVID-19) rapidly spread worldwide and was soon declared a pandemic by the World Health Organisation (WHO). This highly contagious virus has had a significant impact on individuals, society, and the economy (Yu *et al.*, 2020). Although the virulence of the COVID-19 virus has weakened, resulting in a significant reduction in the severity and mortality rate compared to 2020 and 2021, its transmission has further intensified.

Shanghai, encompassing 16 districts, enjoys a superior geographical location and is the financial centre of China that handles most of China's foreign trade and personnel exchange. Its large comprehensive hospitals that integrate technical talents, diagnostics, treatment equipment and facilities, have rapidly expanded from initial outpatient triage and technical guidance to designated medical institutions, with functions including special treatment of patients with severe symptoms. On March 6, 2022, the Omicron variant of the novel coronavirus struck Shanghai. Due to the high contagiousness of the then new variant, Shanghai faced a severe challenge and implemented comprehensive prevention and control management across the city. Given the recurring resurgence of the pandemic, prevention and control remains long and arduous, designated COVID-19 hospitals, serving as specialized medical institutions for COVID-19 patients, can play a crucial role. During the early phases of local outbreaks, there were surges of new patients that strained available medical resources (Aydin *et al.*, 2021). The problem of selecting emergency facilities became critical due to this sudden public health incident. To determine the optimal location for emergency facilities and minimizing costs, a model covering the maximum number of demand points with the optimum number of facilities designed and applied (Alizadeh *et al.*, 2020; Oksuz *et al.*, 2020). In Indonesia, Sitepu *et al.* (2019, 2023) applied this model identifying six locations in Palembang, Sumatra to serve eight districts, where unknown distances were considered to optimize the locations of emergency units. Emergency facility location for COVID-19 treatment involves managing limited medical resources such as beds, staff and medicaments, while also considering rapidly changing patient numbers with varying severity of disease. Understanding how to flexibly deploy emergency medical facilities within the pandemic cycle, improve rescue efficiency and minimize economic loss is of crucial, practical importance.

Literature review

The problem of emergency facility location mainly includes the P-median problem (finding the location of facilities covering a specified area at a minimized total cost). If a facility location is hard to solve with respect to nondeterministic polynomial time, the problem is said to be NP-hard; heuristic algorithms are often employed. Genetic algorithms, with rapid and random global search capability, have proven effective in solving facility location problems (Jaramillo *et al.*, 2002). With the further development of location research, many scholars have combined dynamic location with emergency facility issues, treating the location problem as a long-term, ongoing study. Xi *et al.* (2013) constructed an emergency rescue facility model considering rescue time constraints based on a modified P-median problem and solved it using Variable Neighborhood Search (VNS), a metaheuristic method for solving a set of combinatorial optimizations (Mladenović & Hansen, 1997). Ma *et al.* (2016) noting the lack of scenarios where post-disaster shelters fail, built a supplementary selection model for such failures based on the P-median problem. Murad *et al.* (2021) developed a location-allocation P-median model attempts to optimize health care services network and to put forward location recommendations to maximize service coverage.

Fernandes *et al.* (2014) presented a chromosome representation encoding the locations of distribution centres and the allocation of customers to solve a two-stage capacitated facility location problem, while Nasiri *et al.* (2018) proposed a bi-level genetic algorithm to solve capacitated competitive facility location problem. The modified algorithm incorporates specialized mechanisms to handle the partial demand satisfaction and capacity constraints of facilities. Bhattacharjee *et al.* (2023) used an improved genetic algorithm to solve the hierarchical single-allocation hub median facility location problem, where the algorithm applied includes a local search algorithm to fine-tune solutions after the standard genetic algorithm operations. Based on set-covering location model, some scholars figured out the optimum locations of emergency facilities below the cost originally calculated. Doungpan *et al.* (2018) established a facility location model based on the set-covering problem that optimized the selection of emergency management facilities during the pre-disaster phase. Sitepu *et al.* (2019) created an emergency location model for sanitation facilities based on the set-covering problem and solved the model using a branch and bound solver through LINGO (Cunningham & Schrage, 2004). Luo *et al.* (2022) proposed a new local search algorithm dubbed 'Novel Unordered Set-Covering' (NuSC), which effectively solves the set-covering problem through unordered search. Hashemi *et al.* (2022) have provided another new algorithm including a fitness function that evaluates the qualification of subsets and solves complex set-covering problems without conventional restrictions. Basic location problems usually only consider facility locations within a single time period. However, in practical applications, facility location could be a long-term, continuous decision-making process due to factors that change over time, thereby giving rise to dynamic location problems. Marques *et al.* (2018) considered uncertainty in fixed and allocated costs as well as in potential facility localization and possible customer sets. They explicitly considered 'regret', a function understood as the loss caused by not choosing the optimal solution. Zhang *et al.* (2019) established a two-stage coverage location model for emergency medical rescue networks under multiple modes, expanding the research in large-scale disaster rescue management. Allman and Zhang (2020) proposed a generic mixed-integer, linear programming framework for determining the optimal location and relocation of mobile production modules given time-varying demand, whereas Pourghader Chobar *et al.* (2021) provided a tourist hub location problem for essential commodities with non-negligible demand dynamics. Fergani *et al.* (2022) presented a generic mixed-integer, linear programming formula that can formalize the dynamic facility location problem, while Yan *et al.* (2022) segmented customer demand into multiple phases and compared the costs of static and dynamic location through case studies.

