Integrated Emergency Medical Facility Location and Patient Dispatching Under Uncertainty

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IEEE Transactions on Intelligent Transportation Systems, 2025. https://doi.org/10.1109/TITS.2025.3584100

***Abstract*—In the face of a sudden public health emergency caused by a new infectious disease, it is necessary to establish a multi-level emergency medical facility (including primary and superior facilities) to address the surge in medical needs. In this context, traditional hospitals are responsible for patient screening, primary emergency medical facilities are responsible for treating mild cases, and superior emergency medical facilities are responsible for treating severe cases. Against the backdrop of uncertainties such as patient self-referral and the autonomous progression of the disease, we address an important problem of integrated emergency medical facility location and patient dispatching under uncertainty and propose a multi-stage stochastic programming model to formulate the problem. For a deterministic model under a given set of scenarios, a Decomposition-based Dual-level Heuristic (DDH) algorithm is proposed to efficiently solve the problem, where the upper level employs tabu search to optimize the location scheme, and the lower level utilizes a patient allocation heuristic to provide an optimized patient dispatching solution. Numerical experiments are conducted using Wuhan, China, the epicenter of the COVID-19 outbreak, as an example. The results show that the DDH algorithm achieves high quality solutions close to those obtained by state-of-the-art solver CPLEX but with significantly reduced computational overload. The DDH algorithm is also compared with the progressive hedging algorithm and genetic algorithm, showing its superior performance in terms of solution quality and computational efficiency. Through extensive data analysis, valuable conclusions and managerial insights are obtained, providing useful references for emergency response in similar public health emergencies in the future.**

***Index Terms*—Emergency Medical Facility Location; Patient Dispatching; Uncertainty; Multi-stage Stochastic Programming; Heuristic Algorithm.**

I. Introduction

Pandemic and epidemic influenzas are public health concerns that have caused major life losses over the past several hundred years [1]. Since the 21st century, various epidemic infectious diseases have broken out worldwide, including atypical pneumonia, H1N1 influenza, Middle East Respiratory Syndrome, West African Ebola virus, and the novel coronavirus pneumonia (abbreviated as 'COVID-19'). As an infectious public health emergency, the COVID-19 has a severe and versatile impact on urban lifestyles. Meanwhile, the demand for high-quality health services continues to increase year after year, while hospitals encounter more and more difficulties in terms of limited medical resources [2]. Roberto Azevêdo, the Director-General of the World Trade Organization, said that the impact of the COVID-19 is more severe than the financial crisis twelve years ago, causing global economic downturns and mass unemployment, challenging socio-economic growth and public health service systems.

Rapid construction of emergency medical facilities is needed to provide temporary treatment space and meet urgent medical needs when traditional health facility expansion methods are unable to meet the surge in medical demand [3]. Emergency medical facilities can be converted from schools, parks, and gymnasiums, or built as temporary sites using modular construction methods. Based on the characteristics of the patient population they mainly serve, these facilities are categorized into different levels and integrated into a multi-level healthcare system, forming a tiered medical service network geared towards public health emergencies. The location and treatment capacity of emergency medical facilities need to be determined based on their functional positioning and service coverage [4], thereby improving the overall patient recovery rate in the region. Research on the location selection of emergency facilities has significant implications in medical treatment [5], disaster relief [6], and emergency logistics [7]. Specifically, fully considering the challenges in treating different disaster situations helps in designing reasonable locations for emergency medical facilities, improving the quality and efficiency of emergency medical services. In the control of the COVID-19 pandemic, the well-known mobile cabin hospitals and two specialty field hospitals, namely the Huoshenshan hospital and Leishenshan hospital [8], constructed in Wuhan city of China, played a significant role. Building mobile cabin hospitals and specialty field hospitals became crucial measures to alleviate the pressure of regional medical treatment.

This study is based on the medical treatment needs of sudden infectious public health events and considers a tiered medical service network consisting of three levels of hospitals. Level 3 hospitals refer to primary hospitals capable of screening infected individuals; level 2 hospitals are primary emergency medical facilities (i.e., mobile cabin hospitals),

This work was supported in part by the National Natural Science Foundation of China (Grant No. 71971172, 72271240, 72371200), Hunan Provincial Natural Science Foundation of China (Grant No. 2022JJ30671) and Northwestern Polytechnical University (Grant No. CX2022057, D5000220376). (*Corresponding author: Yuning Chen*.)

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capable of treating mild-symptom patients; level 1 hospitals are superior emergency medical facilities (i.e., specialty field hospitals), capable of treating severe-symptom patients. The primary and superior emergency medical facilities serve as supplements to the designated hospitals and intensive care hospitals, respectively, and need to be established after the outbreak of a sudden infectious public health event.

Patients with different conditions have varying needs for medical resources, necessitating the categorization and treatment of patients based on their conditions [9]. In other words, the functional positioning of medical institutions at different levels in a tiered medical service network should be considered, and patients should be assigned to appropriate medical institutions for treatment. In large-scale disaster relief scenarios, categorized treatment for patients can improve the overall treatment efficiency of a given region. Given the limited treatment capabilities of hospitals, emergency medical facilities, as a supplement to the existing medical system, provide additional treatment capacity to handle certain types of patients [10]. In the tiered medical service network, individuals can be either non-infected or infected, the latter of which are further divided into mild and severe cases considering the conditions of the patients. Thus, one concern is how to transfer infected patients to appropriate hospitals for treatment based on their conditions. Moreover, during major public health emergencies, patients vary in their physical conditions and preferences for medical treatments. Some choose to be transferred to appropriate hospitals under the arrangement of emergency centers (referred to as 'non-self-directed patients'), while others opt to go to a hospital of their choice (referred to as 'self-directed patients'). Such self-directed choices, which are made by patients who lack global information, may cause a surge in medical demand at certain hospitals, leading to an imbalance in the workload of various hospitals. For example, after the confirmation of human-to-human transmission of COVID-19 on January 20, 2020, a surge in suspected and panic visits occurred in various hospitals in Wuhan. The surge in medical demand primarily came from self-directed patients. Thus, the decisions of self-directed patients have a significant impact for both the patient transfer strategy among various hospitals, and the site selection of emergency medical facilities [3], [11]. Therefore, to improve the treatment capability of the region, it is essential not only to categorize and treat mild and severe cases, but also to consider the impact of self-directed patients on patient dispatching.

Under the aforementioned tiered medical service network, we divides the treatment process of patients into two stages based on the progression of their conditions. The first stage of treatment is for patients who are either unknown to be infected or have mild symptoms. The former will spontaneously go to the primary or designated hospitals for screening and will be transferred to Level 2 hospitals if found infected. The latter will be directly transferred to Level 2 hospitals. The second stage of treatment requires transferring patients who have progressed from mild to severe cases to Level 1 hospitals for treatment.

Based on the above tiered medical service network and patient treatment process, we study integrated emergency medical facility location and patient dispatching problem under uncertain environments, which is abbreviated as IEMFLPD_U. IEMFLPD_U takes into account uncertain factors such as the scale of patients, the number of self-directed patients at various demand points, the proportion of mild cases, and the proportion of severe cases. The goal requires to minimize the construction cost of emergency medical facilities and the transfer cost of patient dispatching. The main contributions of our work are as follows:

(1) We propose a multi-stage stochastic programming (MSP) model for the IEMFLPD_U, which integrates a two-level emergency medical facilities location stage for determining the primary and superior emergency medical facilities, and patient dispatching stages for allocating patients among various levels of hospitals, considering representative medical demand scenarios. Note that the patient dispatching stages are further divided into two stages to handle mild and severe cases, respectively, taking into account the evolution of the patient's condition and role of different levels of hospitals.

(2) We propose a Decomposition-based Dual-level Heuristic (DDH) algorithm for solving the IEMFLPD_U problem. The algorithm seeks a high-quality solution to the IEMFLPD_U by solving its deterministic model under given scenarios. The DDH algorithm employs a bi-level optimization framework. The upper level generates a facility location plan with a tabu search procedure, where the general solver is used to solve a reduced and relaxed MSP model to quickly evaluate the solution quality. The lower level generates a patient dispatching plan, following the obtained facility location plan, for each scenario with a greedy heuristic.

(3) Numerical experiments based on real-world case data are conducted, and extensive experiments and analyses have been performed. The results indicate that compared to the CPLEX solver, progressive hedging algorithm (PHA) and genetic algorithm (GA), the DDH algorithm shows higher solving efficiency, achieving high-quality solutions in a reasonably short time. Moreover, sensitivity analyses are performed for the treatment capabilities of existing medical institutions and the proportion of self-directed patients, providing insights into real-world applications of the problem.

The remainder of the paper is organized as follows. Section II reviews the related works in the literature. Section III presents the problem description and the MSP model. Section IV elaborates on the DDH algorithm. Section V conducts a case study analysis on the Wuhan city of China to validate the effectiveness of the approach and provides management insights. Section VI presents concluding remarks and some suggestions for future research.

II. Literature Review

In this section, we review the related literature from facility location in emergency scenarios, emergency medical location and patient dispatching, and medical service network design.

A. Facility Location in Emergency Scenarios

For the location of emergency medical facilities in disaster events, the main research focuses are on the location of casualty collection points, emergency medical centers, and emergency supply warehouses. For example, Drezner et al. [4] formulated the casualty collection points location problem as a multi-objective model. They proposed a descent heuristic algorithm and a tabu search algorithm for solving the problem. Jia et al. [6] established a general facility location model for large-scale emergencies, which aims to find the minimum number of emergency medical facilities required based on meeting medical needs. Huang et al. [11] proposed a general facility location model for large-scale emergency disaster scenarios, considering that residents in some areas cannot rely on their nearest facilities. They used dynamic programming approach for the location on a network, and further developed an efficient algorithm for optimal locations on a general network. Gu et al. [9] studied the medical relief shelter location problem considering the severities and geographical locations of patients. They proposed a mixed integer programming model and developed a greedy algorithm to solve the problem. Zhang et al. [12] studied the location problem of emergency service facilities under uncertainty. They proposed an uncertain set covering model, and transformed it into an equivalent deterministic location model to solve. Wang et al. [13] studied the integrated emergency supply planning problem faced by a regional healthcare coalition. They proposed a multi-objective two-stage stochastic programming model to solve the problem and employed a linear weighting method.

