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Optimal logistics scheduling with dynamic information in emergency response: Case studies for humanitarian objectives

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A B S T R A C T

The mathematical model of infectious disease is a typical problem in mathematical modeling, and the common infectious disease models include the susceptible-infected (SI) model, the susceptible-infected-recovered model (SIR), the susceptible-infected-recovered-susceptible model (SIRS) and the susceptible-exposed-infected-recovered (SEIR) model. These models can be used to predict the impact of regional return to work after the epidemic. In this paper, we use the SEIR model to solve the dynamic medicine demand information in humanitarian relief phase. A multistage mixed integer programming model for the humanitarian logistics and transport resource is proposed. The objective functions of the model include delay cost and minimum running time in the time-space network. The model describes that how to distribute and deliver medicine resources from supply locations to demand locations with an efficient and lower-cost way through a transportation network. The linear programming problem is solved by the proposed Benders decomposition algorithm. Finally, we use two cases to calculate model and algorithm. The results of the case prove the validity of the model and algorithm.

A R T I C L E I N F O

Keywords:
Logistic;
Humanitarian logistics;
Optimization;
Multi-objective;
Dynamic information;
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Benders decomposition algorithm;
Mixed integer programming;
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1. Introduction

In recent years, a variety of natural disasters occur frequently in the world, e.g., a 7.1 earthquake injured 12 thousand people in Qinghai province in 2010, a 7.0 earthquake occurred in Ya'an city in April 2013, etc. They have catastrophic effects on the society and everyone's daily life in many aspects such as injuries, property damage and even loss of life [1]. How to effectively respond to unpredictable and irregular emergency events such as dynamic resource allocation has become of primal importance worldwide [2].

Epidemic events usually follow major natural disasters and cause secondary damage to the people in the disaster areas. For example, dysentery, measles, pinkeye and epidemic encephalitis B may break out after an earthquake. Once an epidemic breaks out, it will cause incalculable losses. Therefore, it remains imperative for every country to be prepared for emergency rescue if an infectious disease breaks out. Ensuring the supply of medical resources would always be the most important factor in the prevention and treatment of the epidemic diffusion.

Emergency medicine resource allocation is aimed to aid people and allocate relief distribution with dynamic information in surviving during and after an infectious disease occurs. The public officials need to face and solve many critical issues, the most important of which is how to timely and reasonably distribute the emergency medicine resources to the epidemic area so that the delay cost [3] of rescue medicine resources can be minimised and the rescue vehicle running time can be minimised. The delay cost of rescue medicine resources can be regarded as the standard to capture the social costs of shortage of rescue resources, which is called deprivation costs, has been roundly proposed and classified in Holguin-Veras *et al.* [4]. Due to the complexity and uncertainty of the emergency logistics, material supply and distribution is more difficult. First of all, it is difficult to obtain the demand information of emergency material resources, especially for the epidemics with uncertain infectivity. Second, rescue time is a critical factor after medical emergency events occur, the delay of material supply can cause inestimable loss. Finally, managers and decision makers need to distribute the emergency materials to affected areas as quickly and effectively as possible.

In this paper, a time-space network model for the humanitarian logistics problem with logistics in controlling epidemic diffusion is proposed. It couples a forecasting mechanism for the number of people who need to treat based on the SEIR model [5] and a multistage programming model for the humanitarian logistics and transport resource. Our contribution includes that the dynamic demand of the medical resource based on the epidemic diffusion pattern of SEIR model is used in a multistage programming model for optimal allocation and transport of such resource and the linear programming problem is solved by the Benders decomposition algorithm which is better than ant colony algorithm and genetic algorithm in computational accuracy.

Our paper is organized as follows. In Section 2, we review the literature relevant to our study. In Section 3, we build the time-space network model, which combines a demand forecast model based on the epidemic diffusion rule. The solution procedure for the optimization model is proposed in Section 4. In Section 5, we report the results of computational studies and sensitive analysis. Finally, we discuss the conclusions and suggest future research directions in Section 6.

2. Literature review

Our contribution is connected with four research branches: 1) the mathematical formulations of the epidemic diffusion mechanism; 2) the multistage programming model on the humanitarian logistics and transport resource; 3) the combination of medical model and humanitarian logistics model: 4) the solution methodology, such as Benders decomposition algorithm, genetic algorithm and ant colony algorithm.

There are many analytical works on epidemic diffusion including SIR epidemic models, Susceptible-Infected-Susceptible (SIS) epidemic model, SIRS epidemic model, SEIR epidemic model, susceptible-exposed-infected-recovered-susceptible (SEIRS) epidemic model and so on. In these models, most of them are developed by ordinary differential equations. To develop the epidemic diffusion mechanism, Li *et al.* [6] study the spread dynamics of a stochastic SIRS epidemic model with nonlinear incidence and varying population size, which is formulated as a piece wise deterministic Markov process. Fan *et al.* [7] present a SIR epidemic model with generalized nonlinear incidence rate. Song *et al.* [8] propose a SEIR reaction-diffusion model, where the disease transmission and recovery rates can be spatially heterogeneous. Yang and Wang [9] introduce a new SEIRS epidemic model with time delay on a scale-free network.

Some of these models are used in the complex and actual problems. Bolzoni *et al.* [10] investigate the time-optimal control problem in SIR epidemic models, focusing on different control policies: vaccination, isolation, culling, and reduction of transmission. Guo *et al.* [11] explore the global behaviour of a stochastic SIRS epidemic model with media coverage. Britton and Ouédraogo [12] introduce an SEIRS epidemic with disease fatalities in a growing population. Anparasan and Lejeune [13] propose an epidemic response model in resource-limited countries that determines the number, size, and location of treatment facilities, deploys critical medical staff, locates ambulances to triage points, and organizes the transportation of severely ill patients to treatment facilities. The SEIR model is used to solve the dynamic medicine demand information in humanitarian relief phase. These models can be used to predict the impact of regional return to work after the epidemic. There are other forecasting methods, which are widely used in other fields, such as the artificial neural network [14], the artificial intelligence [15], and so on.

To deal with the complexity and difficulty in solving the humanitarian logistics and transport resource scheduling problem, we summarize the research for the humanitarian logistics and transport resource scheduling problem in recent years. The literature review of humanitarian logistics summarizes the research status in this field. Farahani *et al.* [16] summarize the mass casualty management including five steps: (i) Resource dispatching/search and rescue, (ii) on-site triage, (iii) on-site medical assistance, (iv) transportation to hospitals and (v) triage and comprehensive treatment. Baffoe and Luo [17] use a systematic literature review coupled with an axiological philosophical lens approach to developing a Humanitarian Logistics Digital Business Ecosystem (HLDBE) framework as an alternative way to sustain the humanitarian logistics operations and reliefs through hybrid humanitarian- business logistics sector. Wang *et al.* [18] study the routing problem of unmanned vehicles considering path flexibility. Anbal *et al.* [19] use a new technology to solve the intelligent traffic management. Wang *et al.* [20] discusses the model of joint distribution of fast-moving consumer goods.

To optimize the process of humanitarian logistic problem, Zhou *et al.* [21] design a multi-objective optimization model for multi-period dynamic emergency resource scheduling (ERS) problems. Othman *et al.* [22] propose a multi-agent-based architecture for the management of Emergency Supply Chains (ESCs), in which each zone is controlled by an agent. A Decision Support System (DSS) states and solves, in a distributed way, the scheduling problem for the delivery of resources from the ESC supplying zones to the ESC crisis-affected areas. Ferrer *et al.* [23] build a compromise programming model for multi-criteria optimization in humanitarian last mile distribution and illustrate the multi-criteria optimization using a realistic test case based on the Pakistan floods, 2010.

