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RESEARCH ARTICLE

Integrated Design of Emergency Medical and Material Distribution Networks During the Epidemic Outbreak Period

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ABSTRACT During the epidemic outbreak period, the number of infected people increased explosively. In order to effectively contain the further spread of the epidemic and treat infected people, it is necessary to make reasonable planning for the treatment of infected people and the distribution of materials. In this paper, a multi-objective mixed-integer programming model for the integrated design of emergency medical and material distribution networks is developed, in which the location of medical points, the allocation of infected people, and the distribution of medical materials are addressed in the multi-stage planning. Then, the multi-objective model is solved by the augmented ε-constraint method. A realistic case study on Huangpu District of Shanghai in China is conducted to demonstrate the validity of the developed model. The results show that the integrated consideration of the emergency medical network and the material distribution network is more capable of reducing the total transportation distance and decreasing the total operating cost.

INDEX TERMS Epidemic, emergency medical network, material distribution network, dynamic allocation, augmented ε-constraint method.

I. INTRODUCTION

The epidemic outbreak period is defined as a large number of patients with the same disease in the same region within a short period of time. The COVID-19 (Corona Virus Disease 2019) outbreak is the sixth global public health emergency to date. The outbreak of COVID-19 has severely affected the daily lives of people around the world. According to reports, between the date December, 2019 and June 15, 2022, 533,563,676 people have been infected, resulting in 6,319,981 deaths. In 2022, an outbreak occurred in Shanghai, China, with a cumulative total of over 600,000 infected people. In response to the outbreak of COVID-19, Shanghai has set up mobile cabin hospitals to treat infected people. Centralizing the treatment of infected people facilitates control and prevents the further spread of the epidemic. However, challenges remain in treating all those infected and meeting the need for medical materials. For example, because the number of infected people spikes during an outbreak, the infected people cannot all be treated or the medical material needs of those already treated people cannot all be met. As a result, this will not be conducive to the prevention and control of the epidemic, making it increasingly serious. Similar challenges can be seen in the 2020 Wuhan outbreak in China and the 2022 Zhengzhou outbreak in China. In addition, different from traditional logistics, emergency logistics is an important force of a national security system, as it is a logistics activity that provides emergency support for materials and personnel needs in response to unexpected public health events and other emergencies. Therefore, the government establishes an effective emergency logistics system before the outbreak, to choose appropriate emergency medical points (EMPs) and medical material distribution points (MMDPs), to treat infected people and satisfy the medical material needs of these people are critical to support emergency relief operations and respond quickly to outbreaks.

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As the allocation of infected people to each EMP influences the distribution of medical materials. Conversely, the quantity of medical materials that can be received at each EMP also affects the allocation of infected people. It is clear that the emergency medical network and the material distribution network interact with each other. Therefore, the emergency medical network and the material distribution network should be designed in an integrated manner during an epidemic.

This paper integrates the design of the emergency medical and material distribution networks and establishes a multi-objective mixed-integer programming model that considers multi-stage decisions. Using the epidemic data of Huangpu District in Shanghai as an example, the established model is solved by the augmented ε-constraint method, and sensitivity analysis of key parameters is carried out.

This paper contributes to the literature in the following ways. First, we design the emergency medical and material distribution networks in an integrated manner. As far as we know, most of the current studies only deal with one of the two networks. Second, a multi-objective mixed-integer programming model considering multi-stage is established and the augmented ε-constraint method is used to solve the model.

The remainder of this paper is organized as follows. In Section II, a review of the related literatures is provided. In Section III, the problem definition is presented and a multi-objective mixed-integer programming model is formulated. In Section IV, the solution method for the multi-objective model in this paper, the augmented ε-constraint method, is presented. In Section V, a realistic case study on the 2022 COVID-19 epidemic in Huangpu District, Shanghai is presented. In Section VI, conclusions and future research directions are presented.

II. RELATED LITERATURE

Since our work focuses on the integrated design of emergency medical and material distribution networks, in this section, we review the following streams of literatures that are similar to our research: (1) emergency medical network design; (2) material distribution network design; (3) integrated design of emergency medical and material distribution networks.

A. EMERGENCY MEDICAL NETWORK DESIGN

For the location of emergency medical facilities, Sudtachat et al. [1] proposed a relocation strategy that models the location of healthcare facilities with the objective of maximizing desired coverage. Zhang et al. [2] designed a multi-objective optimization method based on genetic algorithms to deal with the location problem of medical facilities. Coco et al. [3] investigated a robust optimization-based robust optimization based maximum coverage siting model. Liu et al. [4] modeled the allocation of medical services facilities to casualties with the goal of maximizing the expected survival rate and the total operating cost. Liu et al [5] constructed a robust siting optimization model for emergency service stations with the objective of minimizing the desired total cost, and proposed an outer approximation algorithm to solve it. Chen et al [6] proposed a model for siting emergency medical facilities based on transport infrastructures. Zarrinpoor et al. [7] developed a hierarchical healthcare facility location-allocation model considering some factors such as the risk of disruption to facilities in the healthcare delivery network. Maleki Coco [8] considered referral systems and developed a multi-objective mixed-integer nonlinear programming model. The above literature only studied the emergency medical network and did not consider the distribution of emergency materials.

B. MATERIAL DISTRIBUTION NETWORK DESIGN

For the location of material distribution points, scholars have studied it from several perspectives. Considering cost factors, Benneyan et al. [9] developed single-stage and multi-stage location-allocation models with the objective of minimizing the total cost. Ekici et al. [10] designed a disease transmission model based on which an emergency material distribution model with the objective of minimizing total cost was developed. Khayal et al. [11] developed a mixed-integer planning model for facility siting with the objective of minimizing total system cost. Loree et al. [12] established a model for the location and distribution of post-disaster emergency materials distribution points with cost minimization as the objective. Haghi et al. [13] constructed a multi-objective planning model considering factors such as fair distribution of emergency materials and total cost minimization, proposed the MOGASA algorithm, and compared it with the NSGA II algorithm to verify the effectiveness of the MOGASA algorithm. However, in the actual process of emergency materials distribution, the low-cost distribution method can not necessarily transport emergency materials to the point of demand in the shortest time, which often affects the efficiency of emergency rescue.

With the deepening of research, more and more scholars began to study the timeliness of emergency materials distribution. Wang et al. [14] and Ren et al. [15] developed a location-allocation model with the objectives of minimizing emergency response time and maximizing satisfaction, Wang et al. [16] developed an emergency logistics network optimization model with the objectives of minimizing logistics operating costs and minimizing total distribution time, taking into account factors such as emergency response speed. Long et al. [17] developed a multi-stage siting-distribution model for emergency materials. Tikani et al. [18] Established a two-stage stochastic nonlinear mixed integer programming model for emergency materials distribution considering time window and other factors. Wang et al. [19] established a multi-regional emergency materials coordination and dispatching model, taking into account factors such as differences in the supply of emergency materials between different regions and uneven reserves of materials, but did not consider the location of emergency materials distribution points. Zhang et al. [20] developed a multi-stage joint material distribution model with the goal of minimizing patient loss and maximizing equity in material distribution. Zhou et al. [21] considered the multi-cycle dynamic emergency material dispatching problem and established an emergency material allocation model with the objective of minimizing the total shortage of material demand and minimizing the total risk of material failing to reach the disaster area in a timely manner. Garza-Reyes et al. [22] improved the efficiency of emergency medical services based on lean thinking and the theory of constraints. Baharmand et al. [23] proposed a location-allocation model that stratifies the topography of the affected area to solve the problem of time and resource constraints in the distribution of emergency materials after a sudden disaster.

