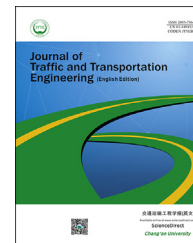




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Original Research Paper

A multi-dimensional robust optimization approach for cold-chain emergency medical materials dispatch under COVID-19: A case study of Hubei Province

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HIGHLIGHTS

- Multi-dimensional robust optimization model was comprehensively composed of cost factors and robustness of solution.
- A hybrid algorithm was redesigned to solve the model, which is formed by Pareto genetic algorithm and IGRA method.
- A high-risk area was taken as a real-world case, an average-cost reduction and a robustness increment with urgencies are gained.

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ABSTRACT

For the optimization problem of the cold-chain emergency materials (CEM) distribution routes with multi-demand centers and soft time windows and to solve dispatching materials to medical treatment institutions in various places of the disaster areas under COVID-19, a multi-dimensional robust optimization (MRO) model was proposed, which was solved by a hybrid algorithm combined Pareto genetic algorithm and the improved grey relative analysis (IGRA). The proposed model comprehensively takes into consideration of the cost factors of the cold-chain logistics and robustness of solution with the purpose of minimizing the costs and maximizing robustness. The availability of the proposed approach and hybrid algorithm were thoroughly discussed and qualified through a real-world numerical simulation test case, which was a previous risk area located at Hubei Province. Research results show an average-cost reduction of 4.51% and a robustness increment of 11.69% in addition to consider the urgencies of demand. Consequently, not only the costs can be slightly reduced and the robustness be heightened, but also the blindness of the distribution can be avoided effectively with the demand urgency being considered. Research result indicates that when combining with the specific process of supplies dispatching in the prevention and control, the proposed approach is in a far better

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agreement in practice, and it could meet the diverse requirements of the emergency scenarios flexibly.

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1. Introduction

For surmounting problems of the illogical allocation of emergency supplies in the prevention and control of COVID-19 as well as the majority of unnecessary personal injury and property loss, this study redesigned an approach of the urban cold-chain emergency material resource dispatching and studied the robust optimization of dispatching in the highway for the purpose of improving the efficiency of cold-chain emergency materials (CEM) distribution. Disasters such as COVID-19 are starting to be part of our daily life, which have fatal devastating effects in terms of human injuries and property damages. Under the novel coronavirus pneumonia (NCP), the government departments are critical to the scientific and reasonable scheduling of the emergency supplies for minimizing the loss of lives and maximizing the efficiency of the rescue operations. Therefore, on the premise of the transportation economy, the robust optimization of CEM distribution path can ensure the vehicles reach the high-risk epidemic areas safely, quickly and economically, thus there is strong applicability, and it is great of momentous practical significance to study this problem.

Path optimization problem is a typical multi-objective planning (MOP) problem. Toward robust optimization of vehicle routing problem (VRP), [Huisman et al. \(2004\)](#), [Sungur et al. \(2008\)](#), [Cao et al. \(2014\)](#), [Haghi et al. \(2017\)](#), [Liu et al. \(2021\)](#), [Ouhimmou et al. \(2019\)](#) and [Hoogeboom et al. \(2021\)](#) aimed to improve the robustness of the vehicle routing scheme and established robust optimization models for VRP. It can be seen that scholars have made some achievements in the research on robust optimization scheduling of emergency supplies.

In recent years, robust optimization has formed a system through lucubrating of [Bertsimas and Goyal \(2013\)](#), which has been widely applied in the field of emergency rescue. [Liu \(2014\)](#), [Li et al. \(2017\)](#), and [Hao and Zhang \(2019\)](#) had united robust optimization with emergency management, but these research findings had not combined special cold-chain materials. Regarding cold-chain logistics distribution, [Sim \(2004\)](#) first proposed a robust optimization (RO) model, and then [Guo and Yang \(2020\)](#) established an RO model for perishable goods scheduling. However, these scholars have not considered emergency factors. [Ma et al. \(2018\)](#) built the multi-objective bi-level robust optimization model considering the transportation risk, costs, and service time window in hazardous materials distribution routes and solved it by means of a hybrid algorithm. It can well complete the multi-objective bi-level optimization on the hazardous materials distributing routes in uncertain environments.