To deal with the efficiency and timeliness in solving the humanitarian objectives, Huang *et al.* [2] characterize the humanitarian objectives of emergency resource allocation and distribution in disaster response operations. And they formulated the humanitarian principles as three objective functions, i.e., lifesaving utility, delay cost and fairness. Garrido and Aguirre [24] present a modelling framework to assist decision makers in strategic and tactical planning for effective relief operations after an earthquake's occurrence. The objective is to perform these operations quickly while keeping its total expenses under a budget. Edward *et al.* [25] consider a joint vehicle and crew routing and scheduling problem in which crews are able to interchange vehicles, resulting in space and time interdependencies between vehicle routes and crew routes. Rajak *et al.* [26] present a hybrid metaheuristic which combines simulated annealing, ant colony optimization and along with long-arc-broken removal heuristic approach for solving the multi-depot vehicle routing problem with simultaneous deliveries and pickups. Sedehzadeh and Deifbarghy [27] present a closed loop food supply chain network. The objectives of the model are to minimize costs, transportation emissions, and unsatisfied foodbanks' demand. Foodbank as the main pillar of social responsibility has been introduced in food chain.

In order to solve the dynamic demand information of emergency material resources in rescue process. Gutjahr and Nolz [28] review recent literature on the application of multicriteria optimization to the management of natural disasters, epidemics or other forms of humanitarian crises. Liu and Xiao [29] model for a dynamic resource allocation problem following an epidemic outbreak in a region. Liu [30] develop a unique time-varying forecasting model for dynamic demand of medical resources based on a SEIR influenza diffusion model. Wang *et al.* [1] construct a multi-objective stochastic programming model with time-varying demand for the emergency logistics network based on the epidemic diffusion rule. Buschiazzo *et al.* [31] consider stockouts costs and inventory maintenance costs in their model for healthcare supplies problem.

To deal with the mixed integer programming problem, Fischetti *et al.* [32] prove that Benders decomposition allows for a significant boost in the performance of a mixed-integer programming solver. And in order to improve computation efficiency, authors investigate the use of proximity search as a tactical tool to drive Benders decomposition. Alkaabneh *et al.* [33] consider the problem of inventory routing in the context of perishable products and find near-optimal replenishment scheduling and vehicle routes, and develop an exact method based on Benders decomposition to find high-quality solutions in reasonable time. Fachini and Armentano [34] present exact algorithms based on logic-based Benders decomposition and a variant, called branch- and- check, for the heterogeneous fixed fleet vehicle routing problem with time windows. Cordeau *et al.* [35] study an effective decomposition approach to the two problems based on the branch-and-Benders-cut reformulation. The proposed approach is designed for the realistic case in which the number of customers is much larger than the number of potential facility locations. Behmanesh and Rahimi [36] use the ant colony optimization to solve the multi-resource job shop scheduling problem. Fei [37] proposes intelligent bionic optimization algorithm based on the growth characteristics of tree branches. The mixed integer programming problem can be solved by other heuristic algorithms, such as genetic algorithms. Although genetic algorithm can improve the computational efficiency, it is often unable to obtain accurate results and is easy to fall into local optimal solutions. When the scale of the problem is large, genetic algorithm is a good choice.

Furthermore, we note that most of the previous epidemic models were innovated by developing differential equation and most of the resource allocation in the humanitarian logistics rarely take into the dynamic demand information. In addition, only a few literatures combine epidemic models with humanitarian logistics. While in reality, the demand for medical resource is dynamic, and the medical resource allocated in early cycles will affect the demand in later periods [29]. In this paper, a novel SEIR epidemic model is used to forecast the time-varying demand in humanitarian logistics. We use a time-space network to describe the humanitarian logistics when an epidemic occurs. In each decision cycle, the problem is constructed as a linear programming model to solve for the delay cost minimizing and vehicle running time minimizing. A Benders decomposition algorithm is compared with other heuristic algorithms in solving humanitarian logistics with dynamic demand information.

3. The mathematical model

3.1 Problem description

A disaster often causes epidemics, i.e., cholera, typhoid fever, dysentery often ravage disaster area after the floods. Therefore, it is important that government and social organization send medicine and vaccine to the disaster area in time. A large amount of distribution costs can be generated when the drug is delivered. Decision makers need follow the low-budget principle in the delivery process. Our research problem is how to distribute and deliver medicine resources from supply locations to demand locations with an efficient and lower-cost way through a transportation network.

Due to the complexity and unpredictability of disasters and the property of the epidemics, as time goes on, demand of infectious disease patients is changed. In our paper, dynamic demand is defined as the number of people requiring treatment. Firstly, we use SEIR model to calculate the number of infected people. Then the demand of infected people in disaster area can be simulated in the forecasting model for the time-varying demand. Finally, we construct time-space network of the humanitarian logistics model to optimize delay cost and transportation cost functions.

In our model formulation, we use a time-space network to describe entire delivery process. The time-space network of the humanitarian logistics is shown in Fig. 1. In the time-space network, decision cycle is divided into several discrete time units $t = 0, 1, 2, \ldots, \mathrm{T}$. t represents the decision point for the decision cycle. There are three arcs in the time-space network: (1) holding arc, i.e., arc (a); (2) allocation arcs, i.e., arc (b), which represents that vehicle originates at a distribution center at time t and arrives at a demand point at time t', $0 \leq t < t' \leq$ T, t'- t is the vehicle running time on the arc; arc (c), which represents that vehicle originates at a demand point at time t and arrives at a demand point at time t', $0 \leq t < t' \leq$ T; (3) return arc, i.e., arc (d), which represents that vehicle originates at a demand point at time t and arrives at a distribution center at time t', $0 \leq t < t' \leq$ T.

Let D denote the collection of all distribution centers and N denotes the collection of all nodes. If node $i, j \in D$, node i and j represent distribution center, otherwise, node i and j represent demand point. We use ij to denote the arc in geography network. Let A denote the collection of arcs in geography network. Let k represent the vehicle number respectively. Let K denote the collection of vehicles. We use Q_k to represent the maximum loading capacity of the vehicle k. α denotes the cost conversion coefficient.

There are two types of decision variables in the whole rescue vehicle dispatch period. Let $y^k_{it,jt'}$ represent the flow originating at node i at time t and arriving at node j at time t'. $y^k_{it,jt'}$ is a binary decision variable. We view $y^k_{it,jt'}$ as the vehicle selection decision variables. There is an arc (it, it'), which allows the vehicle resource to stay at the same node from time t to time t'. We use N^T and A^T to denote the collections of nodes and arcs in the time space network. Let x^k_{jt} represent the resource allocated to node j and received at time t by vehicle k, and x^k_{jt} is the distribution decision variable.