In summary, the existing literature provides substantial research on the dynamic facility location problem. However, given the abruptness of public health events and the dynamic changes in the number of patients and medical resources, a dynamic model can effectively address the aforementioned issues. Although fairly comprehensive research has been carried out on the location of emergency facilities, interest in the location of emergency medical facilities is still limited, something which has been highlighted by the outbreak of the COVID-19 (Liu *et al.*, 2022). This paper proposes the building of a set-covering location model for designated COVID-19 hospitals that systematically carries out dynamic set-covering location searches incorporating treatment cycles. It focuses on designated COVID-19 hospitals with limited medical resources (beds, staff and healthcare resources) considering dynamic changes in patient numbers and symptom severity by combining dynamic location problems with designated COVID-19 hospital location research. The application of the model is illustrated with a case study based on the outbreak of COVID-19 in Shang Hai, China. Although the epidemic has now gradually passed in China, our kind of research remains important for the location of general emergency health facilities.

We focused on decision-making for hospital locations at the lowest possible costs. Potential infectious disease surges could lead to severe medical congestion shortages with regard to beds and healthcare staff, including constraints on medical resources for treating COVID-19 patients. In addition, a rational location selection for emergency supplies storage facilities is crucial to ensuring the effectiveness and efficiency of emergency rescue operations (Dong *et al.*, 2021), while symptom differences could result in additional costs (Gu *et al.*, 2018). Since the quantity of patients and symptom severity may change dynamically in various regions over time and availability of resources needs to reflect the changes in demand, the model selects the process from the initial spread of an epidemic to its peak and divides it into three phases as the object of theoretical study (Ng *et al.*, 2020; Chakraborty *et al.*, 2021) as this can adequately reflect the changes in the growth of the epidemic while simplifying the model.

Materials and Methods

The model

The first phase of our work corresponds to the initial phase of the pandemic (2-8 April) when the total number of patients was 3,415. The second phase corresponds to the growth phase of the pandemic (9-15 April) when the total number of patients had increased to 13,448, while the third phase refers to the peak phase of the pandemic (16-22 April). During this phase, the total number of patients reached 18,500. These three phases were translated into a mathematical model aimed at minimizing isolation ward construction as well as operational and transportation costs. The objective function of the model was to cover all demand without exceeding the resource capacity limits at the facility points. We wished to identify the optimal location selection for designated COVID-19 hospitals along with patient allocation strategies for different severity levels (Figure 1).

Basic assumptions

i) The patient capacity of the designated COVID-19 hospitals is constrained by medical resources; ii) The locations of the designated COVID-19 hospitals have continuity. If a hospital is selected for the treatment of COVID-19 patients during a specific time interval, it should remain open as a designated COVID-19 hospital in the following period; iii) The allocation of COVID-19 patients has continuity. If patients are assigned to a specific hospital during a certain period, they should continue to receive treatment in that hospital in the next period until they recover; iv) The pandemic's progression can be divided into three phases; v) COVID-19 patients are categorized into two types based on severity: Type 1 consists of mild cases and Type 2 of patients, who demand more intense care requiring varying amounts of medical resources; vi) The treatment cycle for Type 1 patients is 7 days, with 14 days for Type 2 patients; vii) Every COVID-19 patient receives sufficient treatment, and no death occurs during their hospital stay; and viii) The isolation ward construction cost of the hospital is related to the number of beds at the facility, while the isolation ward operational cost is associated with the number of medical staff.

The mathematical base

Points and sets as given in Table 1; parameters in Table 2 and decision variables in Table 3

Objective functions and model constraints

In summary, the dynamic location model for designated COVID-19 hospitals for the treatment of COVID-19 were constructed as follows (for explanation of symbols see Tables 1, 2 and 3):

$$Min \sum_{j\in J} x_j^T k_j^T + \sum_{i\in I}\sum_{j\in J}\sum_{s\in S}\sum_{t\in T} v_{is}^t y_{ijs}^t d_{ij} r + \sum_{j\in J}\sum_{t\in T} x_j^t h_j^t \tag{1}$$

$$s.t. \sum_{j\in J} y_{ij1}^t = 1 \ \forall i \in I, t \in T \tag{2}$$

$$\sum_{j\in J} y_{ij2}^t = 1 \ \forall i \in I, t \in T \tag{3}$$

$$\sum_{s\in S}\sum_{i\in I} y_{ijs}^t v_{is}^t p_1^s \le c_j^1 x_j^t - \sum_{i\in I} y_{ij2}^{t-1} v_{i2}^{t-1} p_1^2 \ \forall j \in J, t \in T \tag{4}$$

$$\sum_{s\in S}\sum_{i\in I} y_{ijs}^t v_{is}^t p_2^s \le c_j^2 x_j^t - \sum_{i\in I} y_{ij2}^{t-1} v_{i2}^{t-1} p_2^2 \ \forall j \in J, t \in T \tag{5}$$

$$y_{ijs}^t \le x_j^t \ \forall i \in I, j \in J, t \in T, s \in S \tag{6}$$

$$x_j^{t-1} \le x_j^t \ \forall j \in J, t \in T \tag{7}$$

$$x_j^t \in \{0,1\} \ \forall i \in I, j \in J, t \in T, s \in S \tag{8}$$

$$y_{ijs}^t \in [0,1] \ \forall i \in I, j \in J, t \in T, s \in S \tag{9}$$

The objective function (1), where x^T_j=1 represents a designated COVID-19 hospital constructed at location j for at least one phase throughout the entire treatment cycle and 0 otherwise, aims to minimize the sum of the isolation ward construction costs of the designated COVID-19 hospitals, *i.e.* the transportation costs for COVID-19 patients to these hospitals and the operational costs of isolation ward. Constraints (2) and (3) ensure that all COVID-19 patients of every severity level must receive treatment at each time phase, while constraints (4) and (5) ensure that the medical resources consumed by COVID-19 patients transported to the designated COVID-19 hospitals at each phase do not exceed the