Considering material demand forecasting, Albareda-Sambola et al. [24] developed a facility siting model assuming that healthcare demand obeys a Bernoulli distribution. Mohammadi et al. [25] assumed that medical demand obeyed a Poisson distribution and developed a multi-objective mathematical planning model with the objectives of minimizing total cost and minimizing total time. He et al. [26] proposed an improved demand forecasting model to establish a model for the distribution of emergency material. Hou et al. [27] developed a dynamic planning stochastic model for the distribution of medical materials by building an improved SEIAR model to forecast the demand for materials. Wu et al. [28] developed an urban emergency material distribution model based on the emergency material distribution cloud platform and designed a genetic algorithm to solve the model. However, the above literatures had not considered the integration of emergency medical and material distribution networks.

C. INTEGRATED DESIGN OF EMERGENCY MEDICAL AND MATERIAL DISTRIBUTION NETWORKS

In order to better solve the problems arising from emergency activities, some scholars have started to study integrated networks, but the research results are relatively few. Yi et al. [29] established a dynamic logistics coordination model by considering the distribution of materials and the transfer of casualties in disaster areas. Sheu et al. [30] established a three-stage emergency response network by considering the shelter network, medical network, and distribution network. Camur et al. [31] developed a dynamic optimization model for marine evacuation in large-scale emergency rescue events, considering the distribution of personnel in the affected area and the distribution of rescue materials. The above literatures are all studies on the emergency rescue of natural disasters and emergencies, but not on public health emergencies. Luo et al. [32] developed a model for the distribution of emergency materials and patient allocation in a large-scale epidemic, but only considered a secondary emergency supply distribution network consisting of community hospitals and emergency hospitals. In actual emergency rescue, due to the quantity of emergency materials at the emergency materials distribution point is limited, and the materials need to be allocated from the supply point to fully meet the material needs of each demand point, the second-level emergency logistics network is usually unable to meet the needs of emergency materials at demand points.

In sum, although numerous scholars have conducted studies on the emergency medical network and material distribution network from different perspectives, to our knowledge, there have been no studies on the emergency medical and three-level material distribution networks in the context of the epidemic, in which these networks have been considered in an integrated manner. In addition, there is little literature that considers the stock levels of emergency materials at the distribution points and the supply points after each emergency material distribution stage is completed, and the emergency material distribution models established fail to automatically convert the stock levels of materials after the completion of the previous stage of distribution into the replenishment of materials for the next stage. The distribution plan of emergency materials is different at each stage, and the inventory of materials is also different, which affects the formulation of the distribution plan of materials.

III. PROBLEM DEFINITION AND FORMULATION

In this paper, the integrated design of the emergency medical and material distribution networks is aimed at areas where the epidemic outbreak occurred. Such an area has public infrastructures (parks and gymnasiums) that can support emergency activities. When an outbreak occurs, infected people need to be transported to EMPs, while medical materials are transported from medical material supply points (MMSPs) to EMPs via MMDPs. Because the number of infected people changes dynamically over time, the integration of the emergency medical and material distribution networks should be designed with multi-stage in mind.

Figure 1 shows the structure of the integrated emergency medical and material distribution network. The integrated design of the emergency medical and material distribution network includes the determination of the location of EMPs and MMDPs, the number of infected people who are treated at each stage of EMPs, the quantity of medical materials that are transported at each stage from MMSPs to MMDPs, and the quantity of medical materials that are transported at each stage from MMDPs to EMPs, as well as the corresponding flows.

Before constructing a multi-objective model for the integrated design of emergency medical and material distribution networks under the epidemic outbreak, four assumptions are made:(1) At each stage, the replenishment quantities of medical materials in MMSPs and the infection rate are known. (2) Only mild infected people are considered. (3) A sufficient number of transport vehicles can be mobilized after the outbreak. (4) As there is more than one type of medical materials required for EMPs and the demand is high, these medical materials are normally distributed separately. Thus, this paper only considers the distribution of a type of medical materials.

A. NOTATIONS

The following notations are used in III.B to present the formulation.

Sets	
I	set of patient areas, indexed by i
J	set of candidate EMPs, indexed by j
H	set of candidate MMDPs, indexed by h
G	set of MMSPs, indexed by g
T	set of stages, indexed by t
Parameters	
A_j	maximum capacity of EMP j, it indicates that the maximum number of infected people that can be admitted to an EMP
B_h	maximum volume of MMDP h
θ_i	quantity of residents in patient area i
p_t	infection rate of stage t
s_t	cure rate of infected people at stage t
k_j	construction cost of EMP j
c_{jt}	cost of treating per unit of infected people at stage t of EMP j
n_h	construction cost of MMDP h
e_{ht}	cost of storing per unit of medical materials at stage t of MMDP h
w	transfer costs per unit of distance and per unit of infected people
f	transportation cost of per unit of distance and per unit of medical materials
ψ_{ij}	distance between patient area i and EMP j
ϖ_{hj}	distance between MMDP h and EMP j
d_{gh}	distance between MMSP g and MMDP h
v	volume per unit of medical materials
q_{gt}	replenishment quantities of medical materials for MMSP g at stage t
u	demand per unit of medical materials
M	a very large positive number
Variables	
r_{jt}	number of infected people who have been cured in EMP j at stage t
ϑ_h	a binary variable, 1 indicates that candidate MMDP h is selected as MMDP; otherwise, 0
x_j	a binary variable, 1 indicates that candidate EMP j is selected as EMP; otherwise, 0
y_{ijt}	number of infected people who are allocated from patient area i to EMP j at stage t
α_{ght}	quantities of medical materials that are allocated from MMSP g to MMDP h at stage t
β_{hjt}	quantities of medical materials that are allocated from MMDP h to EMP j at stage t

B. MODEL

In this section, a multi-objective model for the integrated design of emergency medical and material distribution networks is built.

$$\min z_1 = \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\left(y_{ijt}\psi_{ij}\right) + \sum_{g\in G}\sum_{h\in H}\sum_{j\in J}\sum_{t\in T}\left(\alpha_{ght}d_{gh} + \beta_{hjt}\varpi_{hj}\right) \quad (1)$$

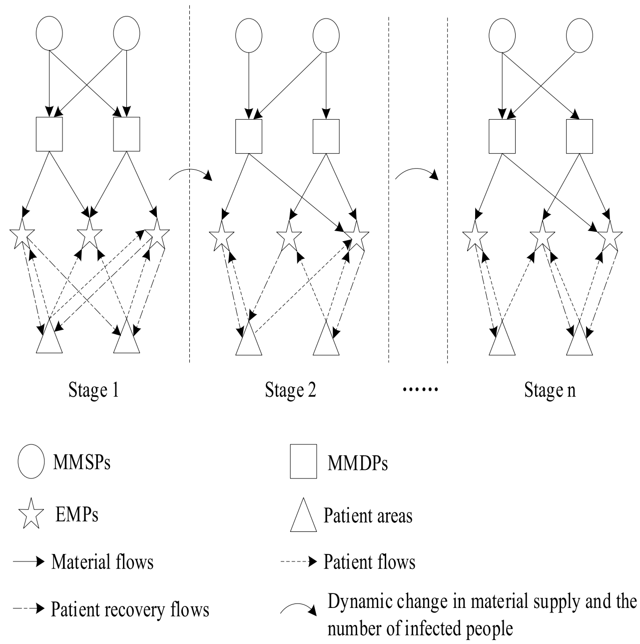

FIGURE 1. Structure of the integrated emergency medical and material distribution network.