In addition, there is abundant research on the location of emergency medical centers and ambulance stations, which offers considerable guidance for solving the emergency medical facility location problem. Hashenmi et al. [14] proposed an integer programming model for locating emergency medical centers. They used the GAMS software and developed a GA to solve the problem. Their study indicated that the correct location of emergency medical center and ambulances can have a positive impact on service in emergency situations. Su et al. [15] focused on improving the ambulance deployment method to optimize the distribution of first-aid resources. They refined the double coverage model and developed an ant colony optimization algorithm to solve the problem. Schmid [16] studied the dynamic ambulance relocation and dispatching problem. They proposed an approximate dynamic programming method to solve the problem, and the results showed a 12.89% reduction in response time. Nickel et al. [17] investigated the problem of choosing the location and number of ambulance and their bases in a certain region, considering the uncertainty of the demand. A scenario-indexed formulation was proposed, and a sampling approach was developed to solve the problem.

B. Integrated Emergency Medical Facility Location and Allocation

The research on the emergency medical facility location in the context of sudden public health events is relatively scarce and often integrates the emergency medical facility location problem with other problems, such as casualties allocation, route planning, emergency supplies allocation, and medical staff assignment. For example, Caunhye et al. [3] investigated the problem of integrated alternative care facility location and casualties allocation, considering casualty classification and self-evacuation behaviors. They proposed a three-stage stochastic programming model and developed an algorithm based on Benders decomposition to solve the problem. Yi and Özdamar [18] studied the location-routing problem that integrates vehicle routing with facility location decisions to support healthcare operations and evacuation in disaster response. They developed an integrated location-distribution model and proposed a dynamic programming algorithm to solve the problem. They conducted a case study of an earthquake scenario in Istanbul, Turkey. Liu et al. [10] focused on the facility location and casualty allocation problem, considering casualty triage, health deterioration conditions, and equitable distribution of limited medical resources. They proposed a bi-objective optimization model and developed an iteration method to solve the problem. Luo et al. [5] studied an integrated planning problem of deploying emergency hospitals, allocating emergency medical supplies and managing infected patients. They proposed a multi-period location-allocation model considering the dynamic arrival of emergency medical supplies and infected patients. Lai et al. [19] studied the multi-period integrated planning problem of vaccination station location and medical professional assignment, considering the uncertain demand for multiple types of vaccines over multiple periods. They proposed a two-stage stochastic mixed integer linear program, and developed a Benders decomposition-based heuristic algorithm.

C. Medical Service Network Design

By designing an efficient medical service network that includes rational partitioning of service areas and strategic functional positioning of multi-level hospitals, the overall patient treatment efficiency within the region can be improved. Zhen et al. [20] studied the facility network design problem for disaster relief. They proposed an integer programming model to minimize the total cost of establishing the facility network. A Lagrangian relaxation method was proposed for solving the model. Zhang et al. [21] studied the design of preventive healthcare facility network. They built an M/M/1 queue model for each facility to capture the level of congestion, and proposed a location-allocation heuristic solution algorithm to solve the problem. Zhang et al. [22] studied the impact of client choice behavior on the configuration of a preventive care facility network and the resulting level of participation. To this end, they proposed two alternative models, probabilistic-choice model and optimal-choice model. Alizadeh et al. [23] studied the design of a viable healthcare supply chain network for a pandemic. They proposed a multi-level network, including health centers, CT scan centers, hospitals, and clinics, for a pandemic. They developed a MSP method to solve the problem. Döyen et al. [24] studied a humanitarian relief logistics problem. They proposed a mixed-integer linear programming model and designed a Lagrangian relaxation based heuristic method. Zarrinpoor et al. [25] studied the health service network design problem, considering the risk of disruptions of the facilities. They proposed a reliable hierarchical location-allocation model based on a two-stage robust optimization approach. A Benders decomposition based solution procedure is developed to solve the model.

III. Problem Description and Formulation

This section first presents the problem description, and then formulates the MSP model for the problem.

A. Problem Description

The hierarchical medical service network considered in the IEMFLPD_U is shown in Figure 1. Level 1 hospitals, composed of intensive care hospitals and superior emergency medical facilities, are mainly responsible for treating severe cases. Level 2 hospitals, composed of designated hospitals and primary emergency medical facilities, mainly treat mild cases. Additionally, designated hospitals allow the unscreened patients to receive screen for infection detection. Level 3 hospitals refer to primary hospitals, which can only screen for infections but cannot treat them. Notably, both primary and superior emergency medical facilities are temporary institutions. Each level of emergency medical facility has multiple types, and different types have varying numbers of beds and construction costs.

Once the hierarchical medical service network is established, the treatment process is divided into stages for treating mild and severe cases based on the development of the patient's condition. We assume that at the initial stage of the public health events, only mild cases were present at the demand point, with no severe cases. In the stage for treating mild cases, patients with mild symptoms are allocated to Level 2 hospitals for treatment. In the stage for treating severe cases, patients who have developed severe symptoms are transferred from Level 2 hospitals to Level 1 hospitals for treatment. Importantly, the unscreened patients may choose to go to primary or designated hospitals for screening, potentially leading to some designated hospitals exceeding their treatment capacity. Therefore, in addition to allocating patients diagnosed at Level 3 hospitals to Level 2 hospitals during the stage for treating mild cases, it is also necessary to allocate patients diagnosed at designated hospitals to other Level 2 hospitals.

In IEMFLPD_U, in addition to the uncertainty in the scale of the patient population, there are multiple uncertain factors in the patient treatment process. For instance, uncertain factors in the stage for treating mild cases include the number of patients who self-refer to various Level 3 and Level 2 hospitals from each demand point; the proportion of them who are confirmed cases; the proportion of patients with confirmed diagnosis among non-self-referred patients from each demand point. Uncertain factors in the stage for treating severe cases mainly concern the proportion of mild-symptom patients who develop into severe-symptom patients. The IEMFLPD_U requires determining the location and type of emergency medical facilities at each level in the hierarchical medical service network, as well as the dispatching plan for mild-symptom patients and the referral plan for severe-symptom patients. All these must be considered under the aforementioned uncertainties, aiming to minimize the expected total construction cost of emergency medical facility and the total referral cost while satisfying the patient treatment demands.

B. Multi-Stage Stochastic Programming Model

MSP is a framework for dealing with a set of stochastic events over time [26]. Specifically, in MSP models, the decisions in each stage are taken for an uncertain future, while the corrective decisions must be made in the subsequent stages after the realization of the uncertain events. The decisions in each stage depend on the information that is available to the decision-maker at the current time, as well as the future uncertainties and their possible corresponding decisions. Therefore, it is suitable for modeling the IEMFLPD_U.

We divide the problem into three stages: Stage 1 involves dual-level emergency medical facility location, Stage 2 involves the allocation of mild-symptom patients, and Stage 3 involves the referral of severe-symptom patients. A scenario tree, as shown in Figure 2, is used to represent the uncertain parameters of this problem. Specifically, $\omega \in \Omega$ represents a scenario in the stage of treating patients with mild symptoms, which includes specific patient scale, the proportion of diagnosed patients to undiagnosed ones, the proportion of patients choosing to go to third-level and designated hospitals on their own, and the proportion of such patients who are diagnosed. $P\omega$ represents the probability that scenario ω occurs, and $\sum_{\omega\in\Omega} P(\omega) = 1$. $\beta_\omega \in \mathcal{B}_\omega$ represents a scenario in the stage of treating patients with severe symptoms that occurs after scenario ω, specifically referring to the proportion of mild-symptom patients in each second-level hospital that turn into severe-symptom patients. $P(\beta_\omega|\omega)$ represents the probability that scenario β_ω occurs, and $\sum_{\beta_\omega\in\mathcal{B}_\omega} P(\beta_\omega|\omega) = 1$. The MSP model **P1** is shown below, and the definitions of the relevant symbols can be found in Table I.

$$\textbf{P1:}\ \min \sum_{k=1}^{2} \sum_{h\in\mathcal{H}_k^P} \sum_{l\in\mathcal{L}_k} C_{khl} y_{khl} + \sum_{\omega\in\Omega} P(\omega) Q_1(\boldsymbol{y},\omega) \tag{1}$$

$$\text{s.t.} \sum_{l\in\mathcal{L}_k} y_{khl} \le 1, \quad \forall k = 1,2; h \in \mathcal{H}_k^P \tag{2}$$

$$\sum_{h\in\mathcal{H}_k^P} \sum_{l\in\mathcal{L}_k} y_{khl} \le V_k, \quad \forall k = 1,2 \tag{3}$$

$$y_{khl} \in \{0,1\}, \quad \forall k = 1,2; h \in \mathcal{H}_k^P; l \in \mathcal{L}_k \tag{4}$$

where

$$Q_1(\boldsymbol{y},\omega) \tag{5}$$

$$= \min \sum_{d\in\mathcal{D}} \sum_{h\in\mathcal{H}_2\cup\mathcal{H}_2^P} T_{dh} x_{dh}(\omega) \tag{6}$$

$$+ \sum_{h'\in\mathcal{H}_3\cup\mathcal{H}_2} \sum_{h\in\mathcal{H}_2\cup\mathcal{H}_2^P|h\neq h'} T_{h'h} w_{h'h}(\omega)$$

$$+ \sum_{\beta_\omega\in\mathcal{B}_\omega} P(\beta_\omega|\omega) Q_2(\boldsymbol{y},\boldsymbol{x},\omega,\beta_\omega)$$

$$\text{s.t.} \sum_{h\in\mathcal{H}_2\cup\mathcal{H}_2^P} x_{dh}(\omega) \tag{7}$$

$$= \left(I_d(\omega) - \sum_{h\in\mathcal{H}_3\cup\mathcal{H}_2} \alpha_{dh}(\omega) \right) F_d(\omega), \quad \forall d \in \mathcal{D}$$

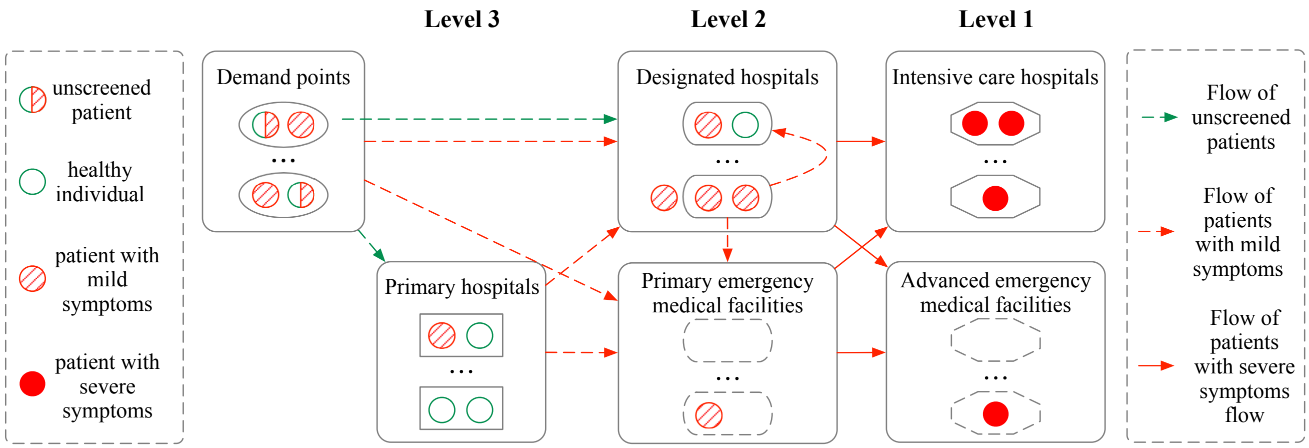

Fig. 1. Schematic diagram of the hierarchical medical service network and patient treatment process