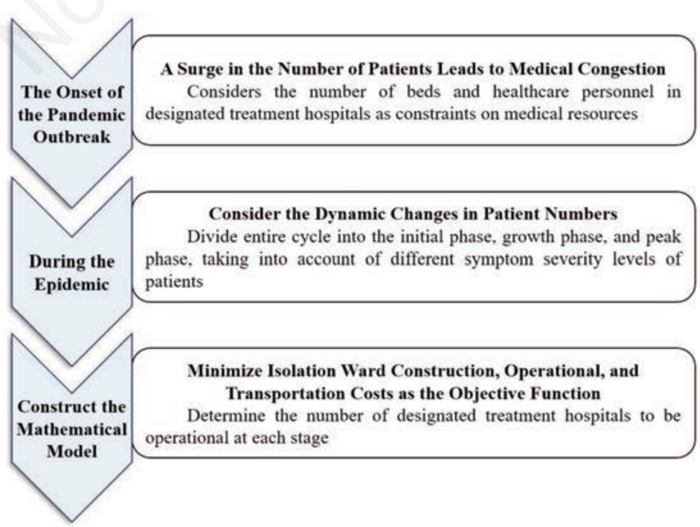

Figure 1. Problem description.

capacity with regard to medical resources for Type 1 and Type 2 patients. Furthermore, patients can only be transported to hospitals that have been chosen as designated COVID-19 facilities. Constraint (6) specifies that at any phase, COVID-19 patients are only allocated to designated COVID-19 hospitals that are operational. Constraint (7) states that once a hospital is selected as a designated one, it will continue to remain open in the subsequent phases. Constraints (8) and (9) specify the range of values that the decision variables can take.

Design of the genetic algorithm

This is a type of NP-hard problem with non-linear constraints, for which application of conventional exact algorithms are challenging. Most studies employ heuristic algorithms, such as genetic ones (Mirjalili, 2019) or simulated, annealing ones (Amine, 2019). Compared to exact algorithms, heuristic algorithms not only take less time, but can also tackle more complex issues (Desale *et al.*, 2015).

Genetic algorithms are prevalent meta-heuristic algorithm (Beheshti *et al.*, 2013) that are widely used in optimization problems across various domains, with extensive applications in scheduling and allocation. It optimizes the population through continuous iterations gradually enhancing individual fitness and is therefore a 'survival of the fittest' approach. This adaptability allows the algorithm to continuously adjust its search strategy and parameters during the search process to adapt to different problems and environments, thereby improving search efficiency and solution accuracy. Furthermore, genetic algorithms have excellent parallel properties, *e.g.*, populations can be divided into multiple subgroups and computed in parallel using different processors, which accelerates the convergence process. Finally, genetic algorithms possess a strong global optimization capability; even when addressing nonlinear problems where the objective function is discontinuous or non-differentiable, they can still adequately determine the solution of the model (Katoch *et al.*, 2021). Given that our model is a high-dimensional and highly non-linear optimization problem, we chose to use a genetic algorithm. Shanmugasundaram *et al.* (2019) proposed the general application of a genetic algorithm to design one-way road networks, while Maleki *et al.* (2021) employed the k-nearest-neighbours technique (k-NN), for which a genetic algorithm is applied for efficient feature selection. The approach has shown 100% accuracy on the lung cancer database already a long time ago (Cover & Hart, 1967).

The dynamic model considers both costs and constraints and reflects the changing characteristics of the decision-making environment over time. To effectively solve the model, the dynamic changes in demand points can be divided into an initial, static phase and a dynamic optimization phase (De Armas *et al.*, 2015):

i) For each location selection phase, the dynamic patient allocation problem is converted into a static problem for that phase; ii) At each phase, when allocating patients to hospitals, a 'greedy strategy' (Zhou *et al.*, 2020) is chosen; and iii) Combined with the idea of dynamic programming (de Souza *et al.*, 2022), the mixed 'greedy-genetic' algorithm is used to solve the model in multiple phase situations.

Table 1. The definition of points and sets.

Notation	Definition
I	The set of regions where COVID-19 patients need to be transported. $i \in I, i=1,2,\dots,n$.
J	The set of designated treatment hospitals for COVID-19. $J \in J, j=1, 2\dots,p$.
T	The current time phase. $t \in T, t=1,2,3$.
M	The set of medical resources available at the designated hospitals. $m \in M, m=1,2$.
S	The set of symptom severity levels for COVID-19 patients. $s \in S$, $s=1,2$.

Table 2. The definition of parameters.