$$\min z_2 = \sum_{i\in I}\sum_{j\in J}\psi_{ij} w y_{ijt} + \sum_{g\in G}\sum_{h\in H}\sum_{j\in J}\sum_{t\in T}\left(d_{gh} f\alpha_{ght} + \varpi_{hj} f\beta_{hjt}\right) + \sum_{j\in J}\sum_{t\in T}\left(c_{jt}\sum_{i\in I} y_{ijt} + k_j x_j\right) + \sum_{h\in H}\sum_{t\in T}\left(e_{ht}\sum_{g\in G}\alpha_{ght} + n_h\vartheta_h\right) \quad (2)$$

s.t.

$$\sum_{i\in I} y_{ijt} \le A_j - \sum_{i\in I}\sum_{t^*=0,\cdots,t-1} y_{ijt^*} + \sum_{t^*=0,\cdots,t-1} r_{jt^*}, \quad \forall j\in J, \forall t\in T \quad (3)$$

$$\sum_{j\in J} y_{ijt} = \theta_i p_t, \forall i\in I, \forall t\in T \quad (4)$$

$$\sum_{i\in I} y_{ijt} \le M x_j, \forall j\in J, \forall t\in T \quad (5)$$

$$r_{jt} = s_t\sum_{i\in I} y_{ijt} + \sum_{i\in I}\sum_{t^\#=0,\ldots,t-1} s_t\left(1-s_t\right)^{t-t^\#} y_{ijt^\#}, \quad \forall j\in J, \forall t\in T \quad (6)$$

$$y_{ij0} = 0, \forall i\in I, \forall j\in J \quad (7)$$

$$r_{j0} = 0, \forall j\in J \quad (8)$$

$$\alpha_{gh0} = 0, \forall g\in G, \forall h\in H \quad (9)$$

$$\beta_{hj0} = 0, \forall h\in H, \forall j\in J \quad (10)$$

$$\sum_{h\in H}\alpha_{ght} \le q_{gt} + \sum_{t^*=0,\cdots,t-1} q_{gt^*} - \sum_{h\in H}\sum_{t^*=0,\cdots,t-1}\alpha_{ght^*},$$

$$\forall g \in G, \forall t \in T, t \neq 0 \tag{11}$$

$$\sum_{g \in G} \alpha_{ght} v \leq B_h \vartheta_h, \forall h \in H, \forall t \in T \tag{12}$$

$$\sum_{j \in J} \beta_{hjt} \leq \sum_{g \in G} \alpha_{ght} + \sum_{g \in G} \sum_{t^*=0,\cdots,t-1} \alpha_{ght^*} - \sum_{j \in J} \sum_{t^*=0,\cdots,t-1} \beta_{hjt^*},$$

$$\forall h \in H, \forall t \in T, t \neq 0 \tag{13}$$

$$\sum_{h \in H} \beta_{hjt} = \sum_{i \in I} u y_{ijt} + u(\sum_{i \in I} \sum_{t^*=0,\ldots,t-1} y_{ijt^*} - \sum_{t^*=0,\ldots,t-1} r_{jt^*}),$$

$$\forall j \in J, \forall t \in T \tag{14}$$

$$\vartheta_h, x_j \in \{0, 1\}, y_{ijt}, \alpha_{ght}, \beta_{hjt}, \mathrm{r}_{jt} \geq 0,$$

$$\forall i \in I, \forall j \in J, \forall h \in H, \forall g \in G, \forall t \in T \tag{15}$$

The objective function (1) is to minimize the total transportation distance, in which the total transportation distance includes the transfer distance of infected people and the transportation distance of medical materials. The purpose is to make the emergency medical points and material distribution points nearby rescue, otherwise the transportation distance will be relatively large, affecting the efficiency of emergency response. The objective function (2) is to minimize the total operating cost including the costs of transferring infected people, distributing medical materials, establishing EMPs, treating infected people, establishing MMDPs and storing medical materials of MMDPs. The purpose is to reduce the cost of emergency rescue as much as possible, because, for some economically underdeveloped countries or regions, unreasonable emergency medical and material distribution networks planning will increase the financial burden. Constraint (3) ensures that the total number of infected people allocated to each EMP at each stage does not exceed its maximum admissible number. Constraint (4) is the infected people at each stage is fully treated. Constraint (5) ensures that infected people are not transferred to EMPs when EMPs are not established. Constraint (6) calculates the number of cured people at each EMP at each stage. Constraint (7) ensures that the number of infected people transfer from each patient area to each EMP at the stage prior to the outbreak is 0. Constraint (8) ensures that the number of infected people who have been cured at each EMP at the stage prior to the outbreak is 0. Constraint (9) ensures that the quantity of medical materials distributed from each MMSP to each MMDP at the stage prior to the outbreak is 0. Constraint (10) ensures that the quantity of medical materials distributed from each MMDP to each EMP at the stage prior to the outbreak is 0. Constraint (11) ensures that the quantity of medical materials delivered by the MMSP to the MMDP does not exceed its storage capacity at each stage. Constraint (12) ensures that the total volume of medical materials received at each stage at the MMDP does not exceed its volume. Constraint (13) ensures that the quantity of medical materials distributed by the MMDP to the EMP at each stage does not exceed their storage capacity. Constraint (14) ensures that the required medical materials are satisfied at each EMP and each stage. Constraint (15) enforces the binary and non-negativity restrictions on decision variables.

IV. SOLUTION METHOD

The augmented ε-constraint method is used to solve multi-objective mixed-integer programming models (Roni et al [33]). The principle is to optimize only one objective, then transform other objectives into constraints. Compared to the weighted sum method, the augmented ε-constraint method can get more effective Pareto solutions. Therefore, we use the augmented ε-constraint method to solve the established multi-objective model. The primary objective of this model is to minimize the total transportation distance and the secondary objective is to minimize the total operating cost. Therefore, equation (1) is kept unchanged, equation (2) is transformed into a constraint condition, and equation (2) is restricted from exceeding the range of threshold ε. So, the original multi-objective model is transformed into the following form:

$$\min z_1 = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} (y_{ijt} \psi_{ij}) + \sum_{g \in G} \sum_{h \in H} \sum_{j \in J} \sum_{t \in T} (\alpha_{ght} d_{gh} + \beta_{hjt} \varpi_{hj}) \tag{16}$$

$$\text{s.t.} \quad (3)-(15) \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} \psi_{ij} w y_{ijt} + \sum_{g \in G} \sum_{h \in H} \sum_{j \in J} \sum_{t \in T} (d_{gh} f \alpha_{ght} + \varpi_{hj} f \beta_{hjt}) + \sum_{j \in J} \sum_{t \in T} (c_{jt} \sum_{i \in I} y_{ijt} + \mathrm{k}_j x_j) + \sum_{h \in H} \sum_{t \in T} (e_{ht} \sum_{g \in G} \alpha_{ght} + n_h \vartheta_h) \leq \varepsilon \tag{17}$$

The value of ε is bounded set on the value of total operating cost.

A. LEXICOGRAPHIC OPTIMIZATION FOR OBTAINING THE RANGE OF ε

The lexicographic optimization approach is to rank the objective functions according to their priority, and add constraints to the optimized solution of the lower priority objective function to ensure that the previously optimized objective function maintains the corresponding optimal value. The calculation steps are as follows:

Step 1: Using equation (1) as the objective function and equations (3)-(15) as the constraints, the optimal solution $z^*, x^*, y^*, \alpha^*, \beta^*$ and the optimal value z_1^* are obtained; substituting the optimal solution into equation (2), the optimal value z_2^* is obtained.

Step 2: Using equation (2) as the objective function and equations (3)-(15) as the constraints; adding the constraint $Z_1 = Z_1^1 + \delta_1, \delta_1 \geq 0$, the optimal solution $z^{**}, x^{**}, y^{**}, \alpha^{**}, \beta^{**}$ and the optimal value z_2^{**} are obtained.