This study sets out to study the vehicle routing problem with time window (VRPTW) problem with the following properties: the soft strictness of the time window for the urgent need of patients receiving the drugs, the uncertainty of the demands in epidemic areas, the uncertainty of the random efficacy loss of drugs in the process of driving, and the psychological burden of the deliverymen entering the high-risk regions. The essence of the study is multidimensional objective robust vehicle routing problem with soft time windows (MORVRPTW); this research builds a robust optimization model and takes a numerical example to verify it. Hubei Province, China, as one of the epidemic areas under COVID-19, its medical resources are overloaded, so that emergency drugs are urgently needed to support medical institutions in Hubei Province. Among the emergency demands, the cold-chain medicine has become an important material. Therefore, this paper will research transportation scheduling plus better robustness and lower cost of CEM and the scheduling comparison of taking consideration of the urgencies for demands or not.

The remainder of this paper is organized as follows. Section 2 reviews the previous studies on the modeling approach of robust optimization for CEM distributing. Section 3 develops a mathematical model to formulate the robust optimization problem for CEM distributing and presents the model solution. Section 4 tests the proposed method framework using a case study and analyzes the comparison of considering the demand urgency or not. Conclusions and future work are discussed in Section 5.

2. Literature review

The occurrence of sudden infectious diseases, earthquakes and other malignant events has caused a major or even devastating blow to human beings, posing a major threat to human survival and social development. The outbreak of sudden events will cause great harm to social life, such as the threat to human life and health, causing serious economic losses and environmental harm. After an emergency occurs, it is indispensable to take timely and effective measures for emergency rescue. The distribution of emergency supplies and cold-chain medical supplies is one of the significant links in emergency rescue, and the distribution path optimization is crucial to realize the efficient deployment of emergency supplies.

With the outbreak of large-scale infectious diseases, the demand for cold-chain drugs and cold-chain vaccines in medical institutions of various epidemic areas has increased sharply, and the transportation scheduling of these special

materials is a difficult task. Therefore, this paper studies this essential problem and provides effective solutions for the scheduling of special materials caused by various unexpected events.

The following literature review presents the studies on the two logistics types: (a) emergency logistics and (b) cold-chain logistics.

2.1. Emergency logistics

The demand for emergency logistics not only comes from natural disasters, but also from man-made disasters. Obviously, recent years have seen a significant growth in human life and property damages caused by anthropogenic and natural disasters. This has prompted researchers in different fields to intensively address the problems of the emergency management. To solve the problem of vehicles scheduling and routes with the aim to enhance the enhancement of rescue efficiency in case of sudden public events, scholars have established a certain foundation in the study of emergency logistics: Ko et al. (2016) improved and applied genetic algorithm to emergency supplies scheduling. The COVID-19 pandemic spreads rapidly around the world currently, and has given rise to huge impacts on all aspects of human society. Rahman et al. (2020) proposed a model which was helpful to reduce casualties and property losses and improve emergency operation. For the supply and distribution of emergency materials, Dalal and Üster (2021) established the robust planning of disaster emergency rescue supply. Shang et al. (2020a) utilized big data techniques to analyze the impacts of COVID-19 on the user behaviors and environmental benefits of bike sharing. Fang et al. (2020) took emergency medical supplies as an example and established the supply and demand mechanism of post-earthquake emergency logistics, which provided the basis for emergency rescue of emergencies. According to the typical characteristics of emergency medical logistics, Chen (2020) established a double-objective vehicle scheduling model. Tang and Ye (2021) built a fair distribution model of emergency medical materials considering multiple distribution centers, multiple demand points, multiple materials and multiple objectives, which enhanced the timeliness of emergency rescue. Wang and Bao (2021) studied the optimization of emergency material delivery schemes in multi-disaster areas. Jing (2021) studied the optimization of emergency logistics distribution resources under emergencies, and achieved certain results. According to the characteristics of emergency medical supplies, Wang et al. (2021a) designed a multi-objective location-allocation model, and the results showed that the model had advantages in scheduling decision-making. Following this, Han et al. (2021) constructed an optimization model of emergency material distribution path with time window constraints, which provided scientific decision-making basis for emergency logistics. As well as this, Liang et al. (2021) established a solution method of emergency medical material distribution model based on genetic algorithm, which improved timeliness. In addition, Chen (2011) set up a double-objective vehicle scheduling model from the perspective of delivery time and disaster-stricken point satisfaction. Lu and Ma (2021) conducted a spatial correlation study of virus

transmission in Hubei Province, China. And we will know the choice behavior of commuters' rail transit mode during the COVID-19 pandemic from a recent study (Tan and Ma, 2021). Ma et al. (2020) constructed an emergency customized bus route optimization method considering the requirements of epidemic prevention and control under public health emergencies. Zhou et al. (2020) studied the unconventional epidemic prevention strategy of urban public transportation under the COVID-19 epidemic.