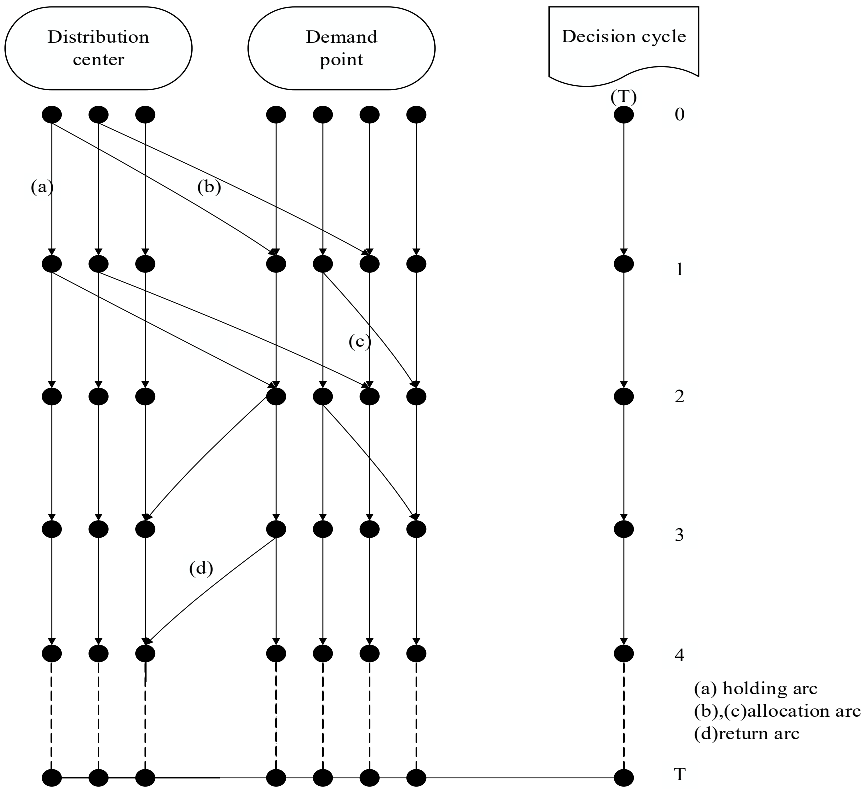

Fig. 1 Time-space network of the humanitarian logistics

3.2 The forecasting model for the time-varying demand

To represent the demand, supply and demand locations, we use the term 'node' uniformly, and use i and j as index. We use $P^t_j \geq 0$ to represent the quantity of unsatisfied demand of the epidemic patients at node j updated at decision point t. In order to calculate the demand of the epidemic patients, we use SEIR model that can simulate susceptible people (S), exposed people (E), infected people (I) and recovered people (R) in disaster area to obtain the number of infected people at node j at time t. We use S_j (t), E_j (t), I_j (t), and R_j (t) to represent, respectively, the number of susceptible people at node j at time t, the number of exposed people at node j at time t, the number of infected people at node j at time t, and the number of recovered people at node j at time t. Fig. 2 shows, without consideration of migration, the natural birth rate and death rate of the population, the epidemic process can be described by a SEIR model based on a small-world network.

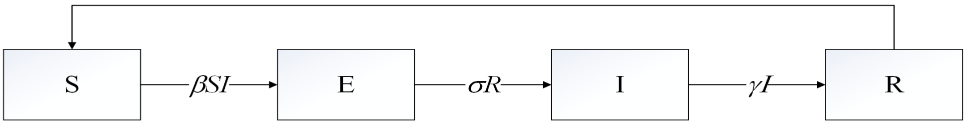

Fig. 2 SEIR model based on a small-world network.

The dynamic system for the SEIR diffusion model is modified based on the literature [38]. It can be rewritten by the following differential equations:

$$\begin{aligned} \frac{dS_j}{d_t} &= -\beta S_j(t) I_j(t), \\ \frac{dE_j}{d_t} &= S_j(t) I_j(t) - \sigma R_j(t), \\ \frac{dI_j}{d_t} &= \sigma R_j(t) - \gamma I_j(t), \\ \frac{dR_j}{d_t} &= \gamma I_j(t), \end{aligned} \tag{1}$$

where β is contact rate (Susceptible to Exposed). σ is incubation rate (Exposed to Infected). γ is recovery rate (Infected to Recovered).

In this study, $I_j(t)$ denote the number of people who need to treat. Therefore, P_j^t with time-varying can be rewritten by:

$$P_j^t = \lambda I_j(t) \tag{2}$$

where λ denotes the proportionality coefficient. λ in this linear forecasting function is adopted by the public-healthcare administrative personnel in controlling the spread of epidemic [2]. Herein, we don't think about the lag effect of earlier medicine allocation.

3.3 Time-space network of the humanitarian logistics

We consider two objectives related to humanitarian logistics: time cost and delay cost. $\sum_{it,jt' \in A^T} \sum_{k \in K} (t' - t) y_{it,jt'}^{\mathrm{k}}$ denotes the total time cost. The accumulated number of medical sources have been delivered by vehicles at node j at time t can be rewritten by $\sum_{k \in K} \sum_{t=0}^{t} x_{jt}^k$. Let $P_j^t - \sum_{k \in K} \sum_{t=0}^{t} x_{jt}^k$ denote the unsatisfied demands at node j at time t. The total delay cost can be rewritten by $\sum_{j \in N} \sum_{t \in T} (P_j^t - \sum_{k \in K} \sum_{t=0}^{t} x_{jt}^k)$. The time-space network of the humanitarian logistics can be rewritten by:

$$Minimize \sum_{j \in N} \sum_{t \in T} (P_j^t - \sum_{k \in K} \sum_{t=0}^{t} x_{jt}^k) + \alpha \sum_{it,jt' \in A^T} \sum_{k \in K} (t' - t) y_{it,jt'}^{\mathrm{k}} \tag{3}$$

$$s.t. \sum_{it \in N^T} y_{it,jt'}^k = 1, \forall jt' \in N^T, k \in K, \tag{4}$$

$$\sum_{jt' \in N^T} y_{it,jt'}^k = 1, \forall it \in N^T, k \in K, \tag{5}$$

$$\sum_{ij \in A} y_{it,jt'}^k = 1, \forall t, t' \in T, k \in K, \tag{6}$$

$$\sum_{it \in N^T} \sum_{k \in K} y_{it,jt'}^k = \sum_{it \in N^T} \sum_{k \in K} y_{jt',it}^k, \forall jt' \in N^T, \tag{7}$$

$$\sum_{\forall jt' \in N^T} x_{jt'}^k \leq Q_k \times \sum_{it,jt' \in A^T} y_{it,jt'}^k, \forall k \in K, \tag{8}$$

$$\sum_{k \in K} x_{jt}^k \leq P_j^t, \forall t \in T, j \in N, \tag{9}$$

$$y_{it,jt'}^k \in \{0,1\}, \forall it, jt' \in N^T, k \in K, \tag{10}$$

$$x_{jt}^k \geq 0, integer, \forall jt \in N^T, k \in K. \tag{11}$$

In this optimization model, the objective function (Eq. 3) is to minimize the total cost of humanitarian logistics. Constraints Eqs. 4-7 are the flow conservation equations. Particularly, constraint (Eq. 4) constraint (Eq. 5) and Constraint (Eq. 6) ensure that each node must be visited in the time-space network. Constraint (Eq. 7) states that each vehicle must get away of the node after it arrives one node in the time-space network. Constraint (Eq. 8) ensures that each vehicle load number of people is smaller and equal to its maximum load at node j. Constraint (Eq. 9) states that the number of delivered medicine resource is smaller and equal to the demand number at node j at time t. Finally, Constraint (Eq. 10) ensures that $y_{it,jt'}^k$ is binary variable. Constraint (Eq. 11) are the nonnegativity of the flows. Such model is a dynamic and multistage programming model.