Step 3: Let $\varepsilon_{\max} = \max(Z_2^*, Z_2^{**}), \varepsilon_{\min} = \min(Z_2^*, Z_2^{**})$. The range of values of ε is thus determined.

B. STEPS OF THE AUGMENTED ε-CONSTRAINT METHOD

Before the calculation can be carried out using the augmented ε-constraint method, the objective function needs to be transformed into a constraint by adding appropriate slack variables or residual variables to the objective function. For the model established in this paper, by adding relaxation variables to equation (2), the original multi-objective model is transformed into the following form. Note that ϕ belongs to the range of 10^{-6} to 10^{-3}.

$$\min z_1 = \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}(y_{ijt}\psi_{ij}) + \sum_{g\in G}\sum_{h\in H}\sum_{j\in J}\sum_{t\in T}(\alpha_{ght}d_{gh} + \beta_{hjt}\varpi_{hj}) - \frac{\phi\lambda}{\varepsilon_{\max} - \varepsilon_{\min}} \tag{18}$$

$$\text{s.t.} \quad (3)-(15) \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\psi_{ij}wy_{ijt} + \sum_{g\in G}\sum_{h\in H}\sum_{j\in J}\sum_{t\in T}(d_{gh}f\alpha_{ght} + \varpi_{hj}f\beta_{hjt}) + \sum_{j\in J}\sum_{t\in T}(c_{jt}\sum_{i\in I}y_{ijt} + \mathrm{k}_j x_j) + \sum_{h\in H}\sum_{t\in T}(e_{ht}\sum_{g\in G}\alpha_{ght} + n_h\vartheta_h) + \lambda = \varepsilon \tag{19}$$

$$\lambda > 0 \tag{20}$$

The calculation steps are as follows:

Step 1: Use the lexicographic optimization approach, and obtain the range of $\varepsilon_{\max}$ and $\varepsilon_{\min}$ of the objective function z_2.

Step 2: Set the constant Ω, $\Delta\varepsilon = \frac{(\varepsilon_{\max}-\varepsilon_{\min})}{\Omega}$, give the Pareto optimal set $\xi = \emptyset$, and set the number of cycles ii as 1.

Step 3: Let $\varepsilon = \varepsilon_{\max} - ii\Delta\varepsilon$, and substitute it into the transformed model. Add it to the set ξ if the constraint is satisfied, then execute step 4; if the constraint is not satisfied, then execute step 4 directly.

Step 4: If $ii \leq \Omega$, $ii = ii+1$, then return to step 3; otherwise terminate the calculation and output the Pareto solution set ξ.

V. CASE STUDY

During the outbreak of the epidemic in Shanghai, the Huangpu District had a large number of newly infected people every day, and faced great challenges in the treatment of infected people and the supply of medical materials, so we use the epidemic data from March 1 to May 31, 2022 in Huangpu District, Shanghai as the case to demonstrate the efficiency of the proposed model and method. From the report released by China's National Health Commission, the average duration of treatment for infected people at EMPs in the Shanghai outbreak is 7 days, so, in order to better set the cure rate of infected people value, we chose 7 days as a stage. In addition, as the outbreak was at the beginning of March and the number of infected people was low, the period from 1 March to 21 March was set as the first stage. So, in this paper, the period from 1 March to 31 May is divided into 11 stages. The proposed model and method are coded in CPLEX and a series of numerical experiments are run on a PC with i5-1035G1 CPU and 8G memory.

A. ESTIMATION OF INPUT DATA

There are 10 streets in Huangpu. Due to the small area of 20.52 square kilometers, we use streets as patient areas, for a total of 10 patient areas. We select 15 large open areas for EMPs, 5 large open areas for MMDPs. We also select Shanghai and Suzhou as MMSPs. The relevant data are chosen based on a realistic situation, while others are generated based on some assumptions, since some data could not be obtained through official reports [34]. We digitize a map of the Huangpu District. The coordinates of each area are indicated by the street office coordinates. Figure 2 shows the geographic location of patient areas, candidate EMPs, and candidate MMDPs. As we select Shanghai and Suzhou as MMSPs are not part of Huangpu District, the MMSPs are not drawn in Figure 2 to better show the geographical location of other points.

The setting and estimation of parameters are presented as follows:

(1) Capacity of EMP$j(A_j)$: These parameters are based on the footprint per bed of the existing EMP at the Expo Urban Footprint Pavilion in Huangpu District.

(2) Volume of MMDP $h(B_h)$: These parameters are obtained by multiplying the area available for the MMDP to be selected by a height of 2 meters.

(3) Number of residents in patient area $i(\theta_i)$: The number of residents in the patient area is extracted from the data published by the National Bureau of Statistics of China (https://www.shhuangpu.gov.cn/).

(4) Infection rate of stage t (p_t): The daily number of infected people in Huangpu District from 1 March to 31 May was obtained from data published by the National Health Commission of China. Thus, we set the infection rate of stage t as the ratio of the number of infected people at each stage t to the total number of people in Huangpu District.

(5) Cured rate of infected people at stage t (s_t): the cured rate of infected people at each stage is set to 1 in this paper.

(6) Construction cost of EMP$_j$ (k_j): In this paper, the value of construction cost for each EMP is the number of beds multiplied by 37,000 (RMB).

(7) Cost of treating per unit number of infected people at stage t of EMP$_j$ (c_{jt}): The cost of treating per unit number of infected people at stage t of EMP$_j$ includes costs of meals and nucleic acid testing, thus, c_{jt} is set to 80 (RMB/per unit).

(8) Construction cost of MMDP h (n_h): In this paper, the value of construction cost of MMDP is the number of the volume multiplied by 100 (RMB).

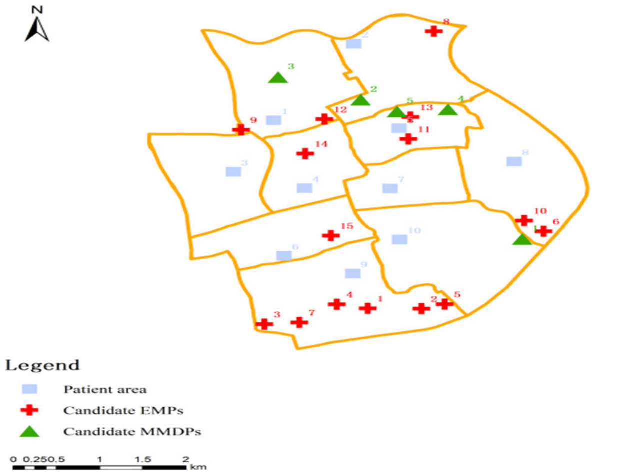

FIGURE 2. The geographic location of patient areas, candidate EMPs, and candidate MMDPs in Huangpu District, Shanghai.

(9) Cost of storing per unit quantity of medical materials at stage t of MMDP h (e_{ht}): e_{ht} is set to 1.5 (RMB/per unit).

(10) Transfer costs per unit of distance and per unit of infected people (w): According to the price list from Shanghai Medical Emergency Center, w is set to 7 (RMB/per unit).

(11) Transportation cost of per unit of distance and per unit of medical material (f): f is set to 1.2 (RMB/ per unit).

(12) Distance between patient area i and EMPj (ψ_{ij}): We use the Euclid distance to calculate the distance between patient area i and EMPj.

(13) Distance between MMDPh and EMPj (ϖ_{hj}): We use the Euclid distance to calculate the distance between MMDPh and EMPj.

(14) Distance between MMSPg and MMDPh (d_{gh}): We use the Euclid distance to calculate the distance between MMSPg and MMDPh.

(15) Volume per unit of medical material (v): Based on product information found from the internet, v is set to 0.04 (m^3).