2.2. Cold-chain logistics

Cold-chain logistics is a vital way to ensure the quality of materials. It is a low-temperature logistics process by means of refrigeration technology. The distribution process is at the core as one of the links of cold-chain logistics. Oswald and Stirn (2007) took a real food market as an example to establish the distribution of cold-chain fruits and vegetables, where the model considers the impact of the perishability as part of the overall distribution costs and a heuristic approach. Tabu-based search is used to solve the problem, which provides a solution basis for the transportation of perishables. Hsiao et al. (2017) aimed at the simultaneous distribution of a variety of agricultural products based on satisfying the product quality required by customers, which built the cold-chain logistics distribution models with multi-temperature co-distribution and adopted the adaptive optimization algorithm based on biogeography. Haghani and Oh (1996) solved the multimodal transport model of the emergency supplies based on the space-time network through Lagrange relaxation and iterative heuristic algorithm. Özdamar and Demir (2012) proposed a hierarchical clustering and path coordination model based on the multi-level clustering algorithm and verified the validity of the model with the corresponding numerical examples. Stochastic time-dependent vehicle routing problem (STDVRP) model without time windows was relatively simple, but the computational complexity was still high. Barbarosoglu and Arda (2004), Mendoza (2011), and Moghaddam et al. (2012) also established a stochastic programming model for VRP. Most of them take the freshness of products and carbon emissions as the main modeling object, whereas few scholars link perishables with transportation in emergency. Following this, Dewi and Utama (2020) designed the hybrid whale optimization algorithm (HWOA) to minimize the distribution cost of the green vehicle routing problem (GVRP). Onwude et al. (2020) gave promising insight towards the use of advanced technologies in reducing losses in the cold-chain of fruits and vegetables. Awad et al. (2020) summarized the literature of cold-chain logistics. Recently, Xiao et al. (2021) designed a hybrid algorithm to solve the vehicle routing problem in cold-chain logistics, which provided a reasonable decision basis for cold-chain logistics. In addition, Zhang et al. (2021) used bi-level programming method to construct the optimization decision model of low-carbon cold-chain logistics distribution system, which provided some ideas for improving energy saving and emission reduction. Chen and Liu (2021) applied ant colony algorithm to the research of cold chain logistics path optimization, which can improve the quality of logistics. Also, Liu (2021) analyzed the optimization strategy of cold chain