4. Solution methodology

To solve the above optimization model, Eq. 1 and Eq. 2 are adopted to calculate the time-varying demand P_j^t firstly. After that, we use Benders decomposition algorithm to solve the mixed integer programming model. Benders decomposition algorithm provides a basic framework to solve MILP through decomposing the original complex problem into two problems, i.e., a master problem and a subproblem [39]. Benders [40] showed that the master problem and the subproblem can be solved successively with information being communicated between them.

We put the vehicle selection decision variables into the master problem and put the distribution decision variables into the subproblem. We set an initial solution $\overline{y_{it,jt'}^k}$. The subproblem can be written as follows:

$$\begin{aligned} & Minimize \ \sum_{j \in N} \sum_{t \in T} (P_j^t - \sum_{k \in K} \sum_{t=0}^{t} x_{jt}^k) + \alpha \sum_{it,jt' \in A^T} \sum_{k \in K} (t' - t) \overline{y_{it,jt'}^k} \\ & s.t. \quad - \sum_{\forall jt' \in N^T} x_{jt'}^k \geq -Q_k \times \sum_{it,jt' \in A^T} y_{it,jt'}^k, \forall k \in K, \\ & \qquad - \sum_{k \in K} x_{jt}^k \geq -P_j^t, \forall t \in T, j \in N, \\ & \qquad x_{jt}^k \geq 0, integer, \forall jt \in N^T, k \in K. \end{aligned} \tag{12}$$

Therefore, the dual problem of Eq. 12, can be obtained below,

$$\begin{aligned} & Maximize \ \pi^T (-Q_k \sum_{it,jt' \in A^T} \overline{y_{it,jt'}^k} - P_j^t) \\ & s.t. \ \pi^T G \leq f, \\ & \pi \geq 0. \end{aligned} \tag{13}$$

G denotes the transposed matrix of the constraint coefficient matrix in model (Eq. 12). f denotes the transposed matrix of objective function coefficient matrix in model (Eq. 12). π^T denotes the dual variables in model (Eq. 13).

There are three possible solution with respect to model (Eq. 13): (1) infeasible, then exit; (2) unbounded, in which case choose any unbounded extreme ray (denoted as $\overline{\pi^T}$)

and add a feasibility cut $\overline{\pi^T}(-Q_k \cdot \sum_{it,jt' \in A^T} \overline{y^k_{it,jt'}} - P^t_j) \leq 0$ into the master problem; (3) bounded, in which case take an optimal solution (denoted as $\overline{\overline{\pi^T}}$) and add an optimality cut $\overline{\overline{\pi^T}}(-Q_k \cdot \sum_{it,jt' \in A^T} \overline{y^k_{it,jt'}} - P^t_j) \leq \theta$ into the master problem.

Therefore, the master problem of the time-space network of the humanitarian logistics can be written as Eq. 14,

$$
\begin{aligned}
& Minimize\ \ \theta + \alpha \sum_{it,jt' \in A^T} \sum_{k \in K} (t'-t) y^{k}_{it,jt'} \\
& s.t. \sum_{it \in N^T} y^k_{it,jt'} = 1, \forall jt' \in N^T, k \in K, \\
& \sum_{jt' \in N^T} y^k_{it,jt'} = 1, \forall it \in N^T, k \in K, \\
& \sum_{ij \in A} y^k_{it,jt'} = 1, \forall t, t' \in T, k \in K, \\
& \sum_{it \in N^T} \sum_{k \in K} y^k_{it,jt'} = \sum_{it \in N^T} \sum_{k \in K} y^k_{jt',it}, \forall jt' \in N^T, \\
& \overline{\pi^T}(-Q_k \cdot \sum_{it,jt' \in A^T} y^k_{it,jt'} - P^t_j) \leq 0, \\
& \overline{\overline{\pi^T}}\left(-Q_k \cdot \sum_{it,jt' \in A^T} y^k_{it,jt'} - P^t_j\right) \leq \theta, \\
& y^k_{it,jt'} \in \{0,1\}, \forall it, jt' \in N^T, k \in K, \\
& \pi \in R.
\end{aligned}
\tag{14}
$$

Through the iteration to solve the master problem and the subproblem, we can obtain the optimal solution of the master problem ($\theta^*, {y^k_{it,jt'}}^*$). We can use ${y^k_{it,jt'}}^*$ to solve the time-space network of the humanitarian logistics, we can obtain the optimal solution (${x^k_{jt}}^*, {y^k_{it,jt'}}^*$).

5. Numerical tests

This section describes the computational results for the proposed mathematical model and solution algorithm. In Subsection 5.1, we describe a numerical example. In Subsection 5.2, we exhibit the computational results with a case design. In Subsection 5.3, we conduct the sensitivity analysis. All the tests in this section were tested on a Lenovo Y400 with Intel Core i5-3230M CPU, 2.60 GHz frequency and 4 GB memory.

5.1 A case study

We cite a case that can reflect the proposed model. We suppose that there are 8 nodes, 30 days, 4 vehicles. The maximum loading capacity of each vehicle is shown in Table 1. The marginal utility from node i to node j is shown in Table 2. S_j (0), E_j (0), I_j (0), and R_j (0) are shown in Table 3. Where $\beta = 0.0001$, $\sigma = 0.2$, $\gamma = 0.5$, $\lambda = 1$. To make the results of the total time cost and the total delay cost in the same magnitude, we set $\alpha = 20$.

Table 1 The maximum loading capacity of the vehicle k(kg)

Vehicle number	1	2	3	4
Vehicle capacity	458	468	574	542

Table 2 The travel time from node i to node j(day)

Node number	1	2	3	4	5	6	7	8
1	0	3	2	3	5	1	8	6
2	3	0	4	3	2	5	7	1
3	2	4	0	6	3	4	2	5
4	3	3	6	0	7	2	1	5
5	5	2	3	7	0	6	3	2
6	1	5	4	2	6	0	4	7
7	8	7	2	1	3	4	0	3
8	6	1	5	5	2	7	3	0

Table 3 The initial value of $S_j(0)$, $E_j(0)$, $I_j(0)$, and $R_j(0)$

	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	$j = 6$	$j = 7$	$j = 8$
$S_j(0)$	10746	11288	14204	11271	14071	11218	14646	11750
$E_j(0)$	0	0	0	0	0	0	0	0
$I_j(0)$	639	650	723	695	670	766	717	710
$R_j(0)$	0	0	0	0	0	0	0	0

5.2 Computational results

Fig. 3 shows that the variation trend of $S_j(t)$, $E_j(t)$, $I_j(t)$, and $R_j(t)$ in the whole rescue process. As we can see, $I_j(t)$ reduces first then increases, $I_j(t)$ is equal 0 at last. This result consistent with the mechanism of infectious diseases.