(16) Replenishment quantities of medical materials for MMSPg at stage t (q_{gt}): The value of q_{gt} is set as shown in Table 1.

(17) Demand per unit of medical materials u: u is set to 1.

(18) A very large positive number M: M is set to 999,999.

B. COMPARISON BETWEEN INTEGRATED AND NON-INTEGRATED MODELS

In this paper, the non-integrated model means that the emergency medical network and the material distribution network are considered separately, and infected people are allocated first and then the medical material is allocated based on the results of the allocation of infected people. In order to better compare the integrated model with the non-integrated model, we use the minimizations of the total transportation distance and the total operating cost as objective functions, respectively. The calculation method for the total transportation distance in the integrated and non-integrated models

TABLE 1. Replenishment quantities of medical materials for MMSPs at each stage.

Stage	Supply points	
	Shanghai	Suzhou
0	0	0
1	4600	4100
2	4500	4600
3	4800	4600
4	4800	4500
5	5200	4800
6	6200	5400
7	5800	4800
8	5500	4400
9	4600	4800
10	4400	4800
11	4600	5200

is showed in Table 2. The calculation method for the total operating cost in the integrated and non-integrated models is showed in Table 3. The calculation results are showed in Tables 4 and 5.

It can be seen from Tables 4 and 5 that the total transportation distance in the integrated model is less than the sum of the values of considering emergency medical network only and considering material distribution network only in the non-integrated model. The total operating cost in the integrated model is also less than the sum of the two values of considering emergency medical network only and considering material distribution network only in the non-integrated model.

C. COMPARISON RESULTS FOR CONSIDERING WITH AND WITHOUT THE INVENTORY STRATEGY

We calculate the total transportation distance and total operating cost to illustrate the advantages of considering with the inventory strategy of MMDPs at each stage. The without considering inventory strategy is calculated as the quantity of medical materials received by MMDPs at each stage are all issued. The calculation model for the total transportation distance considering with and without the inventory strategy is showed in Table 6. The calculation model for the total operating cost considering with and without the inventory strategy is showed in Table 7. The results of the calculation are showed in Table 8.

As can be seen from Table 8, the total transportation distance and total operating cost when considering with inventory strategy are both less than that considering without inventory strategy.

Therefore, a model that takes into account the location of EMPs and MMDPs, and the inventory strategy is more capable of shortening the total transportation distance and

TABLE 2. Calculation steps for the total transportation distance in the integrated and non-integrated models.

Step 1	Calculate the total transportation distance of the model considering the emergency medical network only. The objective function is $\min \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\left(y_{ijt}\psi_{ij}\right)$ Subject to: (3)-(8) $x_j \in \{0,1\}, y_{ijt}, r_{jt} \geq 0, \forall i \in I, \forall j \in J, \forall t \in T$ (21)
Step 2	Calculate the total transportation distance of the model considering the medical material distribution network only. The objective function is $\min \sum_{g\in G}\sum_{h\in H}\sum_{j\in J}\sum_{t\in T}\left(\alpha_{ght}d_{gh} + \beta_{hjt}\varpi_{hj}\right)$ Subject to: (9)-(14) $\vartheta_h \in \{0,1\}, \alpha_{ght}, \beta_{hjt} \geq 0, \forall j \in J, \forall h \in H, \forall g \in G, \forall t \in T$ (22) The optimal solutions r^*, y^*, x^* calculated in Step 1 are substituted into the model.
Step 3	The optimal values obtained in Step 1 and Step 2 are summed to calculate the total transportation distance for the non-integrated model.
Step 4	Calculate the total transportation distance of the integrated model. The objective function is $\min z_1$ Subject to: (3)-(15)

TABLE 3. Calculation steps for the total operating cost in the integrated and non-integrated models.

Step 1	Calculate the total operating cost of the model considering emergency medical network only. The objective function is $\min \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\psi_{ij}wy_{ijt} + \sum_{j\in J}\sum_{t\in T}(c_{jt}\sum_{i\in I}y_{ijt} + k_j x_j)$ Subject to: (3)-(8) $x_j \in \{0,1\}, y_{ijt}, r_{jt} \geq 0, \forall i \in I, \forall j \in J, \forall t \in T$ (23)
Step 2	Calculate the total operating cost of the model considering the medical material distribution network only. The objective function is $\min \sum_{g\in G}\sum_{h\in H}\sum_{j\in J}\sum_{t\in T}(d_{gh}f\alpha_{ght} + \varpi_{hj}f\beta_{hjt}) + \sum_{h\in H}\sum_{t\in T}(e_{ht}\sum_{g\in G}\alpha_{ght} + n_h\vartheta_h)$ Subject to: (9)-(14) $\vartheta_h \in \{0,1\}, \alpha_{ght}, \beta_{hjt} \geq 0, \forall j \in J, \forall h \in H, \forall g \in G, \forall t \in T$ (24) The optimal solution r^*, y^*, x^* calculated in Step 1 are substituted into the model.
Step 3	The optimal values obtained in Step 1 and Step 2 are summed to calculate the total operating cost for the Non-integrated model.
Step 4	Calculate the total operating cost of the integrated model. The objective function is $\min z_2$ Subject to: (3)-(15)

reducing the total operating cost of personnel transfer and medical material distribution, which also verifies the validity of the developed model.

D. PARETO ANALYSIS

The Pareto front surface obtained from the solution is showed in Figure 3. Figure 3 shows that there is a negative correlation between the total transportation distance and total operating cost. That is, as the total operating cost increases, the total transportation distance decreases. This is because that when the total operating cost is larger, the number of EMPs and the number of MMDPs are increased, and the infected people will be allocated to the EMPs which are closer to them first. Similarly, the MMDPs will also be allocated to the EMPs which are closer to them first, such that the total transportation distance decreases.

It can also be seen from Figure 3 that the shape of the Pareto curve becomes steeper when the total operating cost is between 6.6×10^8 RMB and 7×10^8 RMB, which means that a slight increase in the total operating cost has a large impact on the total transportation distance. When the total operating cost is between 7.7×10^8 RMB and 8×10^8 RMB, the Pareto curve shape becomes flatter, which means that increasing the total operating cost has little effect on the total transportation distance. Therefore, for decision-makers, considering the budget earmarked for epidemic relief, the appropriate solution should be chosen according to the actual situation. When the budget earmarked for epidemic relief is

TABLE 4. The total transportation distance of the integrated and non-integrated models.

Model	Integrated model (km)	Non-integrated model: Consider emergency medical network only (km)	Non-integrated model: Consider material distribution network only (km)
Value	2.46×10^6	4.99×10^4	2.43×10^6
Total	2.46×10^6	2.48×10^6	

TABLE 5. The total operating cost of the integrated and non-integrated models.

Model	Integrated model (RMB)	Non-integrated model: Consider emergency medical network only (RMB)	Non-integrated model: Consider material distribution network only (RMB)
Value	6.5928×10^8	6.5625×10^8	3.0409×10^6
Total	6.5928×10^8	6.5929×10^8	

TABLE 6. The calculation model for the total transportation distance considering with and without the inventory strategy.

Model	Considering with the inventory strategy	Considering without the inventory strategy
Objective function	$\min z_1$	$\min z_1$
Subject to	(3)-(15)	(3)-(11), (13)-(15) $\sum_{j \in J} \beta_{hjt} = \sum_{g \in G} \alpha_{ght}, \quad (25)$ $\forall h \in H, \forall t \in T$

TABLE 7. The calculation model for the total operating cost considering and without considering the inventory strategy.