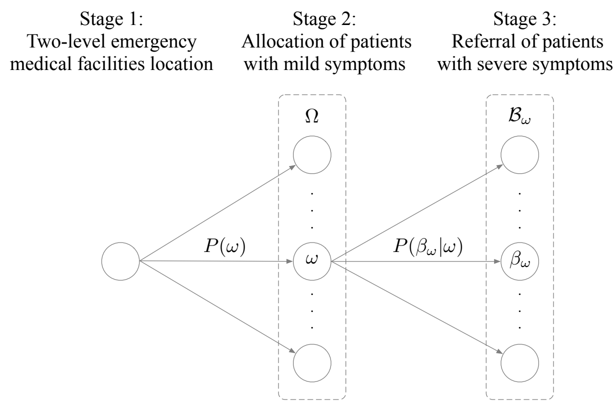

Fig. 2. Scenario tree.

$$\sum_{h\in\mathcal{H}_2\cup\mathcal{H}_2^P|h\neq h'} w_{h'h} = \max\Big\{\sum_{d\in\mathcal{D}} \alpha_{dh'}(\omega)F_d^{SE}(\omega) - O_{h'}, 0\Big\}, \quad \forall k=2,3; h'\in\mathcal{H}_k \tag{8}$$

$$\sum_{d\in\mathcal{D}} x_{dh}(\omega) + \sum_{d\in\mathcal{D}} \alpha_{dh}(\omega)F_d^{SE}(\omega) + \sum_{h'\in\mathcal{H}_3\cup\mathcal{H}_2|h'\neq h} w_{h'h}(\omega) - \sum_{h'\in\mathcal{H}_2\cup\mathcal{H}_2^P|h'\neq h} w_{hh'}(\omega) \leq O_h, \quad \forall h\in\mathcal{H}_2 \tag{9}$$

$$\sum_{d\in\mathcal{D}} x_{dh}(\omega) + \sum_{h'\in\mathcal{H}_3\cup\mathcal{H}_2|h'\neq h} w_{h'h}(\omega) \leq \sum_{l\in\mathcal{L}_2} A_{2,l}y_{2,hl}, \quad \forall h\in\mathcal{H}_2^P \tag{10}$$

$$x_{dh}(\omega)\in\boldsymbol{N}, \ \forall d\in\mathcal{D}; h\in\mathcal{H}_2^P\cup\mathcal{H}_2 \tag{11}$$

$$w_{h'h}(\omega)\in\boldsymbol{N}, \ \forall h'\in\mathcal{H}_2\cup\mathcal{H}_3; h\in\mathcal{H}_2^P\cup\mathcal{H}_2|h'\neq h \tag{12}$$

where

$$Q_2(\boldsymbol{y},\boldsymbol{x},\omega,\beta_\omega) = \min \sum_{h'\in\mathcal{H}_2\cup\mathcal{H}_2^P} \sum_{h\in\mathcal{H}_1\cup\mathcal{H}_1^P} T_{h'h}(\omega)z_{h'h}(\beta_\omega) \tag{13}$$

$$\text{s.t.} \sum_{d\in\mathcal{D}} \varphi_d(\beta_\omega)x_{dh}(\omega) + \sum_{d\in\mathcal{D}} \varphi_d^{SE}(\beta_\omega)\alpha_{dh}(\omega)F_d^{SE}(\omega) + \sum_{h'\in\mathcal{H}_3\cup\mathcal{H}_2|h'\neq h} \phi_{h'}^{SE}(\beta_\omega)w_{h'h}(\omega) - \sum_{h'\in\mathcal{H}_2\cup\mathcal{H}_2^P|h'\neq h} \phi_h^{SE} w_{hh'}(\omega) \leq \sum_{h'\in\mathcal{H}_1\cup\mathcal{H}_1^P} z_{hh'}(\beta_\omega), \quad \forall h\in\mathcal{H}_2 \tag{14}$$

$$\sum_{h'\in\mathcal{H}_3\cup\mathcal{H}_2} \phi_{h'}^{SE}(\beta_\omega)w_{h'h}(\omega) + \sum_{d\in\mathcal{D}} \varphi_d(\beta_\omega)x_{dh}(\omega) \leq \sum_{h'\in\mathcal{H}_1\cup\mathcal{H}_1^P} z_{hh'}(\beta_\omega), \ \forall h\in\mathcal{H}_2^P \tag{15}$$

$$\sum_{h'\in\mathcal{H}_2\cup\mathcal{H}_2^P} z_{h'h}(\beta_\omega) \leq O_h, \quad \forall h\in\mathcal{H}_1 \tag{16}$$

$$\sum_{h'\in\mathcal{H}_2\cup\mathcal{H}_2^P} z_{h'h}(\beta_\omega) \leq \sum_{l\in\mathcal{L}_1} A_{1,l}y_{1,hl}, \quad \forall h\in\mathcal{H}_1^P \tag{17}$$

$$z_{h'h}(\beta_\omega)\in\boldsymbol{N}, \quad \forall h'\in\mathcal{H}_2\cup\mathcal{H}_2^P; h\in\mathcal{H}_1\cup\mathcal{H}_1^P \tag{18}$$

The first-stage objective function (1) aims to minimize the construction costs and the expected subsequent patient transfer costs, where the patient transfer cost $Q_1(\boldsymbol{y},\omega)$ is the optimization goal of stage 2. Constraint (2) ensures that at most one emergency medical facility can be built at each candidate location. Constraint (3) ensures that the total number of new primary and superior emergency medical facilities cannot exceed their planned numbers. Constraint (4) defines the range of decision variable values for stage 1.

The second-stage objective function (5) aims to minimize the expected transportation costs for mild patients, as well as for severe patients, where $Q_2(\boldsymbol{y},\boldsymbol{x},\omega,\beta_\omega)$ is the optimization goal for stage 3. Constraint (7) calculates the number of confirmed patients taking non-voluntary treatment from the demand points to secondary and tertiary hospitals. Constraint (8) calculates the number of confirmed patients with voluntary treatments transferred from existing secondary and tertiary hospitals to other secondary hospitals. Specifically, this study only allows patients exceeding the treatment capacity of a

TABLE I
NOTATIONS FOR MSP MODEL

Symbol	Parameter description
Sets	
$\mathcal{H}$	Existing hospital set ($h = 1, ..., \|\mathcal{H}\|$)
$\mathcal{H}^P$	Candidate emergency medical facility locations ($h = 1, ..., \|\mathcal{H}^P\|$)
$\mathcal{L}$	Types of emergency medical facilities ($l = 1, ..., \|\mathcal{L}\|$)
$\mathcal{H}_k \subset \mathcal{H}$	Existing hospitals of level k, $k = 1, 2, 3$. Here, $\mathcal{H}_1$ refers to Level 1 hospitals, $\mathcal{H}_2$ to Level 2, and $\mathcal{H}_3$ to Level 3
$\mathcal{H}^P_k \subset \mathcal{H}^P$	Candidate level k emergency medical facility locations, $k = 1, 2$. Here, $\mathcal{H}^P_1$ refers to superior facilities, $\mathcal{H}^P_2$ to basic facilities
$\mathcal{L}_k \in \mathcal{L}$	Types of level k emergency medical facilities, k = 1, 2. Here, $\mathcal{L}_1$ refers to superior facilities, $\mathcal{L}_2$ to basic facilities
$\mathcal{D}$	Medical demand points ($d = 1, ..., \|\mathcal{D}\|$)
Ω	Scenarios in the stage 2 ($\omega = 1, ..., \|\Omega\|$)
$\mathcal{B}_\omega$	Scenarios in the stage 3 corresponding to scenario ω ($\beta_\omega \in \mathcal{B}_\omega$)
Parameters	
V_k	Maximum number of level k emergency medical facilities that can be built
O_h	Treatment capacity of existing hospital h, where $h \in \mathcal{H}_3, O_h = 0$
A_{kl}	Treatment capacity of type $l \in \mathcal{L}_k$ in level k emergency medical facilities
C_{khl}	Cost of building type $l \in \mathcal{L}_k$ emergency medical facility at candidate location $h \in \mathcal{H}^P_k$
T_{ij}	Transfer cost from location i to location j
$P(\omega)$	Probability of scenario ω occurring
$P(\beta_\omega\|\omega)$	Probability of subsequent scenario β_ω occurring in scenario ω
$I_d(\omega)$	Number of patients at demand point d in scenario ω
$\alpha_{dh}(\omega)$	Number of self-referred patients from demand point d to hospital $h \in \mathcal{H}_2 \cup \mathcal{H}_3$ in scenario ω
$F_d(\omega)$	Proportion of diagnosed patients among non-self-referred patients at demand point d in scenario ω
$F^{SE}_d(\omega)$	Proportion of diagnosed patients among self-referred patients at demand point d in scenario ω
$\varphi_d(\beta_\omega)$	Proportion of diagnosed patients developing into severe cases among non-self-referred patients at demand point d in scenario ω
$\varphi^{SE}_d(\beta_\omega)$	Proportion of diagnosed patients developing into severe cases among self-referred patients at demand point d in scenario ω
$\phi^{SE}_h(\beta_\omega)$	Proportion of diagnosed patients developing into severe cases among self-referred patients at existing Level 2 and Level 3 hospitals $h \in \mathcal{H}_2 \cup \mathcal{H}_3$ in scenario ω, where $\phi^{SE}_h(\beta_\omega) = \sum_{d\in\mathcal{D}} \varphi^{SE}_d(\beta_\omega) F^{SE}_d(\omega)\alpha_{dh}(\omega) / \sum_{d\in\mathcal{D}} \alpha_{dh}(\omega)$
Variables	
y_{khl}	Binary variable y_{khl} equals 1 if a level k emergency medical facility is built at candidate location $h \in \mathcal{H}^P_k$ for type $l \in \mathcal{L}_k$, and 0 otherwise
$x_{dh}(\omega)$	Number of diagnosed non-self-referred patients allocated from demand point d to Level 2 hospital h in scenario ω
$w_{h'h}(\omega)$	Number of diagnosed patients allocated from existing Level 2 or Level 3 hospital h' to other Level 2 hospital h in scenario ω
$z_{h'h}(\omega)$	Number of severe cases transferred from Level 2 hospital h' to Level 1 hospital h in scenario ω

hospital to be transferred to other hospitals for treatment. Constraints (9) and (10) specify that the actual number of patients treated at each secondary hospital cannot exceed its treatment capacity. Constraints (11) and (12) define the range of decision variable values for stage 2.