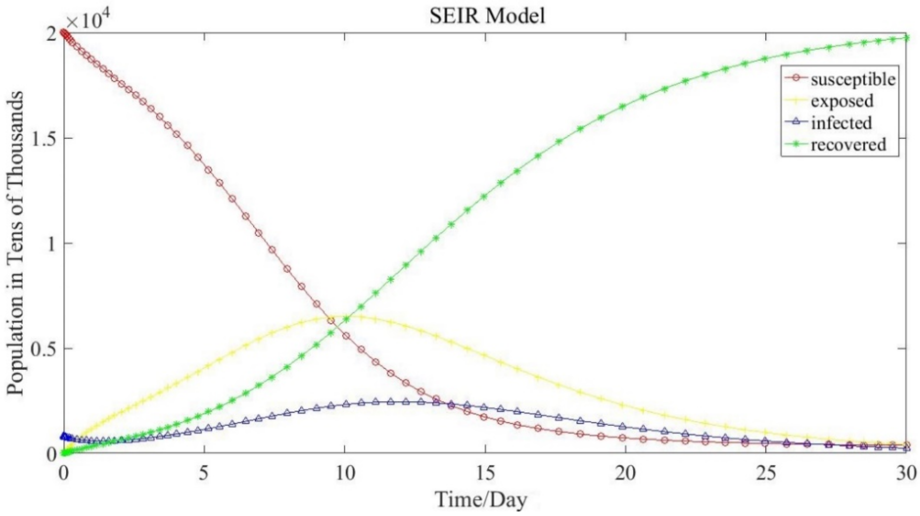

Fig. 3 The results of $S_j(t)$, $E_j(t)$, $I_j(t)$, and $R_j(t)$

Node 1 is distribution center. The driving route of each vehicle is node 1-6-4-7-3-5-2-8-1. Vehicles arrive time at node are 1, 3, 4, 6, 9, 11, 12, 18 days respectively. The delivery medicine resources number of all vehicles on each node are shown in Table 4. As shown in Table 4, the number of delivery medicine resource by all vehicles on node 6 is 143, 96, 172, and 208, respectively, and is bigger than other nodes. The medicine resources of other nodes are optimized according to the number and geographical location of infectious diseases. Therefore, this result conforms to reality according to the result of $S_j(t)$, $E_j(t)$, $I_j(t)$, and $R_j(t)$ in Fig. 3.

Fig. 4 shows the upper and lower bounds obtained by Benders decomposition algorithm are equal at the 12th iteration and will not change any more. Before that, the upper and lower bounds converge continuously. Experimental results show the effectiveness of the proposed model and algorithm.

Table 4 The delivery medicine resources number of all vehicles on each node

	node 1	node 2	node 3	node 4	node 5	node 6	node 7	node 8
Vehicle 1	0	98	33	65	76	143	20	23
Vehicle 2	0	20	107	47	54	96	83	61
Vehicle 3	0	45	131	23	74	172	48	81
Vehicle 4	0	71	60	40	8	208	75	90

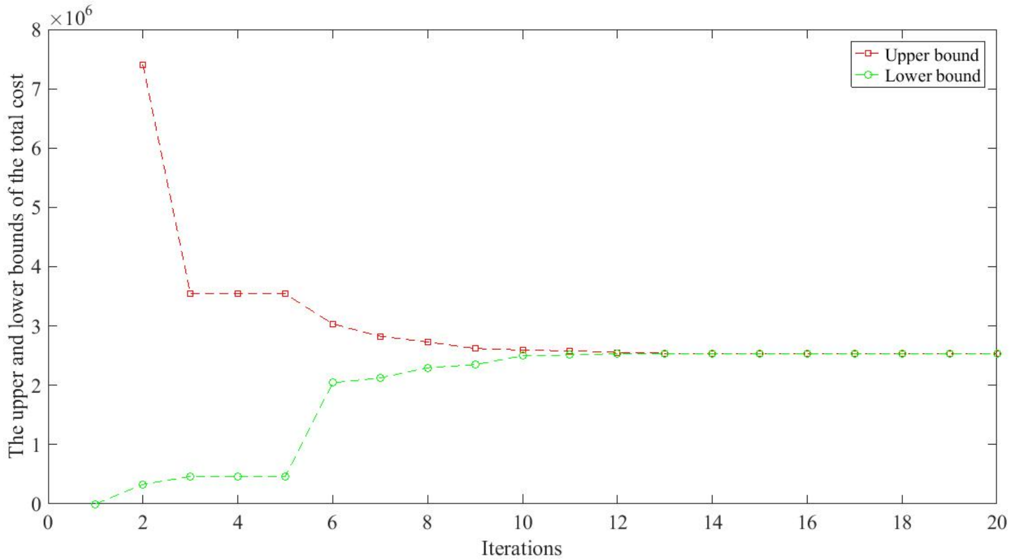

Fig. 4 Convergence of upper and lower bounds

5.3 Sensitivity analysis

In this section, a sensitivity analysis of the three key parameters (β, σ, γ) in the demand forecasting model is conducted. Fig. 5 shows the relationship between the different β and the number of infected people. Obviously, the greater β is, the more the number of infected people is, and the greater the gradient of demand is. Therefore, β should be selected appropriately in a practical problem.

As Fig. 6 shows, σ takes on five values ranging from 0.1 to 0.5. The larger σ is, the larger the demand is, and the greater the gradient of demand is. As Fig. 7 shows, γ also takes on five values ranging from 0.1 to 0.5. The lower σ is, the larger the demand is.

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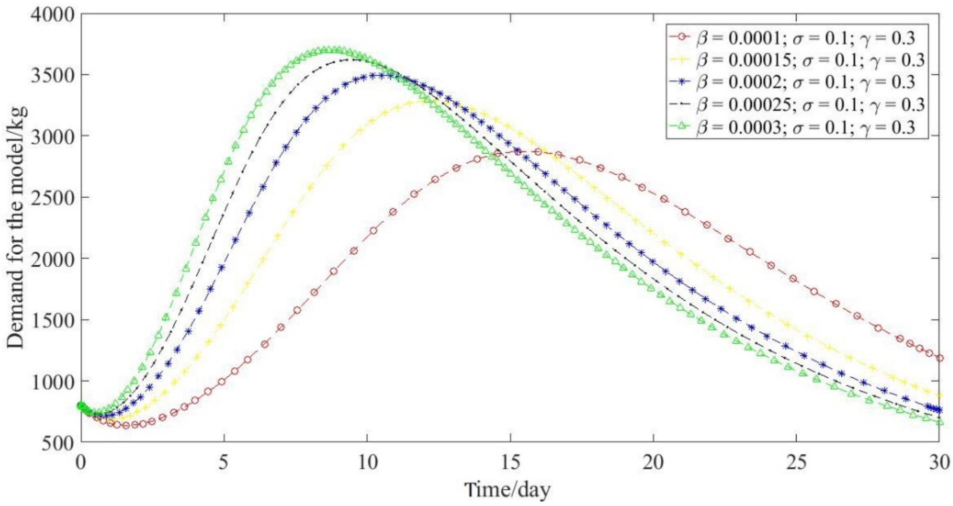