Model	Considering the inventory strategy	Considering without the inventory strategy
Objective function	$\min z_2$	$\min z_2$
Subject to	(3)-(15)	(3)-(11), (13)-(15) $\sum_{j \in J} \beta_{hjt} = \sum_{g \in G} \alpha_{ght}, \quad (26)$ $\forall h \in H, \forall t \in T$

limited, solutions that invest too much money and have less impact on the total transportation distance should be avoided to choose.

As can be seen from Figure 3, it is not possible to obtain a solution that simultaneously optimizes both objective functions, thus, the decision-maker needs to choose the appropriate solution according to the actual situation. In order to help the decision-maker choose the solution more scientifically, two loss indicators are constructed in this paper, namely loss indicator LD_i for the objective functions z_1 and loss indicator LC_i for the objective functions z_2, which are calculated as follows.

$$LD_i = \frac{\max z_1 - z_{i,1}}{\max z_1 - \min z_1} \quad (27)$$

$$LC_i = \frac{\max z_2 - z_{i,2}}{\max z_2 - \min z_2} \quad (28)$$

TABLE 8. The total transportation distance and total operating cost of considering with and without the inventory strategy.

Objective function	Considering the inventory strategy	Considering without the inventory strategy
Total transportation distance(km)	2.46×10^6	2.48×10^6
Total operating cost (RMB)	6.5928×10^8	6.5934×10^8

TABLE 9. The loss level values of various solutions.

Solution	z_1	z_2	LD_i	LC_i
1	2,460,808	794,266,962	100%	0.00%
2	2,460,826	769,624,959	98.42%	19.38%
3	2,460,880	763,519,929	93.60%	24.18%
4	2,461,176	741,986,265	67.39%	41.11%
5	2,461,245	696,956,935	61.28%	76.52%
6	2,461,938	667,098,443	0.00%	100%

Note that $\max z_1$ and $\max z_2$ denote the maximum values of the objective functions z_1 and z_2 in all solutions, respectively; $\min z_1$ and $\min z_2$ denote the minimum values of the objective functions z_1 and z_2 in all solutions, respectively; $z_{i,1}$ and $z_{i,2}$ denote the values of the objective functions z_1 and z_2 in solution i, respectively. The loss level values of various options are showed in Table 9, and the decision-maker can choose the appropriate option based on the actual situation and the acceptance level of the two loss indicators. For example, if the decision maker can accept at most 70% of the loss of the objective function z_1, then the solution with the lowest loss of the objective function z_2, solution 4 can be selected among the solutions for which the LD_i value is eligible.

We choose the solution with the smallest transportation distance among all Pareto solutions to show the integrated network. The integrated networks of stages 6 and 8 are showed in Figures 4 and 5, respectively.

E. SENSITIVITY ANALYSIS

In order to analyze the impact of parameters in the model on the Pareto front surface, four main parameters including the infection rate, the replenishment quantities of medical materials for MMSPs, the capacities of EMPs, and the volumes of MMDPs are selected for analysis.

(1) Impact of different infection rates on the Pareto front surface

By holding other parameters constant, the infection rate is varied by −50%, −25%, +15%, and +25% at each stage in turn, and the effect of changing infection rate on the Pareto front surface is observed, as shown in Figure 6. We choose the solution with the smallest operating cost among all Pareto solutions having the same infection rate as an example for our analysis. The numbers and locations of EMPs and MMDPs under different infection rates are showed in Table 10. When

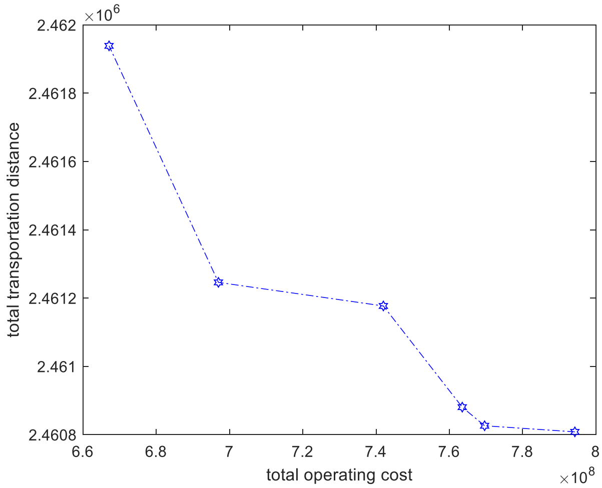

FIGURE 3. Pareto front surface.

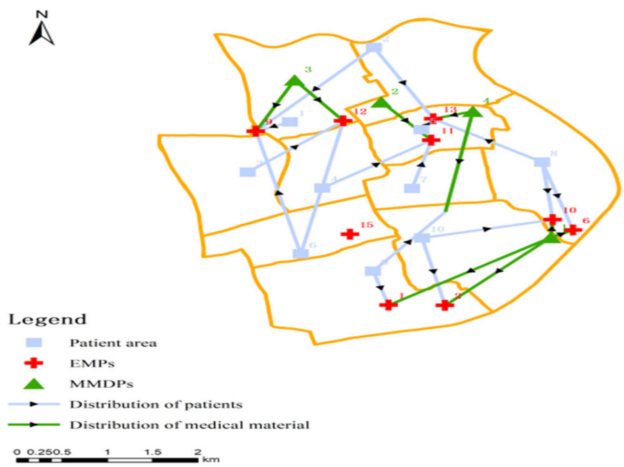

FIGURE 4. Integrated network for stage 6.

the infection rate is increased by 25% at each stage, there is no viable solution. This is because that when the infection rate is increased by 25%, the demand for medical materials increases, while the quantities of medical materials at MMSPs do not meet the needs of all infected people. It can be seen from Figure 6 that the Pareto front surface shifts upwards as the infection rate is increased. This is consistent with the reality. As the infection rate is increased, the number of infected people to be treated is increased, resulting in an increase in the total transportation distance from the transfer of infected people and the distribution of medical materials. It indicates that decision-makers should actively deploy medical material and ensure adequate supply of medical material. Otherwise, when the number of infected people is large, it may not be possible to find a feasible plan for the transport of infected people and the distribution of medical material.

Table 10 shows that as the infection rate increases, the number of selected EMPs gradually increases and an increasing number of EMPs with larger capacity are being selected. This is due to the fact that as the infection rate increases,

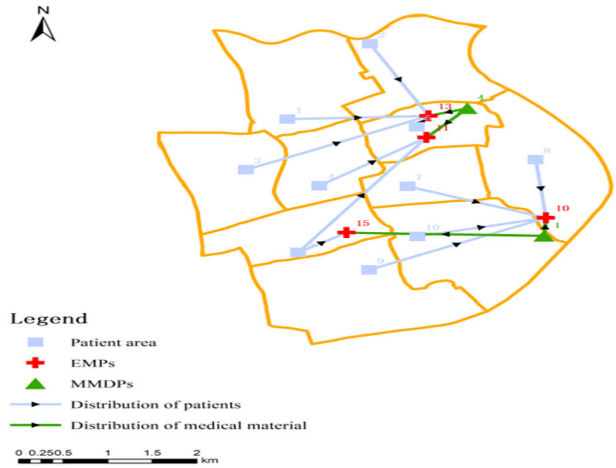

FIGURE 5. Integrated network for stage 8.

more people become infected and more beds are needed to accommodate these infected people. At the same time, as the infection rate increases, the quantities of required medical materials also increase, leading to the change in the number of MMDPs. These results indicate that when the number of infected people is large, decision-makers should select a large number of alternative EMPs and MMDP to ensure full admission of infected people and meet the needs of medical material of infected people.