The third-stage objective function (13) aims to minimize the transportation costs for severe patients. Constraints (14) and (15) specify that all severe patients at each secondary hospital need to be transferred to Level 1 hospitals for treatment. Constraints (16) and (17) specify that the actual number of patients treated at each Level 1 hospital cannot exceed its treatment capacity. Constraint (18) defines the range of decision variable values for stage 3.

To clarify the evolution of decisions across different stages, we presents an illustrative example of the IEMFLPD_U problem with 1 demand point d_1 and 1 primary/designated/intensive care hospital (h_1, h_2, h_3). Hospital h_2 has 500 beds, while h_3 has 100 beds. There are 1 possible location and 2 types for each primary/superior emergency medical facility. Moreover, in stage 2, there are 2 scenarios, and in stage 3, each scenario from stage 2 branches into 2 new scenarios, resulting in 4 scenarios in stage 3. Figure 3 provides detailed information and shows a feasible solution. The top of the figure illustrates stage 1 decisions, while the bottom shows decisions for stages 2 and 3.

IV. DECOMPOSITION-BASED DUAL-LEVEL HEURISTIC ALGORITHM

To solve the IEMFLPD_U, we firstly transform the MSP model **P1** into a deterministic model **P2** by using scenario-based approach. Specifically, the scenarios set Ω and $\mathcal{B}_\omega$ in model **P1** are replaced by a set of representative scenarios, including stage-2 scenario set $\mathcal{S}$ and stage-3 scenario sets $\mathcal{S}'_\omega$ ($\omega \in \mathcal{S}$). Then, the model **P2** is a mixed-integer linear program (MILP) and can be solved by general solvers.

$$\textbf{P2:}\ \min \sum_{k=1}^{2} \sum_{h\in\mathcal{H}^P_k} \sum_{l\in\mathcal{L}_k} C_{khl} y_{khl} \tag{19}$$
$$+ \sum_{\omega\in\mathcal{S}} P(\omega) \Bigg(\sum_{d\in\mathcal{D}} \sum_{h\in\mathcal{H}_2\cup\mathcal{H}^P_2} T_{dh} x_{dh}(\omega)$$
$$+ \sum_{h'\in\mathcal{H}_3\cup\mathcal{H}_2} \sum_{h\in\mathcal{H}_2\cup\mathcal{H}^P_2 \mid h\neq h'} T_{h'h} w_{h'h}(\omega)$$
$$+ \sum_{\beta_\omega\in\mathcal{S}'_\omega} P(\beta_\omega|\omega) \sum_{h'\in\mathcal{H}_2\cup\mathcal{H}^P_2} \sum_{h\in\mathcal{H}_1\cup\mathcal{H}^P_1} T_{h'h}(\omega) z_{h'h}(\beta_\omega) \Bigg)$$
s.t. Constraints $(2)-(4), (7)-(12), (14)-(18)$

It is worth noting that we collected real data to generate representative scenarios, which cover most of the possible situations. Although these scenarios are not exhaustive and may omit some low-probability scenarios, they are sufficient to provide a robust solution for the IEMFLPD_U problem.

While tackling facility location problems with commercial solvers like CPLEX and Gurobi is challenging, researchers

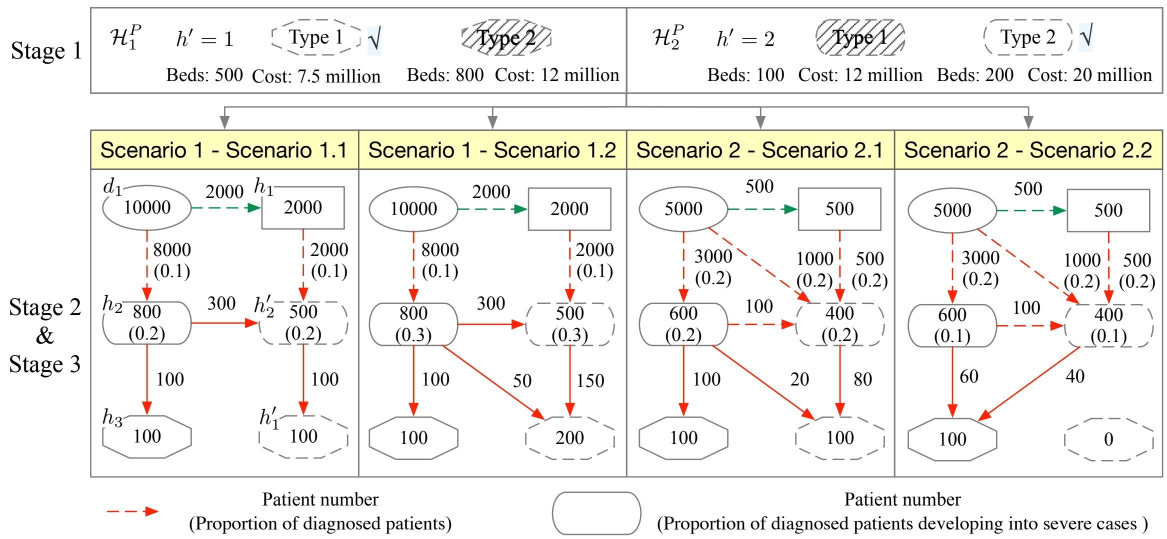

Fig. 3. An illustrative example of the IEMFLPD_U.

usually propose metaheuristic algorithms for solutions, including evolutionary algorithms [27], [28], and particle swarm optimization algorithm [29], etc. Therefore, we propose a Decomposition-based Dual-level Heuristic (DDH) algorithm to solve the model **P2**. We decompose the IEMFLPD_U into a two-level facility location subproblem (TLFLP, corresponding to stage 1) and a fixed location patient dispatching subproblem (FLPSP, corresponding to stages 2 and 3). The two subproblems are solved iteratively until a given stopping criterion is met. The framework of the DDH algorithm is shown in Algorithm 1. Initially, a Two-Level Facility Location Initialization algorithm (Section IV-A) is used to generate facility location $\boldsymbol{y}^{(0)}$, followed by a *Patient Dispatching Heuristic* algorithm (Section IV-C) to initialize the patient dispatching under this specific facility location $(\boldsymbol{x}^{(0)}, \boldsymbol{w}^{(0)}, \boldsymbol{z}^{(0)})$. The resulting objective value is denoted as $Obj^{(0)}$. Afterwards, a *Two-Level Facility Location Local Search* algorithm (Section IV-B) based on tabu search is used to optimize the facility location for the TLFLP, and a *Patient Dispatching Heuristic* algorithm is used to generate the patient dispatching for the FLPSP. The above process is repeated until the maximum number of iterations $MaxIter$ is reached.

A. Initial Solution Generation for Two-Level Facility Location

The purpose of generating an initial solution for the two-level facility location is to quickly produce a high-quality starting point for the subsequent local search algorithm. In model **P2**, the feasibility of the facility location mainly depends on whether the capacity constraints of the Level 1 hospitals (9), (10) and the Level 2 hospitals (16), (17) are met. Given that patient volumes vary in different scenario samples s, the algorithm for generating the initial solution of the two-level facility location starts with a feasible facility location under the scenario with the largest patient volume and then quickly adjusts to find the least number of facility locations that satisfy all scenarios.

Algorithm 1 Outline of the proposed DDH algorithm

Require: a given problem instance *NP*, a set of scenarios $\mathcal{S}$, maximum iteration number $MaxIter$
Ensure: the best solution $(\boldsymbol{y}^*, \boldsymbol{x}^*, \boldsymbol{w}^*, \boldsymbol{z}^*)$ with its objective value Obj^* found during the search

```
y^(0) ← TwolevelFacilityLocationInitialization(NP, S)
(x^(0), w^(0), z^(0), Obj^(0)) ← PatientDispatchingHeuristic(NP, y*, S)
Initialize tabu list TL^(0), location selection history PT^(0), set
  k ← 0, y* ← y^(0), x* ← x^(0), w* ← w^(0), z* ← z^(0), Obj* ← Obj^(0)
while k ≤ MaxIter do
    (y^(k+1), PT^(k+1), TL^(k+1)) ← TwolevelFacilityLocationLocalSearch(NP, S, y^(k), PT^(k), TL^(k))
    (x^(k+1), w^(k+1), z^(k+1), Obj^(k+1)) ← PatientDispatchingHeuristic(NP, y^(k+1), S)
    if Obj^(k+1) < Obj* then
        Obj* ← Obj^(k+1), y* ← y^(k+1), x* ← x^(k+1), w* ← w^(k+1), z* ← z^(k+1)
    end if
    k ← k + 1
end while
```

The framework of the algorithm for generating the initial solution for two-level facility location is shown in Algorithm 2. It first uses a general MIP solver to obtain the facility location $\boldsymbol{y}'$ under the scenario s^L which has the largest number of patients. Then, combining this location $\boldsymbol{y}'$, it calculates the cost-benefit values of each facility location according to Equation (20) and sorts them in an ascending order to create priority sequences $\mathcal{R}_1$ and $\mathcal{R}_2$ for the locations of superior and primary emergency facilities. Subsequently, locations and types of facilities are added in sequence from the priority sequences $\mathcal{R}_1$ and $\mathcal{R}_2$ until the patient needs of all scenarios are met. The formula for calculating the cost-benefit value is shown in Equation (20).

$$Avg\_cof_{kh} = \sum_{l \in \mathcal{L}_k} Cof_{khl} - My'_{khl}, \forall k = 1, 2; h \in \mathcal{H}_k \quad (20)$$

Algorithm 2 Outline of the TwolevelFacilityLocationInitialization

Require: a given problem instance *NP*, a set of scenarios $\mathcal{S}$
Ensure: the initial solution $\boldsymbol{y}^{(0)}$