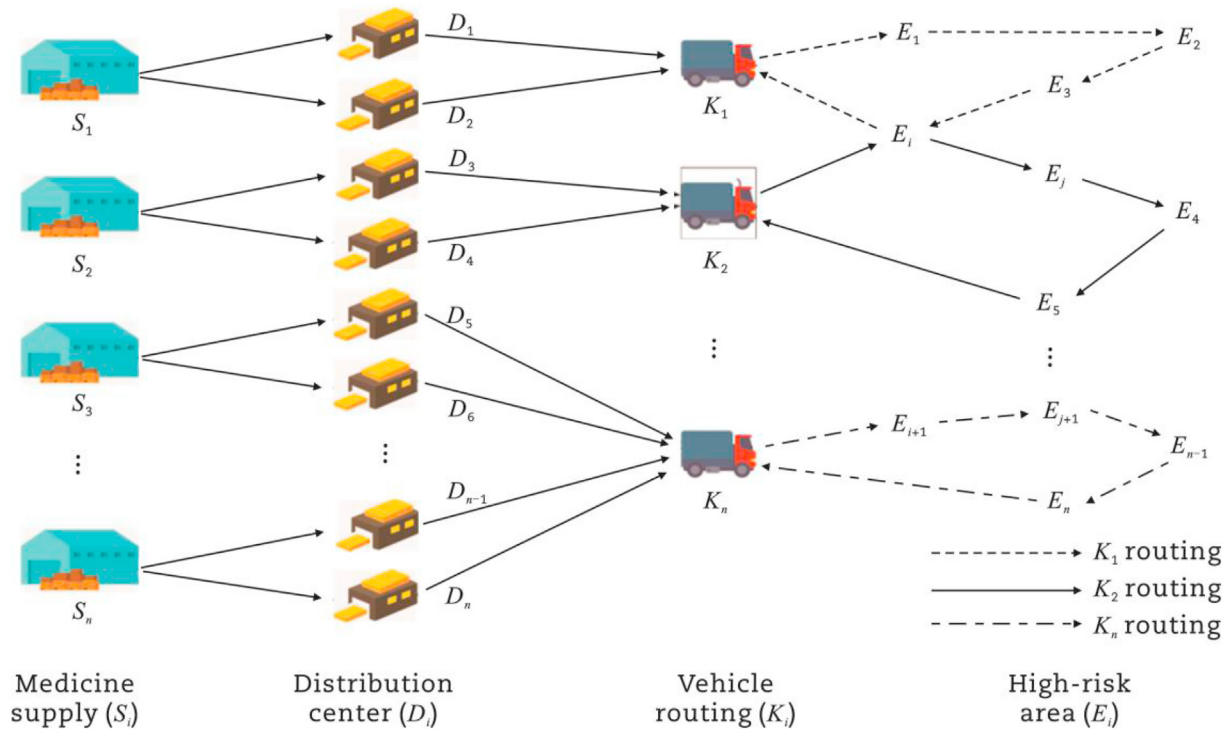


Fig. 1 – Diagram of distribution work for cold-chain emergency logistics-COVID-19.

logistics distribution path of fresh agricultural products. From the perspective of value for customer and satisfaction, Wang et al. (2021b) established a mathematical model of the time-varying path of urban cold chain logistics and verified and analyzed it. As well as this, Liu et al. (2021) established a distribution path optimization model for cold-chain material with the lowest comprehensive distribution cost as the objective function, and designed an algorithm to solve the problem. Ren et al. (2020) constructed a mathematical model of cold chain vehicle route optimization to minimize the total cost, and designed a new ant colony algorithm by integrating and innovating traditional algorithms. With considering the interference factors such as delivery time and delivery risk of multi-temperature cold-chain logistics, Ding (2021) built a multi-temperature cold-chain logistics vehicle delivery path optimization model and designed an algorithm to solve it. Also, Shen et al. (2021) established the model and solved it by genetic algorithm with considering the cargo loss and carbon emission factors in the process of cold-chain logistics. Actually, the existing studies on cold-chain logistics has adopted different models and methods, and the contribution can be applied to different problems in this field.

2.3. Research gap

To sum up, urban road networks are typical complex systems, which are crucial to our society and economy. Topological characteristics of a number of urban road networks purely based on physical roads rather than routes of vehicles or buses are investigated in order to discover underlying unique structural features (Shang et al., 2020b). In accordance with research findings, previous studies showed that most of the

existing researches focus on the optimization of the distribution path in the case of separating the cold-chain and emergency factors, yet, only some research results are aimed at the distribution path in case of cold-chain and emergency are considered simultaneously. In addition, the model built by the predecessors did not regard the robustness rate as a single objective for the CEM distribution problem or did not consider the psychological panic of the deliverymen when entered the high-infectious epidemic areas. In the fight against NCP, the field of cold-chain medicine supplies is pivotal to support high-risk areas, and the optimized transport scheduling of cold-chain emergency medicine has become a shortcoming while supporting epidemic areas, therefore, the main content of this research is to seek a better distribution plan for this shortcoming field. Since former studies are limited to combine the exploration of cold-chain and emergency factors, it is significant to conduct the research on this topic to give an in-depth understanding of the robust optimization of distribution path for CEM.