Parameter	Definition
d_{ij}	The distance from region *i* to designated treatment hospital *j*.
c_j^m	The quantity of medical resource *m* at designated treatment hospital j.
h_j^t	The operational cost for isolation ward at hospital *j* when open as designated COVID-19 facility during time phase *t*.
k_j^T	The isolation ward construction cost for hospital *j* when open as designated COVID-19 facility.
p_m^s	The consumption of medical resource *m* by a patient of severity level *s*.
r	The transportation cost for patients.
v_{is}^t	The number of COVID-19 patients of severity level *s* in region *i* in time phase *t*.

Table 3. The definition of decision variables.

Variable	Definition
y^t_{ijs}	the proportion of COVID-19 patients of severity level *s* from region *i* transported to designated treatment hospital j during time phase *t*.
x^t_j	1 A designated treatment hospital is constructed at location *j* during phase *t*. 0 No designated treatment hospital is constructed at location *j* during phase *t*.

Genetic encoding

In the implementation of genetic algorithms, the method of encoding impacts the operation of genetic operators, such as cross-over and mutation operators, directly, which determines the high or low efficiency of the genetic algorithm's iteration. Generally, binary encoding and real-number encoding are the most commonly used encoding methods. Binary encoding is relatively simple to implement and facilitates cross-over and mutation operations. However, for the optimization problems of continuous functions, due to the discontinuity in the decision variable space, its local search capability is weaker. In practical applications, genetic algorithms utilizing real-number encoding have broader applications, especially in solving continuous optimization problems.

In the model constructed in this paper, the decision variables include $x_j$and y_{ij}, where x_j is a 0-1 variable suitable for binary encoding and y_{ij} a real number between 0 and 1. To simplify the model, it is essential to unify different types of decision variables. Therefore, we adopted real-number encoding and performed simulated binary decoding x_j, which means that both x_j and y^{ij} are represented by real numbers between 0 and 1. The length of the encoding is the total number of x_j and y_{ij} (see flowchart in Figure 2). During the decoding process, the encoding where x_j is located is rounded to obtain 0-1 decision variables.

The core idea of the 'greedy algorithm' is to ensure that the local solution is the optimal solution under ambient circumstances, with the hope of approximating the global optimal solution (Barron *et al.*, 2008). The 'greedy algorithms' implemented in this paper allocate patients in a single phase as follows.

Step 1: Determine all the open designated COVID-19 hospitals $j \in J$ and areas $i \in I$ where patients have not yet been assigned.

Step 2: Deal first with the area with the most patients, *i.e.* area i in set I, prioritizing allocation to the nearest open designated COVID-19 hospital. If a hospital is full, and there is no extra capacity, remove it from set J; if all patients from area I have been allocated, remove area i from set I.

Step 3: Repeat Step 2 until all patients have been assigned.

Dynamic programming

Since the conditions at the start of a single phase are given and the greedy algorithm can get the optimal solution for each phase, a backward induction combined with a genetic algorithm should be adopted for planning. The steps, shown in Figure 3, include the following.

Step 1: Start with the last phase and use the genetic algorithm to allocate patient numbers from the three phases to each hospital proportionally, while ensuring that the resource constraints are met.

Step 2: Use the greedy algorithm to determine the number of patients each area should allocate to each hospital in the last phase and update the phase variables.

Step 3: Use this updated state as the initial state for the previ-

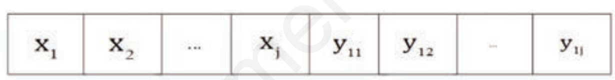

Figure 2. Encoding the genetic algorithm structure diagram.

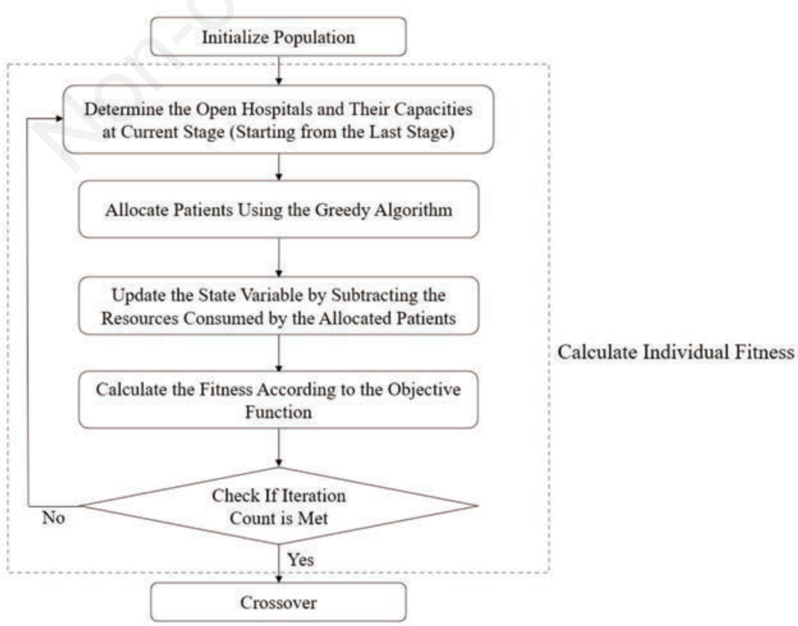

Figure 3. Flowchart describing the dynamic programming.

ous phase and repeat step 2.

Step 4: Iterate until all phases a have been counted for.