$\boldsymbol{y}' \leftarrow$ GeneralSolver(*NP*, s^L)
Create priority sequences of superior emergency medical facilities $\mathcal{R}_1$ and primary emergency medical facility $\mathcal{R}_2$ according to Eq.(20) and solution $\boldsymbol{y}'$, set $\boldsymbol{y}^{(0)} \leftarrow \emptyset$
for $k = 1, 2$ **do**
  repeat
    $h \leftarrow$ the first element of $\mathcal{R}_k$
    $\boldsymbol{y}^{(0)} \leftarrow \boldsymbol{y}^{(0)} \cup \{y_{khl} | l = \arg\min Coff_{khl}, \sum_{l\in\mathcal{L}_k} y'_{khl} = 1; l = l^L, \sum_{l\in\mathcal{L}_k} y'_{khl} = 0\}$, $\mathcal{R}_k \leftarrow \mathcal{R}_k \setminus \{h\}$
  until the solution $\boldsymbol{y}^{(0)}$ is feasible or $\mathcal{R}_k = \emptyset$
end for

In this case, the parameter M is a very large positive integer, and the formulas for calculating $Cof_{1,hl}$ and $Cof_{2,hl}$ are shown in Equation (21) and Equation (22), respectively.

$$Cof_{1,hl} = \frac{C_{1hl} + \sum\limits_{d\in\mathcal{H}_2\cup\mathcal{H}_2^P} T_{dh}}{A_{1,h}}, \forall h \in \mathcal{H}_1^P; l \in \mathcal{L}_1 \tag{21}$$

$$Cof_{2,hl} = \frac{C_{2hl} + \sum\limits_{d\in\mathcal{D}\cup\mathcal{H}_3\cup\mathcal{H}_2} T_{dh}}{A_{2,h}}, \forall h \in \mathcal{H}_2^P; l \in \mathcal{L}_2 \tag{22}$$

The above cost-benefit formula comprehensively considers the construction costs of facility point h for all types l, the cost of transferring to facility point h, and the open status of facility point h under scenario s^L.

B. Two-Level Facility Location Local Search

The *Two-Level Facility Location Local Search* algorithm aims to optimize facility location. Neighborhood structure plays an important role in the local search method [30]. Specifically, given a facility location $\boldsymbol{y}$, its neighboring solutions can be obtained through two types of move operators, including the facility open operator and the facility modification operator. First, the facility open operator, denoted as Operator$_1(\boldsymbol{y}, l)$, is applied for unopened facility locations h. It sequentially attempts to open facility type $l \in \mathcal{L}_h$ for location h. Second, the facility shift operator, denoted as Operator$_2(\boldsymbol{y}, l')$, is applied for all the opened facility h with type l'. It tries either to close this facility location or to change this opened facility to another type $l \in \mathcal{L}_h \setminus \{l'\}$. Specifically, when Operator$_2(\boldsymbol{y}, l')$ is applied, location h switches to type l' if originally built as type l, or closes if originally built as type l'.

The framework of the *Two-Level Facility Location Local Search* algorithm is shown in Algorithm 3. Given an initial facility location $\boldsymbol{y}$, the algorithm sequentially employs the Operator$_1$ and Operator$_2$ to perform neighborhood search on superior emergency medical facilities $h \in \mathcal{H}_1^P$ and primary emergency medical facilities $h \in \mathcal{H}_2^P$. Specifically, the search for facility locations at each level of emergency medical facilities is carried out, and the starting facility location h for each round of search is obtained based on the solution of the previous round. In this algorithm, the last facility location h that was searched using the j-th operator for the k-level emergency medical facilities is recorded using the location history PT_{kj}. The starting facility location for this round is $h = PT_{kj}+1$. If $\mathcal{H}_k^P$ has been completely searched, the search will begin from the facility location with the smallest index in that level. Whenever a new facility location $\boldsymbol{y}'$ is obtained and it satisfies the capacity constraints, a general solver is used to quickly calculate its objective value, which is only an approximate estimate, used for rapid quality assessment of the solution. To be specific, we solve a relaxed **P2** model, where the value of y_{khl} is fixed and variables $x_{dh}(\omega)$, $w_{h'h}(\omega)$, and $z_{h'h}(\omega)$ are treated as continuous. It is worth noting that the algorithm adopts a tabu search strategy to avoid falling into local optima. The tabu list TL records the rounds in which the type l of emergency medical facility h was modified, with a tabu tenure of T, meaning that the modification operation will not be accepted in the next T rounds of search.

Algorithm 3 Outline of the TwolevelFacilityLocationLocalSearch

Require: a given problem instance *NP*, a set of scenarios $\mathcal{S}$, a solution $\boldsymbol{y}$, a tabu list TL, a location selection history $PT = \{PT_{kj} | k = 1, 2, j = 1, 2\}$, the best objective value Obj^* obtained so far
Ensure: the best solution $\boldsymbol{y}^*$ found during the search

for $k = 1, 2$ **do**
  for $j = 1, 2$ **do**
    repeat
      $h \leftarrow$ a facility location selected from $\mathcal{H}_k^P$ according to location selection history PT_{kj}
      for $l \in \mathcal{L}_h$ **do**
        $\boldsymbol{y}' \leftarrow$ Operator$_j(\boldsymbol{y}, l)$
        if solution $\boldsymbol{y}'$ is feasible **then**
          $Obj' \leftarrow$ GeneralSolver(*NP*, $\boldsymbol{y}'$, $\mathcal{S}$)
        end if
        if ($Obj' < Obj^*$ and $Obj' < Obj$) or ($Obj' < Obj$, while $\boldsymbol{y}$ is not forbidden by the tabu list TL) **then**
          $Obj \leftarrow Obj'$, $\boldsymbol{y}^* \leftarrow \boldsymbol{y}'$
        end if
      end for
    until all the facility locations in $\mathcal{H}_k^P$ are checked or a feasible solution is found
    $PT'_{kj} \leftarrow$ Update PT_{kj}
  end for
  $TL' \leftarrow$ Update TL
end for

C. Patient Dispatching Heuristic Algorithm

Given a facility location $\boldsymbol{y}$, in the *Two-Level Facility Location Local Search*, we solve linear programming model to quickly estimate its objective value. However, this is not sufficient, and we still need to find high-quality patient dispatching solutions to accurately evaluate the overall solution. Since that the patient dispatching for each scenario is independent, we can obtain the patient dispatching for each scenario separately. Therefore, we propose a *Patient Dispatching Heuristic* algorithm to optimize patient dispatching for each scenario. Specifically, for scenario s, the algorithm considers the capabilities of medical facilities at each level and follows the nearest-transport treatment principle. It makes sequential decisions for mild patient allocation and severe patient transportation. Priority is given to treating patients with a confirmed diagnosis who sought treatment independently at designated hospitals. The specific steps of the algorithm are as follows:

- **Step 1**. Based on the number of confirmed patients among those who sought treatment on their own at the designated hospital $h \in \mathcal{H}_2$, update the remaining treatment capacity of hospital h and calculate the number of mild patients who have not been treated in Level 2 and Level 3 hospitals;
- **Step 2**. Sequentially determine the dispatching for confirmed patients who did not seek treatment on their own at each demand point. Patients are primarily allocated to Level 2 hospitals with smaller transportation costs and available treatment capacity, generating the decision $\boldsymbol{x}_s$ and updating the remaining treatment capacity of the Level 2 hospitals;
- **Step 3**. Sequentially determine the dispatching for confirmed patients in Level 3 hospitals, and for confirmed patients who exceed the treatment capacity in Level 2 hospitals. Patients are primarily allocated to Level 2 hospitals with smaller transportation costs and available treatment capacity, thereby generating the decision $\boldsymbol{w}_s$;
- **Step 4**. Sequentially decide the transportation scheme for severe case patients in Level 2 hospitals. Patients are primarily allocated to level 1 hospitals with smaller transportation costs and available treatment capacity, thereby generating the decision $\boldsymbol{z}_s$.

Once the patient dispatching for each sample scenario s is obtained, calculate the objective function value Obj for the given facility location $\boldsymbol{y}$ and patient dispatching $(\boldsymbol{x}, \boldsymbol{w}, \boldsymbol{z})$.

V. Case Study

A. Experimental Data

To validate our proposed MSP model and DDH algorithms, we generate problem instances based on the real-world data. These problem instances consist of scenario features and case features. Scenario features include patient scale, self-referred patient ratio, confirmed patient ratio, mild and severe patient ratios, and occurrence probabilities of each scenario. Case features include the distribution of healthcare demand points in the target city, population characteristics, hospital locations and their treatment capabilities, locations and capabilities of primary and superior emergency medical facilities. The scenario features are mainly set based on reported data online, while case features are sourced from the geographical data of the target city. We mainly study the experimental results for Wuhan city of China.

1) Scenario Features: Based on the COVID-19 data in Wuhan, we set 12 scenarios for the experiment. The specific settings of the scenarios are as follows.

① Patient scale. Data on medical demand (patient scale) are generated randomly. First, we set 12 scenarios according to the ratio of the number of patients received at fever clinics in Wuhan to the total population (12,326,518 according to the seventh census). Then, we randomly generate a number of patients within given ratio for each scenario. Note that specific data on daily admissions to fever clinics in Wuhan are difficult to obtain. We got the rough numbers from the news materials. Specifically, the number of people received at city-wide fever clinics was around 2,900-13,000 from late January to mid-February 2020. Therefore, the proportion of total fever clinic receptions to the total population is set between 0.0001-0.001, and for the most severe infection scenario, the patient scale ratio is expanded to 0.002.

② Self-referred patients. According to Caunhye and Nie [3] and the news that reported the number of new patients in Wuhan a few days after the lockdown on January 24, 2020, we assume that if the proportion of new cases to the total population exceeds 0.002%, the number of self-referred patients is zero. Otherwise, the proportion of self-referred patients is 80%. Self-referred patients are randomly allocated according to the distance from demand points to primary and designated hospitals, and it is assumed that self-referred patients randomly go to the one of nearest ten hospitals.

③ Confirmed patient ratio and scenario occurrence probability. We obtained historical COVID-19 data in Wuhan from December 1, 2019, to March 19, 2021, from the nCov2019 library (using R programming language). By calculating the occurrence days corresponding to each new patient number, and excluding days with no new confirmed patients, we set the ratio of confirmed patients to the total population and the occurrence probability of each scenario. Specific data are shown in Table II and Table III.

④ Severe Patient Ratio. The proportion of severe patients among confirmed patients is simply set at 0%, 5%, 10%, 15%, and 20% based on news materials.

The characteristics of the 12 scenarios are shown in Table IV, and the relationship between the scenarios can be seen in the Figure 4.