Fig. 5 The results of sensitivity analysis with different β

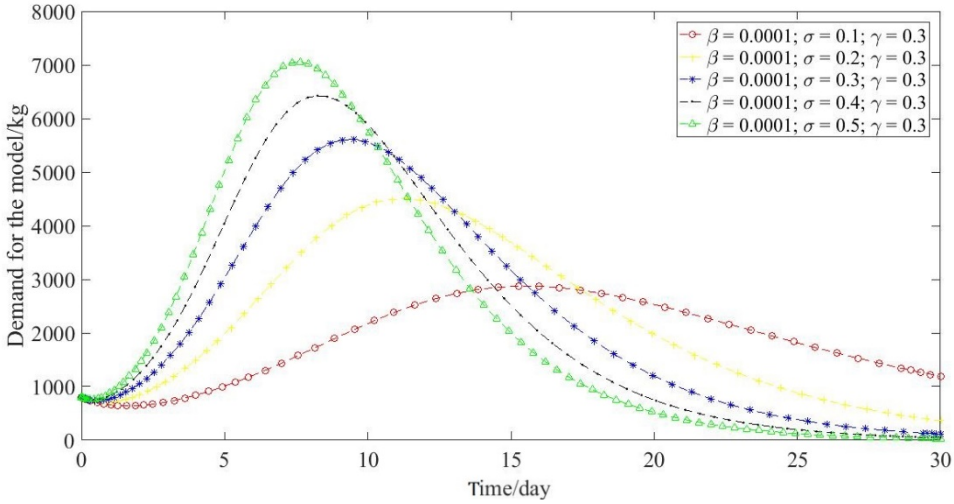

Fig. 6 The results of sensitivity analysis with different σ

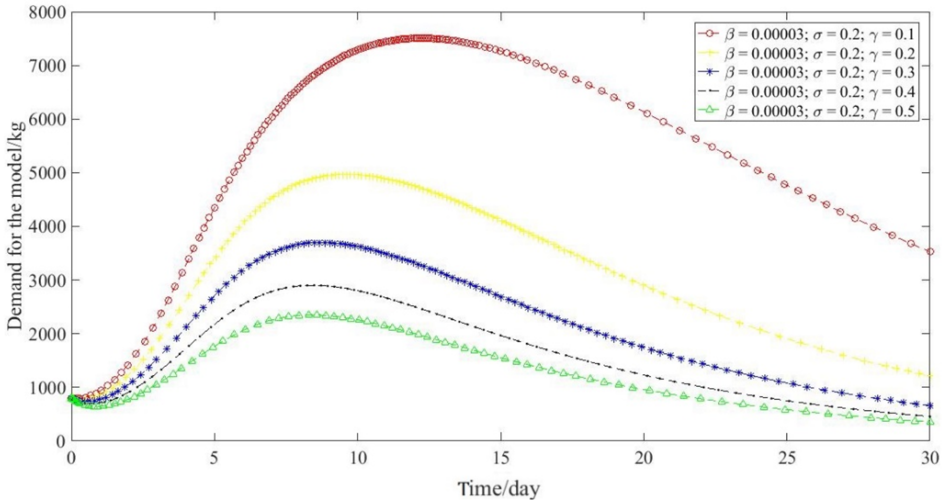

Fig. 7 The results of sensitivity analysis with different γ

5.4 Algorithm comparison

Genetic algorithm is a heuristic search and optimization technique inspired by natural evolution. They have been successfully applied to a wide range of real-world problems of significant complexity. In addition, ant colony algorithm is a class of metaheuristics which are inspired from the behaviour of real ants. The original idea consisted in simulating the stigmergic communication, therefore these algorithms are considered as a form of adaptive memory programming. Therefore, in order to compare the difference between Benders decomposition algorithm and genetic algorithm, ant colony algorithm, a time-space network model for the humanitarian logistics problem with logistics in controlling epidemic diffusion is also solved by a genetic algorithm and an ant colony algorithm in this paper.

Fig. 8 shows the optimization results of the genetic algorithm and the ant colony algorithm. The optimal value by the ant colony algorithm don't converge any more in 15th iteration, and the optimal value by the genetic algorithm don't converge any more in 23rd iteration. This result proves that the convergence performance and the computational accuracy of the ant colony algorithm is better than the genetic algorithm. The computing time of the Benders decomposition algorithm, the genetic algorithm and the ant colony algorithm is 10.8 s, 5.2 s and 8.9 s respectively. Therefore, the computational efficiency of the genetic algorithm is better than the other two algorithms. In addition, the optimal solution of the Benders decomposition algorithm, the genetic algorithm, and the ant colony algorithm is 2540084, 2854111, and 2540176, respectively. This result proves that the computational accuracy of the Benders decomposition algorithm is better than the genetic algorithm and the ant colony algorithm.

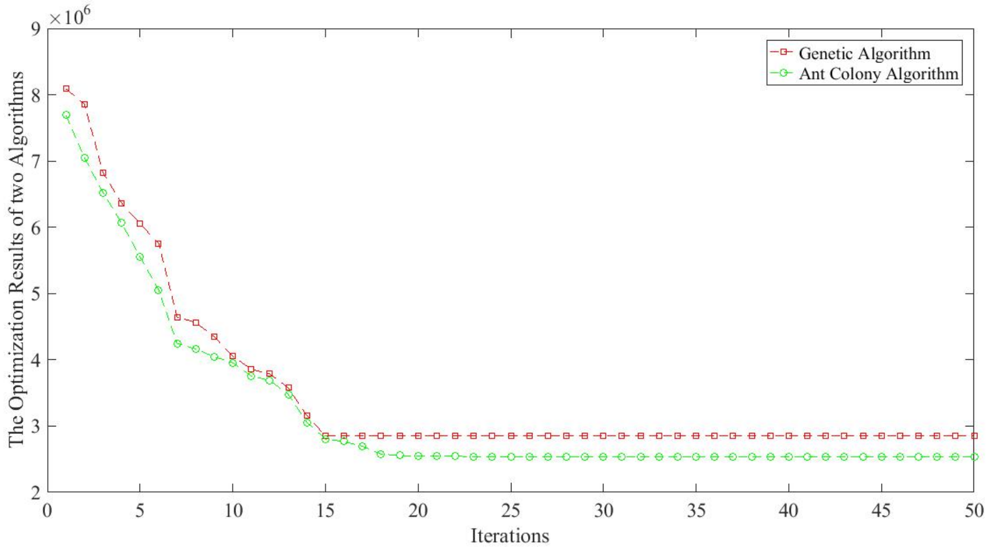

Fig. 8 The optimization results of the genetic algorithm and the ant colony algorithm

5.5 A larger case test

We expand the node and vehicle sizes based on the case in Subsection 5.1. We cite a case that can reflect the proposed model. We suppose that there are 16 nodes, 30 days, 8 vehicles. The maximum loading capacity of each vehicle, the marginal utility from node i to node j and $S_j(0)$, $E_j(0)$, $I_j(0)$, and $R_j(0)$ are expanded by the supposed node and vehicle sizes. Where β = 0.0001, σ = 0.2, γ = 0.5, λ = 1, α =20.

The optimization results of the larger case test by the Benders decomposition algorithm, the genetic algorithm and the ant colony algorithm are shown in Fig. 9. As Fig. 9 shows, the upper and lower bounds obtained by Benders decomposition algorithm are equal at the 14th iteration and will not change any more. Before that, the upper and lower bounds converge continuously.