Encoding

Encode by real numbers for the hospitals open in the last phase and the proportional patient allocation from the three phases. The encoding length is the sum of x^t_j and y^t_{ijs} (Table 3). During decoding, rounding the encoding of x^t_j will give 0-1 decision variables.

Algorithm steps for the multi-phase mixed greedy-genetic algorithm (flowchart in Figure 4)

Step 1: Design encoding and initialize genetic algorithm parameters.

Step 2: Initialize the population.

Step3: Use backward induction to calculate patient allocation ratios for each individual over the three phases and compute the population fitness.

Step 4: Perform cross-over and reapply cross-over if the constraints are not met.

Step 5: perform mutations and reapply mutation if the constraints are not met.

Step 6: Evaluate fitness and select the best individuals for the next population.

Step 7: Check for termination conditions, e.g., reaching the maximum iteration count. If met, output the iteration curve and optimal solution; otherwise, go back to Step 2.

Algorithm validation

Based on the scale of the case data, four examples were randomly generated: 5*10, 10*20, 20*40, and 30*60 as follows.

i) Set the cross-over probability of the genetic algorithm to 0.5, mutation probability to 0.05, population size to 50 and iteration count to 1,000; ii) The optimization models were solved using Gurobi Optimizer, version 10.0.1 (https://support.gurobi.com) on a computer running Windows 10 equipped with AMD Ryzen 7 4800H CPU with 8 cores and 16 threads, base clock at 2.9 GHz and max boost clock at 4.2 GHz, and 16 GB of dual-channel DDR4 3200 MHz RAM. also It should use have GTX 1650TI 4GB GPU and 512GB PCIe NVMe TLC SSD for storage. We set the Gurobi parameters as follows: TimeLimit = 2,400 seconds, MIPGap = 0.001. Modeling and data processing were performed in Python 3.8 (https://www.python.org; Table 4, Figure 5).

Figure 5 presents the solution results for problem sizes of

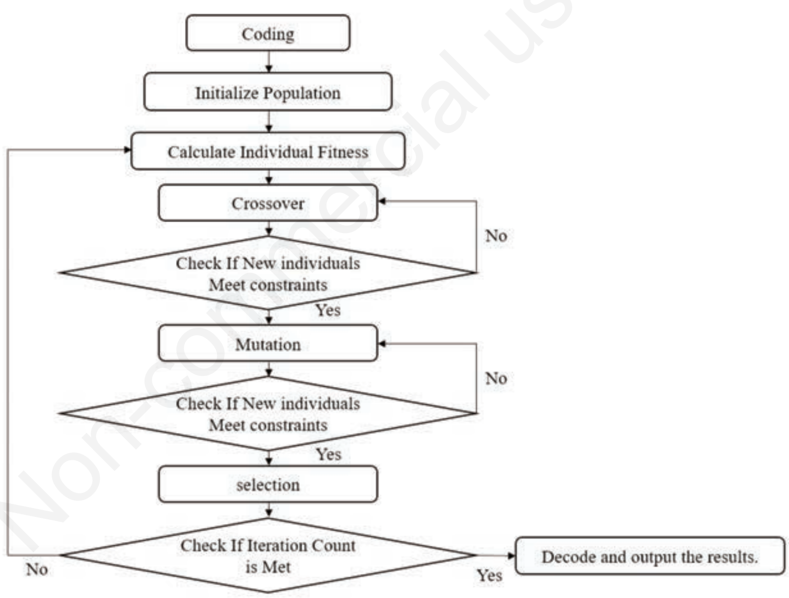

Figure 4. Flowchart describing the genetic algorithm operations.

Table 4. Algorithm efficiency.

Demand/facility points (scale)	Method of solution	Calculation time (sec)
5*10	Genetic algorithm	64.49
5*10	Gurobi	5.16
10*20	Genetic algorithm	78.31
10*20	Gurobi	5.93
20*40	Genetic algorithm	124.91
20*40	Gurobi	463.15
30*60	Genetic algorithm	215.22
30*60	Gurobi	970.42

5*10, 10*20, 20*40, and 30*60 sequentially. The blue lines represent the iterative results of the genetic algorithm, while the red lines represent the solutions obtained by the Gurobi approach. It can be observed that the genetic algorithm designed in this chapter demonstrates good convergence performance for problems of varying sizes.

Table 4 displays the solution times for the genetic algorithm and Gurobi at different problem sizes. For small-scale problems, Gurobi demonstrates higher solving efficiency. However, as the problem size increases, the computation time of the solver escalates significantly. To provide a comparison, we employed both Gurobi and Genetic Algorithm to solve problems of varying scales, with 10 iterations each. Within the given time frame, Gurobi yielded relatively stable results, whereas the results from the genetic algorithm showed some fluctuation. We adopted the best optimization result from the genetic algorithm as the benchmark. In the dynamic location model, across four different scales, the solution range of the genetic algorithm was approximately 101.7% to 102.8% of Gurobi's solution values.

Case study

Shanghai was used as an example where the constructed model was applied for analysis and solution. Considering that the large hospitals in the city have rapidly expanded into designated medical institutions with functions including special treatment of patients with severe symptoms, we selected these hospitals as alternative facilities for hospitals designated to deal with COVID-19 patients. We did not consider patients in the incubation period, who had tested positive by DNA tests but did not require hospital care as they were still without symptoms.