TABLE II
Historical COVID-19 Data in Wuhan from December 1, 2019, to March 19, 2021

Daily new cases	Max new cases/total population	Days	Occurrence frequency (%)
0	0	388	82.03
1-40	3.00×10^{-6}	34	7.19
41-100	6.50×10^{-6}	10	2.11
101-200	1.60×10^{-5}	6	1.27
201-400	3.00×10^{-5}	9	1.90
401-700	5.00×10^{-5}	7	1.48
701-1,300	1.00×10^{-4}	5	1.06
1,301-1,900	1.40×10^{-4}	8	1.69
1,901-3,000	2.50×10^{-4}	5	1.06
3,001-13,436	1.00×10^{-3}	1	0.21

2) Instance Features: Instance feature can be divided into medical resource supply and medical resource demand. The supply side mainly includes existing medical institution data and optional field hospital data. The demand side is primarily based on the population data and street data of the target city. The settings of the instance are as follows.

① Treatment capacity of medical institutions. The treatment capacity of existing hospitals is determined by referring to hospital bed data and news materials. The treatment capacity

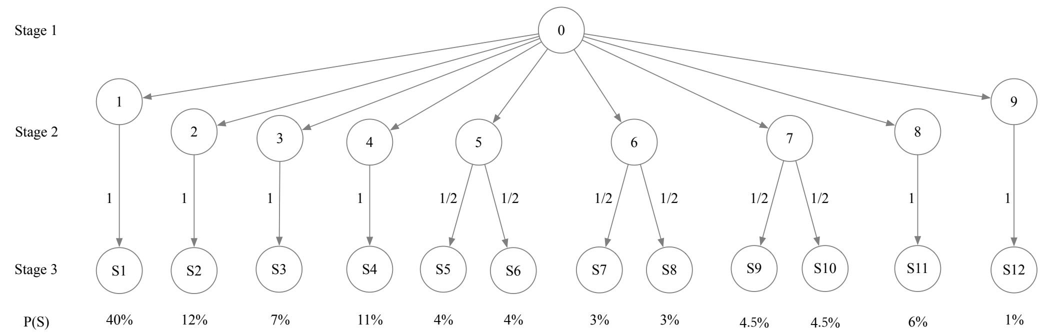

Fig. 4. Scenario Tree

TABLE III
PROBABILITY OF NEW CASES BASED ON HISTORICAL WUHAN DATA

New cases/ total population	Occurrence probability (%)
3.00×10^{-6}	40.00
6.50×10^{-6}	11.80
1.60×10^{-5}	7.10
3.00×10^{-5}	10.60
5.00×10^{-5}	8.20
1.00×10^{-4}	5.90
1.40×10^{-4}	9.40
2.50×10^{-4}	5.90
1.00×10^{-3}	1.20

TABLE V
CATEGORIES OF EMERGENCY MEDICAL FACILITIES

Facility type	Maximum bed capacity	Construction cost (in 10,000 CNY)
Primary emergency medical facilities		
1	300	300
2	500	750
3	800	1,200
4	1,000	1,500
5	1,500	2,250
6	2,000	3,000
Superior emergency medical facilities		
1	500	4,500
2	1,000	9,000
3	1,500	13,500

TABLE IV
SCENARIO SETTINGS

Scenario	Patient scale	Self-diagnosis patients	Confirmed cases/total population	Severe cases/ confirmed cases (%)	Scenario occurrence probability (%)
S1	2,465	1,972	3.00×10^{-6}	0.00	40.00
S2	3,698	2,958	6.50×10^{-6}	5.00	12.00
S3	4,931	3,944	1.60×10^{-5}	5.00	7.00
S4	6,163	0	3.00×10^{-5}	5.00	11.00
S5	7,396	0	5.00×10^{-5}	5.00	4.00
S6	7,396	0	5.00×10^{-5}	10.00	4.00
S7	8,629	0	1.00×10^{-4}	10.00	3.00
S8	8,629	0	1.00×10^{-4}	15.00	3.00
S9	9,861	0	1.50×10^{-4}	10.00	4.50
S10	9,861	0	1.50×10^{-4}	15.00	4.50
S11	11,094	0	2.50×10^{-4}	15.00	6.00
S12	24,653	0	1.00×10^{-3}	20.00	1.00

of emergency medical facilities is determined based on the type of facility. Detailed data is shown in Table V.

② Existing primary/designated/intensive care hospitals. The existing primary, designated and intensive care hospitals are mainly referenced from the official announcements of the State Council. In detail, in the case of Wuhan, there are 63 hospitals, including 2 intensive care hospitals, 15 designated hospitals, and 46 primary hospitals.

③ Candidate locations of primary emergency medical facilities. Primary emergency medical facilities are usually modified from the existing public facilities, such as sports venues, exhibition centers, factories, warehouses, etc. We obtained all locations of these facilities in Wuhan from the Amap application. After filtering out the locations which do not have hospitals within 3 km, 46 candidate locations remain.

④ Candidate locations of superior emergency medical facilities. Superior emergency medical facilities are set up according to specific guidelines, mainly for the treatment of seriously and critically ill patients. In Wuhan, 18 suburban parks are selected as the candidate locations for superior emergency medical facilities.

⑤ Demand points. The demand points in Wuhan are divided according to the streets of the city. According to the government's official data, Wuhan is divided into 13 administrative districts, which include 156 streets.

Figure 5 shows the existing medical service network in Wuhan composed of these four types of nodes. The real-world instance of Wuhan city is publicly available for future research work [1].

Our DDH algorithm was coded in C++ and compiled by GNU g++. The C++ API of the CPLEX solver 12.10.0 is called to solve model. The most difficulty scenario of our instances is $S12$, which has the maximum scale of patients and medical demand. Given this, in our previous experiments, we found that a tabu tenure of 3 allowed the algorithm to efficiently navigate the solution space of the facility location problem without becoming trapped in local optima, given the problem's scale and complexity. Thus, we set $T = 3$. More-

[1]https://github.com/NWPU-ORMS/IEMFLPD_U

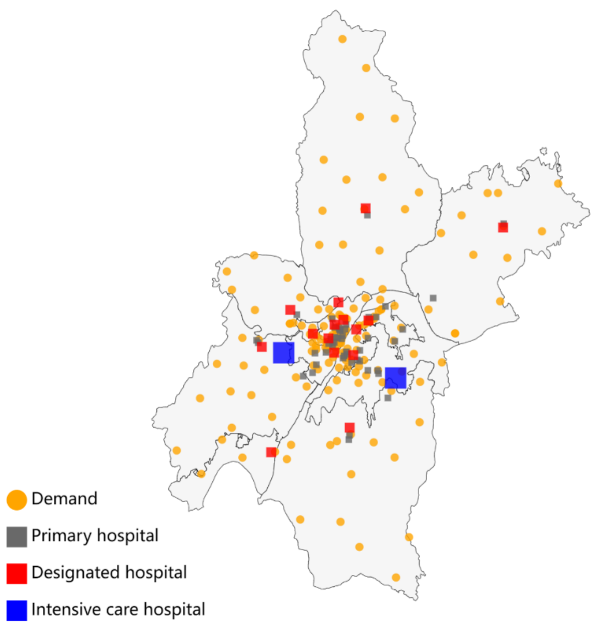

Fig. 5. Existing Medical Service Network in Wuhan

over, we set $MaxIter = 30$. All experiments are executed on a Xeon E5-2670 processor operating at 2.5GHz with 16GB RAW, running Linux with a single thread.

B. Experimental Results

We discuss the experimental results of the proposed DDH algorithm from three aspects. Firstly, we compare the performance of DDH alogrithm with Progressive Hedging Algorithm (PHA), Genetic Algorithm (GA) and CPLEX. Secondly, we analyze the effectiveness of the *Patient Dispatching Heuristic* algorithm on the solution performance. Thirdly, we specifically analyze the obtained two-level emergency medical facility locations and summarize the characteristics. Finally, the effectiveness of the stochastic programming approach is verified.

1) Comparisons of DDH, PHA, GA and CPLEX: To assess the performance of the proposed DDH algorithm, we use the CPLEX solver as the benchmark. Moreover, we implemented PHA [31] and GA [27], which are wildly used in solving the stochastic optimization problems, for comparisons. The details of these two algorithms are as follows.

- **PHA**. The PHA tackles the IEMFLPD_U problem by breaking it into scenario subproblems via augmented Lagrangian theory and iteratively coordinates their solutions. The procedure initiates by setting Lagrangian multipliers (q_v^s, p_v^s, o_v^s) to zero and solving all subproblems ($s \in \bigcup_{\omega\in\mathcal{S}} \mathcal{S}'_\omega$) via CPLEX to obtain initial solutions $(y_v^s, x_v^s, w_v^s, z_v^s)$. Non-anticipative consensus variables $\bar{y}_{v+1}$, $\bar{x}^{\omega}_{v+1}$, and $\bar{w}^{\omega}_{v+1}$ are computed by averaging solutions across scenarios. Convergence is evaluated using metrics γ_y, γ_x, γ_w, (i.e., $\gamma_y = \sum P(s)\|y^s - \bar{y}_{v+1}\|$), with termination thresholds $\xi_y = \xi_x = \xi_w = 0.01$. If unconverged, multipliers are updated via $q^s_{v+1} = q^s_v + \rho(y^s_v - \bar{y}_{v+1})$ (similarly for p^s_{v+1} and o^s_{v+1}) using penalty parameter $\rho = 5$. The objective function of each subproblem is modified by adding linear terms ($q^s_{v+1}y^s$, $p^s_{v+1}x^s$, $o^s_{v+1}w^s$) and quadratic penalty terms ($\frac{\rho}{2}\|y^s - \bar{y}_{v+1}\|^2$, $\frac{\rho}{2}\|x^s - \bar{x}_{v+1}\|^2$, $\frac{\rho}{2}\|w^s - \bar{w}_{v+1}\|^2$). Updated subproblems are resolved iteratively with CPLEX (50-second time limit per iteration) until convergence or time limit is reached.
- **GA**. The GA addresses the IEMFLPD_U problem by decomposing it into TLFLP and FLPSP subproblems, solving TLFLP with GA and embedding FLPSP via the *Patient Dispatching heuristic*. For TLFLP, GA uses a population of chromosomes encoded as $\mathbf{y} = \{l_h | l_h \in \mathcal{L}_h \cup \{0\}, h \in \mathcal{H}_1^P \cup \mathcal{H}_2^P\}$, where 0 indicates no facility at location h. Starting with a randomized initial population, the GA iteratively evaluates each chromosome's fitness by solving embedded FLPSP subproblems via the *Patient Dispatching Heuristic* across all scenarios $s \in \bigcup_{\omega\in\mathcal{S}} \mathcal{S}'_\omega$. New populations are generated through crossover (randomly selecting two parents with 50% probability of inheriting each l_h from either parent) and mutation (10% probability of randomly altering l_h). This process repeats until the time limit is reached.