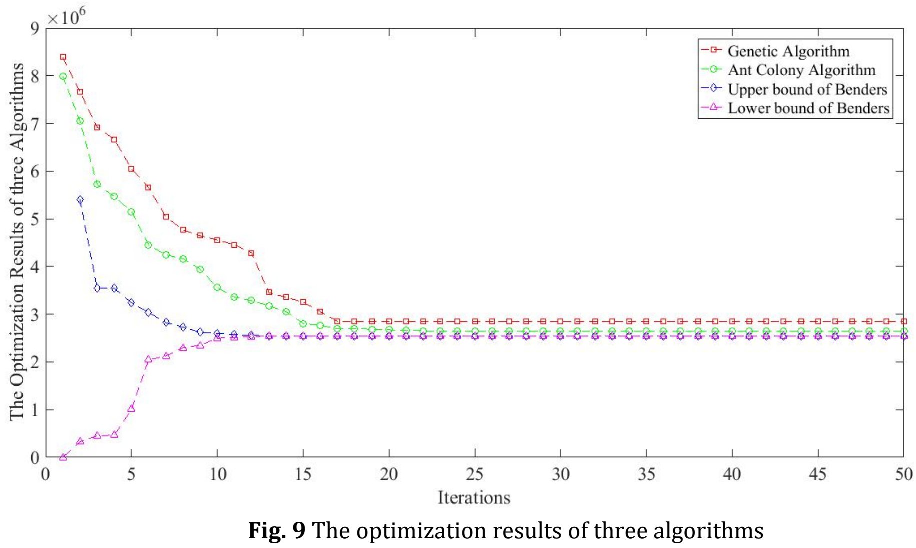

Fig. 9 The optimization results of three algorithms

The optimal value by the ant colony algorithm don't converge any more in 13th iteration, and the optimal value by the genetic algorithm don't converge any more in 24th iteration. Experimental results show the effectiveness of the proposed model and algorithm. The computing time of the Benders decomposition algorithm, the genetic algorithm and the ant colony algorithm is 40.7 s, 26.5 s and 33.4 s respectively. The computational efficiency of the genetic algorithm is better than the other two algorithms. In addition, the optimal solution of the Benders decomposition algorithm, the genetic algorithm and the ant colony algorithm is 2551213, 2896740, 2651176 respectively. This result proves that the computational accuracy of the Benders decomposition algorithm is better than the genetic algorithm and the ant colony algorithm. Therefore, the larger case experimental results show the validity of results in Subsections 5.2 and 5.4 and the effectiveness of the proposed model and algorithm.

6. Conclusion

In this paper, a time-space network model for the humanitarian logistics problem with logistics in controlling epidemic diffusion is proposed. We use the SEIR model which is a new differential equation to solve the dynamic information in humanitarian relief phase. A multistage mixed integer programming model for the humanitarian logistics and transport resource with a time-space network is proposed. The linear programming problem is solved by the Benders decomposition algorithm, the genetic algorithm and the ant colony algorithm. Finally, we use cases to calculate model and algorithm. The computational efficiency of the genetic algorithm is better than the other two algorithms. The results of cases prove that the computational accuracy of the Benders decomposition algorithm is better than the genetic algorithm and the ant colony algorithm and the correctness of the model and algorithm. This paper can improve the efficiency of emergency rescue and reduce the loss of people's lives and property caused by decision-making mistakes. Sensitivity analysis illustrate the effect of parameters on the result. Through sensitivity analysis, the influence of parameters on dynamic information is understood, and the internal relationship between route selection of emergency rescue vehicles and allocation of medical supplies is grasped, so as to provide reference for decision makers, and thus provide experience for future emergency decision-making. Due to the complexity of emergency rescue, only the time cost and delay cost in the process of emergency rescue are considered in this paper, so it is necessary to further study the comprehensiveness of emergency rescue.

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References

[1] Wang, H., Wang, X., Zeng, A.Z. (2009). Optimal material distribution decisions based on epidemic diffusion rule and stochastic latent period for emergency rescue, *International Journal of Mathematics in Operational Research*, Vol. 1, No. 1-2, 76-96, doi: 10.1504/IJMOR.2009.022876.

[2] Huang, K., Jiang, Y., Yuan, Y., Zhao, L. (2015). Modeling multiple humanitarian objectives in emergency response to large-scale disasters, *Transportation Research Part E: Logistics and Transportation Review*, Vol. 75, 1-17, doi: 10.1016/j.tre.2014.11.007.

[3] Cao, J., Han, H., Jiang, Y.-P., Wang, Y.-J. (2018). Emergency rescue vehicle dispatch planning using a hybrid algorithm, *International Journal of Information Technology & Decision Making*, Vol. 17, No. 6, 1865-1890, doi: 10.1142/S0219622018500414.

[4] Holguín-Veras, J., Pérez, N., Jaller, M., Van Wassenhove, L.N., Aros-Vera, F. (2013). On the appropriate objective function for post-disaster humanitarian logistics models, *Journal of Operations Management*, Vol. 31, No. 5, 262-280, doi: 10.1016/j.jom.2013.06.002.

[5] Zhang, J., Ma, Z. (2003). Global dynamics of an SEIR epidemic model with saturating contact rate, *Mathematical Biosciences*, Vol. 185, No. 1, 15-32, doi: 10.1016/S0025-5564(03)00087-7.

[6] Li, D., Liu, S., Cui, J. (2017). Threshold dynamics and ergodicity of an SIRS epidemic model with Markovian switching, *Journal of Differential Equations,* Vol. 263, No. 12, 8873-8915, doi: 10.1016/j.jde.2017.08.066.

[7] Fan, K., Zhang, Y., Gao, S., Wei, X. (2017). A class of stochastic delayed SIR epidemic models with generalized nonlinear incidence rate and temporary immunity, *Physica A: Statistical Mechanics and its Applications*, Vol. 481, 198-208, doi: 10.1016/j.physa.2017.04.055.

[8] Song, P., Lou, Y., Xiao, Y. (2019). A spatial SEIRS reaction-diffusion model in heterogeneous environment, *Journal of Differential Equations,* Vol. 267, No. 9, 5084-5114, doi: 10.1016/j.jde.2019.05.022.

[9] Yang, P., Wang, Y. (2019). Dynamics for an SEIRS epidemic model with time delay on a scale-free network, *Physica A: Statistical Mechanics and its Applications,* Vol. 527, Article No. 121290, doi: 10.1016/j.physa.2019.121290.

[10] Bolzoni, L., Bonacini, E., Soresina, C., Groppi, M. (2017). Time-optimal control strategies in SIR epidemic models, *Mathematical Biosciences*, Vol. 292, 86-96, doi: 10.1016/j.mbs.2017.07.011.

[11] Guo, W., Zhang, Q., Li, X., Wang, W. (2018). Dynamic behavior of a stochastic SIRS epidemic model with media coverage, *Mathematical Methods in the Applied Sciences*, Vol. 41, No. 14, 5506-5525, doi: 10.1002/mma.5094.

[12] Britton, T., Ouédraogo, D. (2018). SEIRS epidemics with disease fatalities in growing populations, *Mathematical Biosciences*, Vol. 296, 45-59, doi: 10.1016/j.mbs.2017.11.006.

[13] Anparasan, A., Lejeune, M. (2019). Resource deployment and donation allocation for epidemic outbreaks, *Annals of Operations Research*, Vol. 283, 9-32, doi: 10.1007/S10479-016-2392-0.

[14] Yee, W.S., Ng, H., Yap, T.T.V., Goh, V.T., Ng, K.H., Cher, D.T. (2022). An evaluation study on the predictive models of breast cancer risk factor classification, *Journal of Logistics, Informatics and Service Science,* Vol. 9, No. 3, 129-145, doi: 10.33168/LISS.2022.0310.

[15] Choi, J.-W., Jeong, E.-R. (2022). Multi-output convolutional neural network based distance and velocity estimation technique for orthogonal frequency division multiplexing radar systems, *Webology,* Vol. 19, No. 1, 4555-4570, doi: 10.14704/WEB/V19I1/WEB19302.