Data generation

To obtain specific hospital data, we programmed a web crawler code through Python 3.8.0 Through fuzzy queries combined with manual screening, the point of interest (POI) data was summarized. During data organization, the following criteria were used for screening.

i) Removal of duplicate data, e.g., if multiple keywords picked up information from the same hospital twice, we only retained one record; ii) Confirmation of administrative areas were checked and confirmed because different areas might correspond to different jurisdictional agencies and medical resources; iii) Given the special circumstances of the COVID-19 pandemic, some additional screening conditions were set, such as the number of medical resources, hospital type, treatment, and monitoring facilities and whether or not quarantine could be established.

After filtering and cleaning the initially obtained 127 POI data, 30 medical institutions were finally retained as alternative facilities for designated COVID-19 hospitals, including 14 first-level hospitals and 16 second-level ones. By extracting the centroid coordinates of the 16 districts of Shanghai through ArcGIS (ESRI, Redlands, CA, USA), the centroids of each district were used as patient aggregation points. The distances between the points of each demand-facility pair were calculated using the geographical coordinate system. The distance matrix is illustrated in Appendix A Tables A1, A2, A3, A4. The number of medical staff was set at 1.3 times the number of available beds, with this calculated resource shown in Appendix Table A5.

We focused on the period from the complete lockdown in Shanghai to the time when the number of patients reached its peak, treating it as the decision-making planning period. Confirmed patients from 2 April to 22 April were statistically analyzed. Based on the epidemic announcements by the Shanghai Municipal Health Commission after excluding asymptomatic patients, we gathered the number of patients in various districts during the entire decision-making planning period. The details are presented in Table 5.

The bed-to-nurse patient care ratios were 1:1 for type 1 patients and 1:3 for type 2 patients. The manufacturing cost per bed is 20,000 Chinese yuan (around USD 2,800) and the medical staff average salary for each period (7 days) 2,000 yuan (around USD 280), while the transportation cost for sending patients to designated COVID-19 hospitals is 1 yuan/km (around 15 US

Table 5. Number of patients.

Shanghai District	Patient in phase 1(no.)	Patient in phase 2 (no.)	Patient in phase 3 (no.)	Patient in total (no.)
Huangpu	129	1069	1,983	3,181
Chongming	11	126	98	235
Xuhui	285	907	1,210	2,402
Changning	108	632	807	1,547
Jing'an	159	360	1,068	1,587
Putuo	130	274	810	1,214
Hongkou	99	708	1437	2,244
Yangpu	123	542	582	1,247
Minhang	1,216	4,947	5,187	11,350
Baoshan	335	1,485	2,349	4,169
Jiading	122	257	802	1,181
Pudong New Area	200	604	813	1,617
Jinshan	126	121	68	315
Songjiang	251	906	796	1,953
Qingpu	52	436	436	924
Fengxian	69	74	54	197

cents). It was assumed that type 1 patients account for 40% of the total number of patients and 10% for type 2 patients.

We divided the decision-making planning period into three 7-day phases: i) Phase1: 2-8; ii) Phase 2: 9-15 April; and iii) Phase 3: 16-22 April

Genetic algorithm cross-over probability was set at 0.5, mutation at p=0.05, the population size at 50, and the iteration time at 1,000. An improved multi-phase genetic algorithm was applied to the dynamic location model using Python 3.8. The iteration results are shown in Figure 6.

Results

According to the solution results presented in Figure 6, the location of designated COVID-19 hospitals and their open status during each phase can be seen in Appendix A Table 6. Here, "1" represents that the facility was chosen and opened in the current phase, while "0" means that the facility was not opened during that phase.

Due to the initial phase of the pandemic, a total of six hospitals were opened. In the second phase, the number of patients increased further, while some patients from the previous phase were still receiving treatment in hospitals. The existing facilities could no longer meet the patient demand, so two more hospitals were added. In the third phase, the number of patients peaked and a significant number of Type 2 patients from the previous phase occupied the available medical resources, necessitating the addition of more medical facilities. At this point, three more hospitals were opened, bringing the total to 11 hospitals throughout the entire treatment cycle. The total cost for designated treatment hospitals was 534,970,063.44 yuan (around USD 75,000,000), with construction cost amounting to 401,580,000.0 yuan (around USD 56,200,000), operational cost at 132,986,000.0 yuan (around USD 18,600,000), and transportation cost at 404,063.44 yuan (around USD 56,600,000). If the multiple phases of an entire treatment cycle

Figure 5. Comparison of computational results.

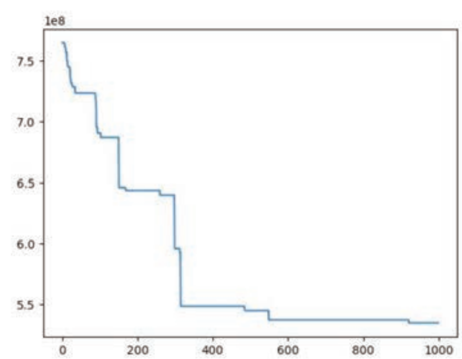

Figure 6. The iterative solution.

were treated as a single phase, the facility locations were determined so that no changes occurred across the whole cycle, *i.e.* using the entire dynamic model as a static location model. This solution found that a total of 15 hospitals were opened during the entire treatment cycle. The results are shown in Appendix Table A 7. According to these results, the total cost for designated COVID-19 hospitals was 647,400,101.15 yuan (around USD 90,600,000), with construction cost amounting to 465,440,000.0 yuan (around USD 65,200,000), operational cost at 181,506,000.0 yuan (around USD 25,400,000), and transportation cost at 454,101.15 yuan (around USD 63,600,000). It was observed that compared to the static location model, the dynamic location model has significant advantages in both construction and operational costs. Specifically, construction cost was reduced by approximately 13.7%, and operational cost by approximately 26.7%. In the static location model, 15 hospitals were required throughout the treatment cycle, whereas the dynamic location model required only 11 hospitals. Additionally, during the treatment cycle, hospitals could be opened gradually based on the increasing number of patients.