Using only one real-world instance may not be sufficient to draw a general conclusion on the performance of the algorithms, we additionally generate 5 artificial instances (Ains_1 - Ains_5) based on the real-world instance (Rins) of Wuhan city. These instances are generated by randomly increasing or decreasing the number of patients, existing hospitals, candidate locations for emergency facilities, and demand points by 5%, 10%, 15% relative to the Rins. All artificial instances are also publicly available for future research work[1].

We run the CPLEX, PHA and GA on the same computing environment as the DDH algorithm, with a 1-hour time limit per instance. Table VI report the computational results of the CPLEX, DDH, PHA, and GA. For each approach, we record the best found objective values Obj and the running time $Time$ for the first time to hit this value for solving each instance. The best objective values among the four approaches are highlighted in **bold**. We compute the percentage gaps $Gap(\%) = (Obj - LB)/LB \times 100$ of the best objective value Obj found by each approach from the best lower bounds (LB) found by CPLEX. Moreover, the symbol "-" indicates that no feasible solution is found.

The results show that our DDH algorithm effectively balances computational efficiency and solution quality. To be specific, CPLEX achieves the best objective values in 2 instances (Ains_1, Ains_3), while our DDH algorithm outperforms the others by obtaining the best solutions in the remaining 4 instances (Rins, Ains_2, Ains_4, Ains_5). Although the DDH algorithm finds the results with percentage gaps ranging from 6.65% to 23.76%, it significantly reduces computational time across all instances compared to CPLEX. By comparison, the GA performs worse by finding feasible solutions with percentage gaps ranging from 174.75% to 341.90%. The PHA performs even worse, failing to find feasible solution for Ains_1 and delivering objective values with percentage gaps between 361.30% to 535.47%. The reason for the poor performance of the PHA may be that it solves quadratic-penalized problems by CPLEX, which is more time-consuming. In conclusion,

TABLE VI
COMPUTATIONAL COMPARISONS AMONG DDH, CPLEX, GA, AND PHA

Ins	CPLEX				GA			PHA			DDH		
	LB	Obj	Time	Gap(%)	Obj	Time	Gap(%)	Obj	Time	Gap(%)	Obj	Time	Gap(%)
Rins	17,066	20,974	3,508	22.90	75,414	3,369	341.90	82,816	185	385.27	**20,837**	435	22.10
Ains_1	18,278	**22,048**	3,568	20.63	47,711	3,288	161.03	-	-	-	22,620	127	23.76
Ains_2	17,308	21,314	3,537	23.15	61,884	3,396	257.55	90,906	310	425.23	**21,195**	153	22.46
Ains_3	27,094	**30,251**	3,595	11.65	64,483	3,548	138.00	172,175	152	535.47	30,488	133	12.53
Ains_4	18,662	22,075	3,600	18.29	51,273	1,194	174.75	86,088	119	361.30	**21,943**	210	17.58
Ains_5	20,921	22,624	3,592	8.14	70,986	3,543	239.31	105,133	109	402.52	**22,313**	110	6.65

these results demonstrate that our DDH algorithm surpasses CPLEX, GA, and PHA, offering a good trade-off between solution quality and computational efficiency.

2) Effectiveness of the Patient Dispatching Method: The combination of solving the relaxed **P2** model and the *Patient Dispatching Heuristic* in the DDH algorithm is the key component to balance the computational efficiency and solution quality of the DDH. Specifically, the relaxed **P2** model is used to quickly approximate the quality of each facility location solution $\boldsymbol{y}$ in the *Two-Level Facility Location Local Search* algorithm, while the *Patient Dispatching Heuristic* is used to exactly evaluate the quality of each local optimal solution $\boldsymbol{y}^*$. To verify the effectiveness of combining these two approaches, two varients of the DDH algorithm, named DDH-V1 and DDH-V2, are designed. In the DDH-V1, we use CPLEX to exactly evaluate the quality of each local optimal solution $\boldsymbol{y}^*$, while in the DDH-V2, we use the *Patient Dispatching Heuristic* algorithm rather than solving the relaxed **P2** model to approximate the quality of each facility location solution.

TABLE VII
COMPUTATIONAL COMPARISONS AMONG DDH, DDH-V1 AND DDH-V2

Ins	DDH			DDH-V1			DDH-V2		
	Obj	Time	Gap (%)	Obj	Time	Gap (%)	Obj	Time	Gap (%)
Rins	20,837	435	22.10	21,788	345	27.67	21,723	189	27.29
Ains_1	22,620	127	23.76	27,651	339	51.28	24,590	135	34.54
Ains_2	21,195	153	22.46	23,166	306	33.85	22,763	202	31.51
Ains_3	30,488	133	12.53	31,837	278	17.50	31,909	267	17.77
Ains_4	21,943	210	17.58	22,572	261	20.95	23,624	276	26.59
Ains_5	22,313	110	6.65	23,798	341	13.75	23,501	215	12.33
Average			17.51			27.50			25.00

Table VII shows the computational results of the DDH, DDH-V1 and DDH-V2. The results show that the DDH achieve better solutions with average percentage gaps of 17.51%, which is superior to DDH-V1 and DDH-V2 with average percentage gaps of 27.50% and 25.00%, respectively. Additionally, the DDH requires less computational time than DDH-V1 and DDH-V2, demonstrating its superior performance in terms of both solution quality and computational efficiency. This suggests that the combination of solving the relaxed **P2** model and the *Patient Dispatching Heuristic* approach used in DDH is more suitable for the IEMFLPD_U problem.

3) Analysis of Two-Level Emergency Medical Facility Location: To present and analyze the results of the two-level emergency medical facility location more directly, we utilized Python to invoke the Map from the pycharts package to draw the district map of Wuhan city. The color of each administrative area is determined by the number of all emergency medical facilities built in it. The visualizations are shown in Figure 6, where "Administrative Region (i, j)" represents the name of the administrative area, the number of superior emergency medical facilities i, and the number of primary emergency medical facilities j. Furthermore, we use Geo in the pycharts package to add specific location coordinates of the emergency medical facilities on the map of Wuhan city, as shown in Figure 7.

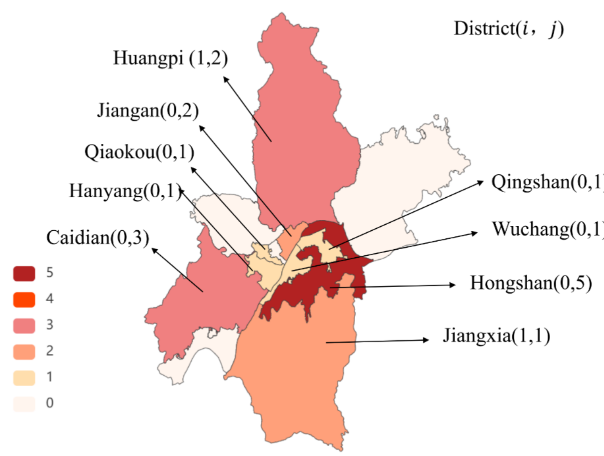

Fig. 6. Distribution of emergency medical facilities in each administrative area

According to the results, from the perspective of geographical locations of administrative areas where the facilities are built, primary emergence medical facilities are mainly constructed in the central administrative area, while superior emergence medical facilities are built in both the northern and southern administrative areas, specifically Huangpi and Jiangxia. As shown in Figure 5, the two intensive care hospitals are located in the eastern and western administrative areas (Caidian and Hongshan). Together with the newly built emergence medical facilities, the location enhances the convenience of transferring severe patients. From the perspective of population size and number of facilities, four administrative areas out of thirteen have more than two emergency medical facilities, accounting for approximately 58% of the total number of facilities and about 31% of the total population.

4) Effectiveness of the Stochastic Programming Approach: To measure the effect of our stochastic programming approach,

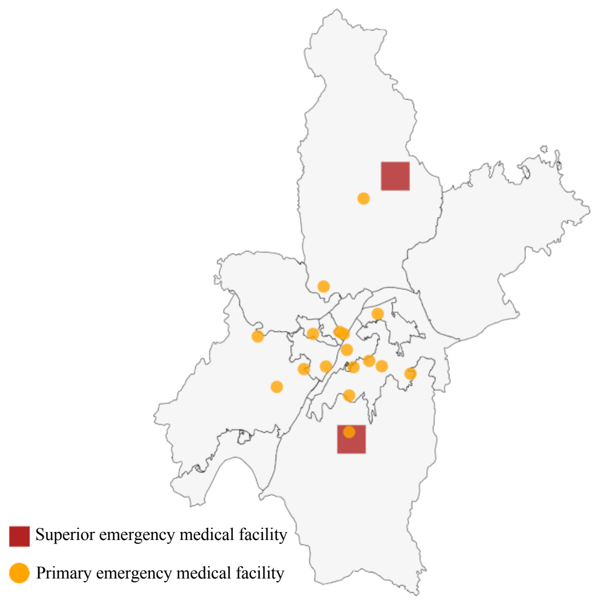

Fig. 7. Specific locations of emergency medical facilities

we make use of the two widely used indicators: the Expected Value of Perfect Information (EVPI) and the Value of the Stochastic Solution (VSS) [32]. For the IEMFLPD_U, an exact calculation of the EVPI and VSS is not possible. Therefore, we give a mechanism to estimate these two measures.

The EVPI measures the value loss due to the inability to accurately predict future scenarios, thus shedding light on losses caused by incomplete information. Assuming that the decision-makers have obtained all the information from all the scenarios, the best solution to the deterministic problem can be calculated as a basis for evaluating the EVPI value. The optimal solution to the deterministic model of the stochastic programming model solved by CPLEX is 20323.37, and the result for the BC experiment is 20854.65. Hence, EVPI = 20854.65 - 20323.37 = 531.28, EVPI(%) = $\frac{531.28}{20323.37} \times 100(\%)$ = 2.61%. The EVPI value is relatively small, indicating that the cost loss caused by incomplete information is 531.28, which is 2.61% of the expected total cost. The smaller EVPI value suggests that our proposed stochastic programming approach is quite effective for solving the IEMFLPD_U problem.