(2) Impact of different replenishment quantities of medical materials for MMSPs on the Pareto front surface

By holding all other parameters constant, replenishment quantities of medical materials for MMSPs are varied by -25%, -15%, +25%, and +50% at each stage in turn, and the effect of changing replenishment quantities of medical materials for MMSP on the Pareto front surface is observed, as shown in Figure 7. We choose the solution with the smallest operating cost among all Pareto solutions having the same replenishment quantities of medical materials for MMSPs as an example for our analysis. The numbers and locations of EMPs and MMDPs under different replenishment quantities of medical materials for MMSPs are showed in Table 11. As can be seen in Figure 7, the Pareto front surface shifts downwards as replenishment quantities of medical materials for MMSPs increases. This is because that as replenishment quantities of medical materials for MMSPs increases, the MMSPs can supply more medical materials to MMDPs, resulting in an increase in the number of EMPs that each MMDP can serve. As a result, the total transportation distance decreases. Increasing the replenishment quantities of medical materials for MMSPs can result in a smaller total transportation distance for the same total operating cost. However, excessive reduction of replenishment quantities of medical materials for MMSPs may lead to unworkable solutions. For example, When the replenishment quantities of medical materials for MMSPs are reduced by 25%, there is no viable solution. This is because when replenishment quantities of medical materials for MMSPs is reduced by 25%, the quantity

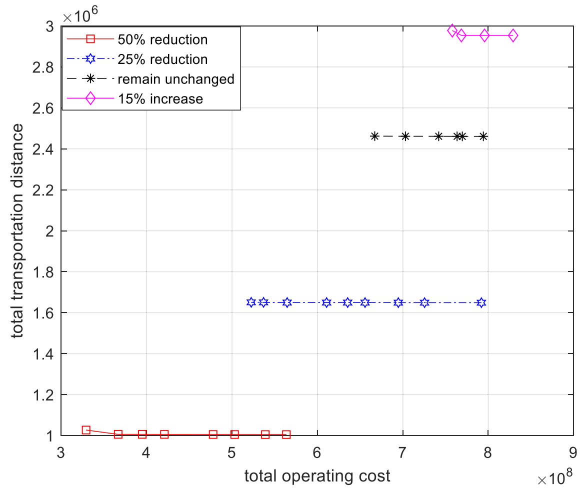

FIGURE 6. Impact of changing infection rates on Pareto front surface.

TABLE 10. The numbers and locations of EMPs and MMDPs under different infection rates.

Infection rate	EMPs	MMDPs
50% reduction	6(1,6,7,13,14,15)	2(1,4)
25% reduction	6(2,4,10,11,12,13)	3(1,3,4)
remain unchanged	8(2,4,6,9,10,11,12,13)	4(1,2,3,4)
15% increase	11(1,2,5,6,8,9,11,12,13,14,15)	4(1,2,3,4)
25% increase	-	-

Note: - represents the infeasible solutions, and the number in brackets in each cell is the selected EMP or MMDP.

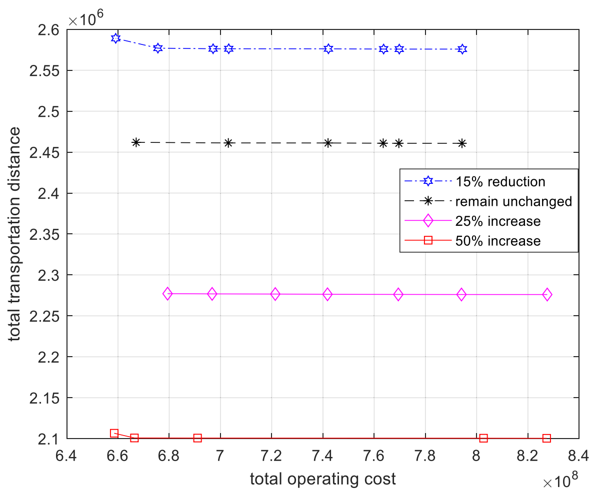

FIGURE 7. Impact of changing replenishment quantities of medical materials for MMSPs on the Pareto front surface.

of medical materials cannot meet the medical material needs of all infected people.

As can be seen from Table 11, changes in replenishment quantities of medical materials for MMSPs influence the number of selected EMPs and MMDPs. The different replenishment quantities of medical materials for MMSPs lead to different choices of EMPs and MMDPs. The above results indicat that the changes in replenishment quantities of medical materials for MMSPs change the values of the total transportation distance and total operating cost, and modify the structure of the emergency medical and material distribution network. Different replenishment quantities of medical materials for MMSPs will select EMPs and MMDPs in different numbers and locations.

TABLE 11. The numbers and locations of EMPs and MMDPs under different replenishment quantities of medical materials for MMSPs.

Replenishment quantities of medical materials for MMSPs	EMPs	MMDPs
25% reduction	-	-
15% reduction	8(1,2,10,11,12,13,14,15)	3(1,3,5)
remain unchanged	8(2,4,6,9,10,11,12,13)	4(1,2,3,4)
25% increase	7(1,6,9,10,11,13,15)	4(1,3,4,5)
50% increase	8(1,2,10,11,12,13,14,15)	3(1,2,4)

Note: - represents the infeasible solutions, and the number in brackets in each cell is the selected EMP or MMDP.

(3) Impact of capacities of EMPs on the Pareto front surface

By holding all other parameters constant, capacities of EMPs are varied by -50%, -25%, +25%, and +50% in turn. Then, the effect of changing capacities of EMPs on the Pareto front surface is observed. As shown in Figure 8. We choose the solution with the smallest operating cost among all Pareto solutions having the same capacity of EMPs as an example for our analysis. The numbers and locations of EMPs and MMDPs under different capacities of EMPs are showed in Table 12. When the capacities of EMPs are reduced by 50%, there is no viable solution. This is because that when the capacities of EMPs are reduced by 50%, the EMPs cannot treat all infected people. As can be seen from Figure 8, the Pareto front surface shifts downwards, as the capacities of EMPs increase. This is because, as the capacities of EMPs increase, more EMPs are established to receive a greater number of infected people who are close to them. It indicates that taking into account the total operating cost, increasing the capacities of EMPs can reduce the total transportation distance. And, When the value of capacities of EMPs are varied from -25% to 0%, the decreased amplitude of the Pareto front surface is the largest; however, with the continued increase of capacities of EMPs, the decreased amplitude gradually decreases. This indicates that the Pareto front surface is particularly sensitive when the capacities of EMPs are small.

As can be seen from Table 12, the number of selected EMPs gradually decreases as the capacity of EMPs increases. This is because that an increase in the capacity of EMP means that more infected people can be treated at each EMP, which is consistent with reality. At the same time, as the number of EMPs increases, the number of selected MMDPs tends to increase and then remain the same. The result indicates that

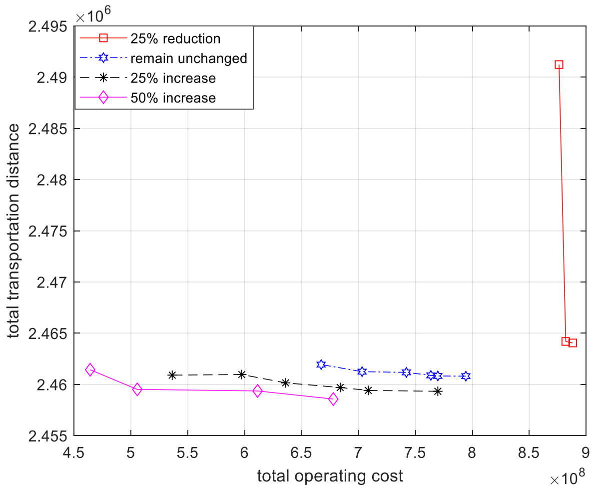

FIGURE 8. Impact of changing capacities of EMPs on the Pareto front surface.