Discussion

This study established a dynamic, set-covering location model for COVID-19 designated hospitals factoring in treatment cycles. Due to the complexity of the pandemic's progression, the dynamic changes in demand arising from an increase in the number of patients must be considered. This paper divided the entire decision-making cycle into three phases since the location of designated hospitals in different phases is influenced by patient allocations and changes in demand during the previous phase. A dynamic location model based on the set-covering problem was constructed to minimize costs for building isolation wards and operations throughout the planning period, as well as the costs related to the transportation of patients, Furthermore, we designed a heuristic algorithm for the dynamic location model. By examining the convergence and computational efficiency of problems of different scales, we demonstrate that this algorithm meets the requirements of the dynamic location model constructed in this study. The results based on actual data published during the epidemic period in Shanghai during the spring of 2022 indicate that the dynamic location model can significantly reduce location costs and optimize resource utilization. This study employed a genetic algorithm to solve the facility location model. Despite the widespread use of genetic algorithms for such problems, they have limitations, such as a strong dependence on the quality of the initial population and a slower search speed due to delayed utilization of feedback information. Future research could consider integrating or comparing other solution algorithms, such as simulated, annealing trajectory-based meta-heuristic algorithm (Amine, 2019) or others. This study also discussed the facility location for designated treatment hospitals during the COVID-19 pandemic. Unlike other emergency facility location problems, the unique infectious nature of the pandemic means that location decisions not only depend on patient distribution and demand, but also on epidemiological characteristics, population density, traffic conditions, and environmental pollution risk assessments. The impact of these factors requires further in-depth exploration in subsequent studies.

Conclusions

Compared to static location models, the dynamic location model has significant advantages with respect to when used to plan construction and operational costs. Specifically, it was shown that the number of designed hospitals can be reduced from 15 to 11. Importantly, the dynamic location model not only reduces emergency expenses for relevant government departments but also lowers resource waste and alleviates the pressure on healthcare personnel through the dynamic allocation of the treatment capacity of designated hospitals.

References

Alizadeh R, Nishi T, 2020. Hybrid set covering and dynamic modular covering location problem: application to an emergency humanitarian logistics problem. Appl Sci 10:7110.

Allman A, Zhang Q, 2020. Dynamic location of modular manufacturing facilities with relocation of individual modules. Eur J Oper Res 286:494-507.

Amine K, 2019. Multiobjective simulated annealing: Principles and algorithm variants. Adv Oper Res 2019:1-13.

Aydin N, Seker S, 2021. Determining the location of isolation hospitals for COVID□19 via Delphi□based MCDM method. Int J Intell Syst 36:3011-34.

Barron AR, Cohen A, Dahmen W, DeVore RA, 2008. Approximation and learning by greedy algorithms. Proj Euclid 36:64-94.

Beheshti Z, Shamsuddin SMH, 2013. A review of population-based meta-heuristic algorithms. Int J Adv Soft Comput Appl 5:1-35.

Bhattacharjee AK, Mukhopadhyay A, 2023. An improved genetic algorithm with local refinement for solving hierarchical single-allocation hub median facility location problem. Soft Comput 27:1493-509.

Chakraborty S, Darbhe K, Sarmah S, 2021. Attended home delivery in Indian public distribution system: an iterated local search approach. J Model Manag 16:1116-37.

Cover T, Hart P, 1967. Nearest neighbor pattern classification. IEEE Trans Inf Theory 13:21-7.

Cunningham K, Schrage L, 2004. The LINGO algebraic modeling language. In: Kallrath, J. (eds) Modeling Languages in Mathematical Optimization. Applied Optimization 88:159-71.

De Armas J, Melián-Batista B, 2015. Variable neighborhood search for a dynamic rich vehicle routing problem with time windows. Comput Ind Eng 85:120-31.

Desale S, Rasool A, Andhale S, Rane P, 2015. Heuristic and meta-heuristic algorithms and their relevance to the real world: a survey. Int J Comput Eng Res Trends 351:296-304.

de Souza EAG, Nagano MS, Rolim GA, 2022. Dynamic Programming algorithms and their applications in machine scheduling: A review. Expert Syst Appl 190:116180.

Dong D, Cui N, 2021. Emergency supply facility location design under disaster conditions: emerging modeling techniques and algorithms. J Phys Conf Ser 1827:012196.