The VSS measures the value gained by considering uncertain information when solving the problem with known distributions of random variables. The calculation of the VSS is given in (23).

$$VSS = \frac{Z_{EEV} - Z_{BEEV}}{Z_{EEV}} \times 100\% \tag{23}$$

where both Z_{BEEV} and Z_{EEV} are actual total costs of the solutions obtained by using our DDH algorithm when applied to a given scenario. The difference is that the former solves the model **P2**, while the latter solves the Expected Value Problem (EVP). In detail, to create the scenario to be considered in the EVP, all parameters are set to their expected values.

The VSS assessment results for various scenarios are shown in Table VIII. The larger the VSS value, the better the solution obtained by solving the model **P2** is compared to the solution obtained by solving the EVP. According to the results, the values of VSS range from 0.65% to 22.02%. This indicates that the solution obtained by solving the model **P2** is better than the solution obtained by solving the EVP.

TABLE VIII
VSS INDICATOR ASSESSMENT RESULTS FOR VARIOUS SCENARIOS

Scenario	Z_{BEEV}	Z_{EEV}	$VSS(\%)$
S1	14,443.18	14,596.75	1.06
S2	14,705.47	14,845.89	0.95
S3	15,023.07	15,124.73	0.68
S4	16,759.32	16,960.86	1.20
S5	18,967.71	19,204.04	1.25
S6	19,303.67	19,548.76	1.27
S7	23,885.61	24,211.29	1.36
S8	24,774.04	25,127.99	1.43
S9	31,428.26	31,592.68	0.52
S10	32,954.84	33,152.95	0.60
S11	43,203.31	44,171.94	2.24
S12	140,622.00	171,585.70	22.02

C. Parameter Sensitivity Analysis

This section further analyses the effect of the parameters, including the treatment capacity of existing hospitals and the proportion of self-referred patients. By conducting sensitivity analysis, we aim to quantify how variations in these parameters influence the overall solution performance and total cost, thus providing valuable management insights on medical facility location and patient dispatching. All above experiments are based on the real-world instance of Wuhan city.

1) The Effect of the Treatment Capacity of Existing Designated and Intensive Care Hospitals: To analyze the effect of the treatment capacity of existing designated and intensive care hospitals for various types of confirmed patients, we consider four scenarios in addition to the experiment DDH, which are given below:

- Experiment EC1: Assuming that these hospitals are opened in batches and some of the medical resources of these hospitals have already been consumed. The remaining treatment capacity varies in different scenarios. Specifically, we set the remaining treatment capacities as 100%, 80%, 60%, and 40% of the original capacity, as shown in Table IX.
- Experiment EC2: In all scenarios, the treatment capacity of existing hospitals is set to 120% of the original capacity.
- Experiment EC3: In all scenarios, the treatment capacity of existing hospitals is set to 140% of the original capacity.

Table X presents the results of the above tree comparative experiments, including the total cost and each component cost. It is clear that the total cost decreases as the treatment capacity of existing hospitals increases. To show the change in costs under different treatment scenarios in a more intuitive way, we calculated the ratio of total cost difference (calculated by comparing the total costs of two experiments with similar treatment capacities), the proportion of construction and

TABLE IX
REMAINING TREATMENT CAPACITY OF EXISTING DESIGNATED AND INTENSIVE CARE HOSPITALS IN DIFFERENT SCENARIOS

Percentage of remaining treatment capacity	Scenario
100%	S1
80%	S2, S3, S4
60%	S5, S6, S7, S8
40%	S9, S10, S11, S12

transfer costs in each experiment, as shown in Table XI. The results indicate a marked decrease in total costs: DDH shows a 41.25% reduction when compared to EC1. Furthermore, the total cost in EC2 is 27.14% lower than that in DDH, and EC3 achieves an additional cost reduction of 36.50% compared to EC2. In addition, as the treatment capacity of existing hospitals increased, the proportion of construction costs in the total costs decreased, while the proportion of transfer costs increased, and the rate of increase in transfer costs gradually increased. This indicates that when the treatment capacity of existing hospitals for confirmed patients increases, the total cost of regional emergency medical facility location and patient dispatching can be significantly reduced.

2) The Effect of the Proportion of Self-Referred Patients: To examine the effect of the proportion of self-referred patients, we consider three scenarios with the same total number of patients, the same total number of confirmed patients, and the same total number of severe patients. The parameter settings for the two comparative experiments are as follows:

- Experiment PC1: Assuming that no patient self-refers to the hospital in all scenarios. All uncertain parameters related to these patients are set to 0 in all scenarios.
- Experiment PC2: Assuming that there are self-referred patients in all scenarios, with a proportion of 80% in scenarios S1, S2, and S3. The uncertain parameter settings in these three scenarios are the same as those in DDH. In other scenarios, the proportion is set to be 50%, while the other uncertain parameters are generated following the methods described in Section V-A1.

Table XII shows the results of the two comparative experiments PC1 and PC2. By comparing experiments DDH and PC1, under the same medical demands and supplies in all scenarios, the total cost of PC1 is slightly higher than that of DDH. Moreover, we can observe that the transfer cost of confirmed patients who self-referred to hospitals in experiment PC1 is 0. Although the construction costs are the same in experiments DDH and PC1, the other two types of transfer costs are higher than the corresponding costs in experiment DDH. Moreover, it can be found that the total cost of PC2 is significantly lower than that of DDH and PC1, while the transfer cost of confirmed patients who self-referred to hospitals in experiment PC2 is significantly higher than that in experiment DDH and PC1.

From the above results, it can be seen that as more patients self-refer to hospitals, the total cost paid by governments and medical institutions in the given region is significantly reduced, and the transfer cost of self-referred patients is transferred to the individual. However, this may lead to higher infection rates due to the wide range of activities of the confirmed patients.

D. Management Insights

Based on the experimental results and analysis, some management insights can be obtained as follows.

- Considering various epidemic scenarios, pre-planning the maximum capacity of existing designated and intensive care hospitals for treating infected patients can shorten the emergency response time at various stages of epidemic development. This helps in balancing the treatment work for all types of patients. However, if the available resources of these existing hospitals for treating infected patients are not well organized in advance, it may lead to organizational chaos within the hospital.
- The construction of more smaller emergency medical facilities is beneficial in reducing the overall costs of emergency medical facility location and patient dispatching, if the construction cost does not decrease significantly with the treatment capacity of the facility. It will also help to reduce the cost of transferring confirmed patients and improve the efficiency of patient treatment.
- With the help of information technology, the given region can be divided into different risk levels according to the epidemic situation. Thus, the medical operating costs can be reduced by allowing patients to self-refer to hospitals in regions with a low risk of epidemic transmission, rather than blocking the entire region.

VI. CONCLUSION

In this paper, we investigated the problem of integrated emergency medical facility location and patient dispatching under uncertain environments. We aimed to minimize the expected construction and transportation costs of two types of emergency medical facilities by building a multi-stage stochastic programming model, including dual-level emergency medical facility location of Stage 1, mild patient allocation of Stage 2, and severe patient referral of Stage 3. We obtained an approximate solution for the original problem by solving its deterministic model for a set of representative scenarios. To achieve this goal, we proposed a Decomposition-based Dual-level Heuristic algorithm. Based on iterative optimization, DDH first generates the initial dual-level facility location solution based on the ratio of facility construction costs to capacity. It then optimizes the facility construction plans by employing a tabu search for dual-level facility location. Finally, it optimizes the referral plans for different types of patients under the given facility location by using a *Patient Dispatching Heuristic* algorithm.

We conducted a case study in COVID-19 epidemic in Wuhan, generating scenario data related to medical demands and case data related to various types of nodes in a tiered medical service network. We performed extensive experiments and analysis to verify the effectiveness of the proposed formulation and algorithm. The results showed that: 1) our DDH algorithm surpasses CPLEX, GA and PHA, offering a good

TABLE X
EXPERIMENTAL RESULTS CONSIDERING DIFFERENCES IN TREATMENT CAPACITY OF EXISTING HOSPITALS

Experiment	Total cost	Construction cost	Non-self-referred confirmed patient transfer cost	Self-referred confirmed patient transfer cost	Severe patient transfer cost
EC1	35,495.26	28,650.00	5,329.54	33.10	1,482.62
EC2	15,195.51	8,400.00	5,324.23	34.11	1,437.17
EC3	9,648.63	2,400.00	5,609.49	45.00	1,594.14

TABLE XI
SUMMARY RESULTS FOR EXPERIMENTS DDH, EC1, EC2, AND EC3

Experiment	Total cost difference ratio (%)	Construction cost proportion (%)	Total transfer cost proportion (%)
EC1	-	80.72	19.28
DDH	41.25	69.77	30.23
EC2	27.14	55.28	44.72
EC3	36.50	24.87	75.13

rade-off between solution quality and computational efciency; 2) expanding the treatment capacity of existing hospitals could reduce the total emergency medical costs, but the patient transportation costs increased to some extent; 3) when the overall proportion of self-referred patients increased, the total emergency medical costs borne by local governments and medical institutions significantly decreased, but this might imply a higher transmission rate. Note that the proposed approach in this work can be applied to the large scale infectious pandemic characterized by varying degrees of severity. These include phases like incubation period (symptoms of the disease are not yet apparent), mild symptoms and severe symptoms. Although we only verified on the COVID-19 pandemic, they can be applied to other large scale infectious pandemic, such as Tuberculosis, SARS, MERS, etc.

Our model has some limitations and several directions for future research can be explored. First, we assumed that only mild cases were present at the demand point, with no severe cases. However, this assumption may not meet the actual conditions in some cases. Thus, future work could explore hybrid scenarios with mild and severe cases at the demand point. This extension requires future validation due to its combinatorial complexity under stochastic scenarios. Second, the static treatment capacity assumption may limit practical applicability. In reality, treatment capacities can change over time due to various factors such as staff shifts, equipment maintenance, or sudden changes in patient inflow. To enhance the applicability and accuracy of our model, future work could incorporate mechanisms for dynamic capacity adjustments. This might involve developing stochastic programming formulations that allow for capacity changes at different time intervals. Third, integrating the typical compartmental models (e.g., SEIR) could capture the changes in patient conditions over time, enabling time-dependent resource allocation policies. This would enhance coordination with public health surveillance systems.

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TABLE XII
EXPERIMENTAL RESULTS CONSIDERING THE DIFFERENCE IN THE PROPORTION OF AUTONOMOUS CONSULTATION PATIENTS

Experiment	Total cost	Construction cost	Non-self-referred confirmed patient transfer cost	Self-referred confirmed patient transfer cost	Severe patient transfer cost
DDH	20,854.65	14,550.00	4,938.03	35.02	1,331.60
PC1	20,971.70	14,550.00	5,078.22	0.00	1,343.48
PC2	14,327.10	9,900.00	2,692.17	682.00	1,053.04

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