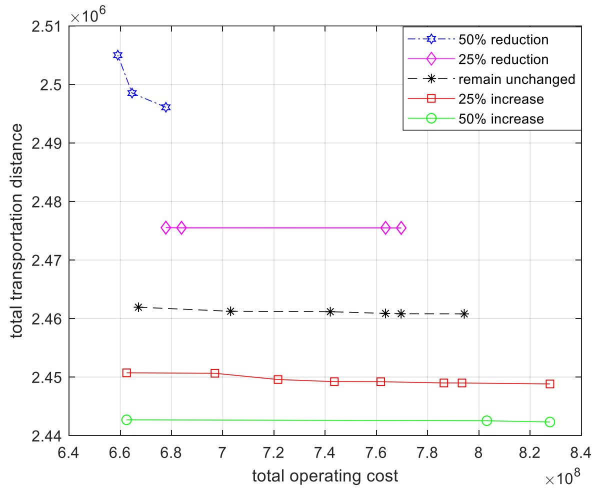

FIGURE 9. Impact of changing volumes of MMDPs on the Pareto front surface.

TABLE 12. The numbers and locations of EMPs and MMDPs under different capacities of EMPs.

Capacities of EMPs	EMPs	MMDPs
50% reduction	-	-
25% reduction	12(1,2,3,4,5,7,8,10,11,12,13,14)	3(1,3,4)
remain unchanged	8(2,4,6,9,10,11,12,13)	4(1,2,3,4)
25% increase	7(2,6,9,10,12,13,15)	4(1,2,3,4)
50% increase	5(4,9,10,12,13)	4(1,2,3,4)

Note: - represents the infeasible solutions, and the number in brackets in each cell is the selected EMP or MMDP.

TABLE 13. The numbers and locations of EMPs and MMDPs under different volumes of MMDPs.

Volumes of MMDPs	EMPs	MMDPs
50% reduction	8(1,2,10,11,12,13,14,15)	5(1,2,3,4,5)
25% reduction	6(9,10,11,12,13,15)	5(1,2,3,4,5)
remain unchanged	8(2,4,6,9,10,11,12,13)	4(1,2,3,4)
25% increase	10(1,2,5,6,9,10,12,13,14,15)	3(1,3,4)
50% increase	10(1,2,5,6,9,10,12,13,14,15)	3(1,3,4)

Note: the number in brackets in each cell is the selected EMP or MMDP.

changes in the capacities of EMPs not only lead to changes in the value of the objective function but also influence the number of selected EMPs and MMDPs due to the interaction between the emergency medical network and the distribution network of material. For example, increasing the capacities of EMPs will result in a smaller number of EMPs and a larger number of MMDP.

(4) Impact of volume of MMDPs on the Pareto front surface

By holding all other parameters constant, volumes of MMDPs are varied by −50%, −25%, +25%, and +50% in turn, and the effect of changing volumes of MMDPs on the Pareto front surface is observed, as shown in Figure 9. We choose the solution with the smallest operating cost among all Pareto solutions having the same volumes of MMDPs as an example for our analysis. The numbers and locations of EMPs and MMDPs are given under different volumes of MMDPs in Table 13. As can be seen from Figure 9, the Pareto front surface shifts downwards, as the volumes of MMDPs increase. This is because that the increased volumes of MMDPs can provide more medical materials to the EMPs in its vicinity, resulting in a reduction in the total transportation distance. It can be concluded that, under the same total operating cost, increasing the volume of MMDPs can reduce the total transportation distance. However, due to the high density of the urban population and limited land resources during an outbreak, when expanding the volume of MMDPs, it is important to ensure that the expanded MMDPs volume can significantly reduce the total transportation distance so that the increased MMDPs volume will be of maximum utility.

Table 13 shows that as the volumes of MMDPs increase, the number of selected MMDPs becomes smaller. This is because that as the volumes of MMDPs increase, each MMDP can receive more quantities of medical materials and distribute the medical materials to more EMPs. Thus, the number of selected MMDPs gradually decreases. Therefore, changes in the volumes of MMDPs not only change the value of the objective function but also change the structure of the emergency medical and material distribution network. For example, increasing volumes of MMDPs will result in a smaller number of MMDPs.

The above sensitivity analysis leads to the following management insights. (1) In the event of an outbreak of epidemic, when the timeliness of medical material distribution and patient treatment is required, decision-makers can take scientific measures based on the sensitivity analysis of the four parameters: infection rate, replenishment quantities of medical materials for MMSPs, the capacities of EMPs, and the volumes of MMDPs. For example, in order to reasonably distribute medical materials and transfer infected people, decision-maker can increase replenishment quantities of medical materials for MMSPs or the volumes of MMDPs. (2) By adopting a location-allocation strategy for the integrated emergency medical and material distribution network, decision-maker can better optimize the entire system network. For example, decision-makers can select EPMs and MMDPs based on the results of sensitivity analysis under different infection rates, avoiding the selection of an excessive number of EPMs and MMDPs.

VI. CONCLUSION

In this study, we address an integrated design of emergency medical and material distribution networks by taking into account the number of infected people and the multi-stage characteristics of dynamic distribution of medical materials after the epidemic outbreak. Then, a multi-objective mixed-integer programming model with the objectives of minimizing the total transportation distance and the total operating cost is established. By taking Huangpu District of Shanghai in China as a case study, Pareto analysis between objectives and sensitivity analysis for key parameters are conducted to verify the effectiveness of the developed model.

Our research provides four major contributions to the planning of emergency medical and material distribution networks during future outbreaks. First, we considered the inventory of emergency medical material at each stage of the MMSPs and MMDPs to establish the multi-stage integrated optimization model of emergency medical and material distribution network, the results show that the integrated model of emergency medical and material distribution networks is more capable of decreasing the total transportation distance and the total operating cost, compared to the non-integrated model. It can provide more effective solutions for emergency rescue decision-makers. Second, there is a negative relationship between the total transportation distance and the total operating cost. If the decision-makers want to reduce the total transportation distance, the total operating cost must be increased. Third, the research results show that the established dual-objective optimization model can effectively balance the total transportation distance and the total operating cost, and obtain the location-allocation solution of EMP and MMDP in the distance-cost compromise can provide decision-makers with multiple options for emergency rescue. Finally, if the timeliness of the emergency response is high, decision-makers can choose to increase replenishment quantities of medical materials for MMSPs, capacities of the EMP, or volumes of MMDPs, depending on the situation so that the total transport distance can be reduced.

Future research can be conducted in four directions. First, in this study, we assumed that the infection rate at each stage is known after the outbreak. However, it is difficult to accurately predict the infection rate in real life, so it is more realistic to develop an integrated optimization model with an uncertain infection rate. Second, we only considered mildly infected people in the modeling, however, requirements for medical material may vary with the degree of infection of each infected people during an outbreak. Therefore, the research on the integration optimization of the uncertain demand for medical material is also the focus of future research. Third, in this study, only one type of medical materials was considered, but in actual epidemic prevention and control, multiple medical materials are needed. Thus, the issue of location-distribution of multi-level facilities considering multiple types of medical materials needs to be studied in depth. Finally, in this study, only the same patient transport vehicle model and the same material distribution vehicle model were considered. In fact, due to the sudden onset of the epidemic, a sufficient number of vehicles of the same vehicle model could not be mobilized within a short time. Moreover, different vehicles have different driving speeds, which have different impacts on patient transport and material distribution. Therefore, the issue of optimizing the integration of emergency medical and material distribution networks considering multiple vehicles needs further study.

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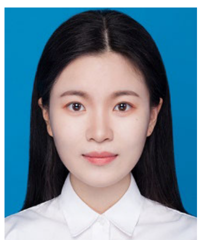

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