Doungpan S, Moryadee S, U-tapao C, Laokhongthavorn Z, 2018. Analysis of Three Emergency Medical Location Models: A Case Study of Thailand. May 2018. Conference: 2018 International Conference on System Science and Engineering

(ICSSE) 1-6.
Fergani C, Idrissi AEBE, Marcotte S, Hajjaji A, 2022. Dynamic location of modular mobile facilities in a hybrid network of hyperconnected and dedicated localisations: application in the chemical industry. Int J Shipp Transp Logist 15:407-34.
Fernandes DR, Rocha C, Aloise D, Ribeiro GM, Santos EM, Silva A, 2014. A simple and effective genetic algorithm for the two-stage capacitated facility location problem. Comput Ind Eng 75:200-8.
Gu J, Zhou Y, Das A, Lee GM, 2018. Medical relief shelter location problem with patient severity under a limited relief budget. Comput Ind Eng 125:720-8.
Hashemi A, Gholami H, Venkatadri U, Karganroudi SS, Khouri S, Wojciechowski A, 2021. A new direct coefficient-based heuristic algorithm for set covering problems. Int J Fuzzy Syst 2:1131-47.
Jaramillo JH, BhaduryJ, Batta R, 2002. On the use of genetic algorithms to solve location problems. Comput Oper Res 29:761-79.
Katoch S, Chauhan S S, Kumar V, 2021. A review on genetic algorithm: past, present, and future. Multimed Tools Appl 80:8091-126.
Liu J, Cao L, Zhang D, Chen Z, Lian X, Li Y, Zhang Y, 2022. Optimization of site selection for emergency medical facilities considering the SEIR model. Comput Intell Neurosci 2022:1912272.
Luo C, Xing W, Cai S, Hu C, 2022. NuSC: an effective local search algorithm for solving the set covering problem. IEEE Trans Cybern 54:1403-16.
Mladenović M, Hansen P, 1997.Variable neighborhood search. Comput Oper Res 24:1097-100.
Ma D, Chu J, Wang Z, Sun T, 2016. Study on disaster shelter complement location problem after disaster shelter failure. World Earthq Eng 32:117-23.
Maleki N, Zeinali Y, Niaki S T A, 2021. A k-NN method for lung cancer prognosis with the use of a genetic algorithm for feature selection. Expert Syst Appl1 64:113981.
Marques MC, Dias JM, 2018. Dynamic location problem under uncertainty with a regret□based measure of robustness. Int Trans Oper Res 25:1361-81.
Mirjalili S, 2019. Genetic algorithm. In: Evolutionary Algorithms and Neural Networks. Studies in Computational Intelligence 780:43-55.
Murad A, Faruque F, Naji A, Tiwari A, 2021. Using the location-allocation P-median model for optimising locations for health care centres in the city of Jeddah City, Saudi Arabia. Geospat Health 16:1002.
Nasiri MM, Mahmoodian V, Rahbari A, Farahmand S, 2018. A modified genetic algorithm for the capacitated competitive facility location problem with the partial demand satisfaction. Comput Ind Eng 124:435-48.
Ng KKH, Lee CKM, Chan FTS, Chen C-H, Qin Y, 2020. A two-stage robust optimisation for terminal traffic flow problem. Appl Soft Comput 89:106048.
Oksuz MK, Satoglu SI, 2020. A two-stage stochastic model for location planning of temporary medical centers for disaster response. Int J Disaster Risk Reduct 44:101426.
Pourghader Chobar A, Adibi MA, Kazemi A, 2021. A novel multi-objective model for hub location problem considering dynamic demand and environmental issues. J Ind Eng Manag 8:1-31.
Shanmugasundaram N, Sushita K, Kumar SP, Ganesh EN, 2019. Genetic algorithm-based road network design for optimising the vehicle travel distance. Int J Vehicle Inf Commun Syst 4:344-54.
Sitepu R, Puspita FM, Ariani I S, Indrawati I, Yuliza E, Octarina S, 2023. Robust set cover problem in determining the optimal location of emergency units in Palembang city with unknown distance. AIP Conf Proc, 2913(1). doi:10.1063/5.0175708.
Sitepu R, Puspita F M, Romelda S, Fikri A, Susanto B, Kaban H, 2019. Set covering models in optimizing the emergency unit location of health facility in Palembang. J Phys Conf Ser 1282:012008.
Xi M, Ye F, Yao Z, Zhao Q, 2013. A modified-median model for the emergency facilities location problem and its variable neighbourhood search-based algorithm. J Appl Math 2013:375657.
Yan L, Grifoll M, Feng H, Zheng P, Zhou C, 2022. Optimization of Urban Distribution Centres: A Multi-Stage Dynamic Location Approach. Sustainability 14;4135.
Yu H, Sun X, Solvang WD, Zhao X, 2020. Reverse logistics network design for effective management of medical waste in epidemic outbreaks: Insights from the coronavirus disease 2019 (COVID-19) outbreak in Wuhan (China). Int J Environ Res Public Health 17:1770.
Zhang M, Zhang Y, Qiu Z, Wu H, 2019. Two-Stage Covering Location Model for Air–Ground Medical Rescue System. Sustainability 11:3242.
Zhou Z, LiF, Zhu H, Xie H, Abawajy JH, Chowdhury MU, 2020. An improved genetic algorithm using greedy strategy toward task scheduling optimization in cloud environments. Neural Comput Appl 32:1531-41.

Online Supplementary Materials

Appendix A

Table A 1 Distance Matrix

Table A 2 Distance Matrix

Table A 3 Distance Matrix

Table A 4 Distance Matrix

Table A 5 Medical Resource Information

Table A 6 Location results during each phase

Table A 7 location results of static model