[16] Farahani, R.Z., Lotfi, M.M., Baghaian, A., Ruiz, R., Rezapour, S. (2020). Mass casualty management in disaster scene: A systematic review of OR&MS research in humanitarian operations, *European Journal of Operational Research,* Vol. 287, No. 3, 787-819, doi: 10.1016/j.ejor.2020.03.005.

[17] Kwapong Baffoe, B.O., Luo, W. (2020). Humanitarian relief sustainability: A framework of humanitarian logistics digital business ecosystem, *Transportation Research Procedia,* Vol. 48, 363-387, doi: 10.1016/j.trpro.2020.08.032.

[18] Wang, Y.D., Lu, X.C., Song, Y.M., Feng, Y., Shen, J.R. (2022). Monte Carlo Tree Search improved Genetic Algorithm for unmanned vehicle routing problem with path flexibility, *Advances in Production Engineering & Management*, Vol. 17, No. 4, 425-438, doi: 10.14743/apem2022.4.446.

[19] Zaldívar-Colado, A., Tripp-Barba, C., Brito-Rojas, J.A., Aguilar-Calderón, J.A., García-Sánchez, O.V., Ramírez-Zambada, L., Zatarain-Montalvo, J.N. (2017). Management of traffic lights for emergency service, *Tehnički Vjesnik – Technical Gazette,* Vol. 24, No. 2, 643-648, doi: 10.17559/TV-20140910051747.

[20] Wang, L., Chen, X.Y., Zhang, H. (2021). Joint distribution models in fast-moving consumer goods wholesale enterprise: Comparative analysis and a case study, *Advances in Production Engineering & Management*, Vol. 16, No. 2, 212-222, doi: 10.14743/apem2021.2.395.

[21] Zhou, Y., Liu, J., Zhang, Y., Gan, X. (2017). A multi-objective evolutionary algorithm for multi-period dynamic emergency resource scheduling problems, *Transportation Research Part E: Logistics and Transportation Review,* Vol. 99, 77-95, doi: 10.1016/j.tre.2016.12.011.

[22] Othman, S.B., Zgaya, H., Dotoli, M., Hammadi, S. (2017). An agent-based decision support system for resources' scheduling in emergency supply chains, *Control Engineering Practice*, Vol. 59, 27-43, doi: 10.1016/j.conengprac.2016.11.014.

[23] Ferrer, J.M., Martín-Campo, F.J., Ortuño, M.T., Pedraza-Martínez, A.J., Tirado, G., Vitoriano, B. (2018). Multi-criteria optimization for last mile distribution of disaster relief aid: Test cases and applications, *European Journal of Operational Research*, Vol. 269, No. 2, 501-515, doi: 10.1016/j.ejor.2018.02.043.

[24] Garrido, R.A., Aguirre, I. (2020). Emergency logistics for disaster management under spatio-temporal demand correlation: The earthquakes case, *Journal of Industrial and Management Optimization*, Vol. 16, No. 5, 2369-2387, doi: 10.3934/jimo.2019058.

[25] Lam, E., Van Hentenryck, P., Kilby, P. (2020). Joint vehicle and crew routing and scheduling, *Transportation Science*, Vol. 54, No. 2, 488-511, doi: 10.1287/trsc.2019.0907.

[26] Rajak, S., Parthiban, P., Dhanalakshmi, R. (2019). A hybrid metaheuristics approach for a multi-depot vehicle routing problem with simultaneous deliveries and pickups, *International Journal of Mathematics in Operational Research*, Vol. 15, No. 2, 197-210, doi: 10.1504/IJMOR.2019.101619.

[27] Sedehzadeh, S., Seifbarghy, M., (2021). Redesigning a closed loop food supply chain network considering sustainability and food banks with different returns, *Economic Computation And Economic Cybernetics Studies and Research*, Vol. 55, No. 4, 85-100, doi: 10.24818/18423264/55.4.21.06.

[28] Gutjahr, W.J., Nolz, P.C. (2016). Multicriteria optimization in humanitarian aid, *European Journal of Operational Research*, Vol. 252, No. 2, 351-366, doi: 10.1016/j.ejor.2015.12.035.

[29] Liu, M., Xiao, Y. (2015). Optimal scheduling of logistical support for medical resource with demand information updating, *Mathematical Problems in Engineering*, Vol. 2015, Article ID 765098, doi: 10.1155/2015/765098.

[30] Liu, M., Zhang, Z., Zhang, D. (2015). A dynamic allocation model for medical resources in the control of influenza diffusion, *Journal of Systems Science and Systems Engineering,* Vol. 24, No. 3, 276-292, doi: 10.1007/s11518-015-5276-y.

[31] Buschiazzo, M., Mula, J., Campuzano-Bolarin, F. (2020). Simulation optimization for the inventory management of healthcare supplies, *International Journal of Simulation Modelling*, Vol. 19, No. 2, 255-266, doi: 10.2507/IJSIMM19-2-514.

[32] Fischetti, M., Ljubić, I., Sinnl, M. (2017). Redesigning benders decomposition for large-scale facility location, *Management Science*, Vol. 63, No. 7, 2146-2162, doi: 10.1287/MNSC.2016.2461.

[33] Alkaabneh, F., Diabat, A., Gao, H.O. (2020). Benders decomposition for the inventory vehicle routing problem with perishable products and environmental costs, *Computers & Operations Research,* Vol. 113, Article No. 104751, doi: 10.1016/j.cor.2019.07.009.

[34] Fachini, R.F., Armentano, V.A. (2020). Logic-based Benders decomposition for the heterogeneous fixed fleet vehicle routing problem with time windows, *Computers & Industrial Engineering*, Vol. 148, Article No. 106641, doi: 10.1016/j.cie.2020.106641.

[35] Cordeau, J.-F., Furini, F., Ljubić, I. (2019). Benders decomposition for very large scale partial set covering and maximal covering location problems, *European Journal of Operational Research*, Vol. 275, No. 3, 882-896, doi: 10.1016/j.ejor.2018.12.021.

[36] Behmanesh, R., Rahimi, I. (2021). Improved ant colony optimization for multi-resource job shop scheduling: A special case of transportation, *Economic Computation And Economic Cybernetics Studies And Research,* Vol. 55, No. 4, 277-294, doi: 10.24818/18423264/55.4.21.18.

[37] Tang, F. (2021) An improved intelligent bionic optimization algorithm based on the growth characteristics of tree branches, *Journal of Intelligent & Fuzzy Systems*, Vol. 40, No. 3, 3821-3829, doi: 10.3233/JIFS-190487.

[38] Liu, M., Liang, J. (2013). Dynamic optimization model for allocating medical resources in epidemic controlling, *Journal of Industrial Engineering and Management,* Vol. 6, No. 1, 73-88, doi: 10.3926/jiem.663.

[39] Han, H., Cao, J., Wang, Y.-J. (2023). A hybrid algorithm of ant colony and benders decomposition for large-scale mix-integer linear programming, *International Journal of Information Technology & Decision Making*, Vol. 22, 1-23, doi: 10.1142/S0219622023500335.

[40] Benders, J.F. (1962). Partitioning procedures for solving mixed-variables programming problems, *Numerische Mathematik,* Vol. 4, 238-252, doi: 10.1007/BF01386316.