3. Methodology

3.1. Problem statement

The rescue work for Hubei Province is the research target in this study. The tasks of the research can be described as follows: the distribution center transported the cold-chain medicine to multiple medical aid agencies of high-risk areas, the maximum load of vehicles, locations of high-risk areas, nominal demands, soft time windows of receiving emergency

Table 1 – Variables of the model.

| Variable | Definition |
|--|--|
| K ($k \in K$) | Vehicle set |
| C ($c_i \in C$) | The aggregate volume of emergency supplies |
| d_i ($i \in N$) | Nominal demand for cold-chain drugs |
| Q ($i, j \in N, k \in K$) | The maximum supply of distribution center |
| d_{ij} ($i, j \in N$) | The distance from epidemic area i to j |
| A_i^{1r}, A_i^{2r} | Resting and unloading time at i (superscript r is only to distinguish it from other similar symbols) |
| RE^e, RE^l | The time window for the patients receiving the medication (superscript e stands for early arrival and l stands for late arrival) |
| $\lambda_1, \lambda_2, \delta$ | Coefficients for consumption cost of bodies |
| T_a, T_b | The lower and upper bounds of drugs storage temperature (subscript a represents the lower bound and b represents the upper bound) |
| $T_{1,0}^{LOSE}$ | The time point at which drugs effect begin to wear off |
| T_s^{LOSE} | The time critical point for complete failure (subscript s stands for critical point) |
| $\xi \in [0, 1]$ | 0-1 integer parameter, when $\xi = 1$, the temperature is lower than the lower bound, when $\xi = 0$, the temperature is higher than the upper bound |
| $T_{2,0}^{Psy}$ | The tipping point of psychological change |
| $C_{2,0}^{Psy}$ | The initial state of psychology |
| E_0, E_1 | The initial fixed salary and compensation salary |
| $\mu_1^{Psy}, \mu_2^{Psy}, \mu_3^{Psy}, \mu_4^{Psy}$ | Psychological compensation or burden factors for compensation of pay, contacting with personnel of the epidemic areas, resting in the epidemic areas and returning to quarantine |
| N_2^{tou} | The number of people in contact with infected areas |
| t_4^{quar} | The isolation periods |
| α, β, ϑ | Auxiliary coefficients |
| N_k | The number of vehicles in use |
| π_{full}, π_0 | Fuel consumption in full and in no-load |
| B_1^k, B_{max}^k | The weight of the transported material and load limit of vehicle k |
| $\epsilon_{CO_2}^k$ | Conversion coefficient between fuel consumption and carbon emission |

supplies, and the distance and time between the areas are all known. The goal is to achieve the optimal vehicle routings scheme plus higher robustness and lower total costs. Also, the distribution work can be shown in Fig. 1.

$G = (V, A)$ is defined as cold-chain emergency logistics network. V includes two subsets, distribution center M and epidemic points set N . A is a set of available links. $DM = (dm_{ij})$ is distance matrix between two places, $(i, j) \in A$, where i and j are points of the distribution network. The delivery will be carried out by multiple vehicles with a limit of 7, and the load limit of 8.5 t for every vehicle.

$$DM = \begin{pmatrix} dm_{11} & dm_{12} & \dots & dm_{1j} \\ dm_{21} & dm_{22} & \dots & dm_{2j} \\ \vdots & \vdots & & \vdots \\ dm_{i1} & dm_{i2} & \dots & dm_{ij} \end{pmatrix} \quad (1)$$

3.2. Symbols of models

Table 1 shows the model variables. The costs adopt economy as dimension: ϖ^1 (the time cost is a yuan/min), ϖ^2 (the penalty cost of physical consumption is b yuan/min), ϖ^3 (the economic compensation of psychological cost is c yuan/burden), ϖ^4 (loss of efficacy value equals to d yuan multiply degree of loss) and ϖ^5 (purchase additional carbon emission allowances from environmental authorities according to the carbon trading policy, 20 yuan/t) are the dimensional unified conversion coefficients of each sub-cost target.

3.3. Mathematical derivation of model

General linear programming (LP).

$$Obj(x) = \min_x \{ C_{cost}^T x : a_i^T x \leq k_i^T b_i, 0 < i \leq N_{cons.} \} \quad (2)$$

where $N_{cons.}$ are constraints, $k_i^T b_i$ represents polynomial of constraints, deterministic parameter b_i of LP transformed into uncertain parameter, \tilde{b}_i formed robust linear optimization.

$$Obj(x) = \min_x \{ C_{cost}^T x : a_i^T x \leq k_i^T \tilde{b}_i, 0 < i \leq N_{cons.}, \forall \tilde{b}_i \in G \} \quad (3)$$

The objective of robust rate is considered separately. The feasibility of the solution is limited by the load limit of vehicles and the soft time windows; also, the robustness is limited by the on-board surplus and the surplus of arrival time. The on-board surplus is the difference value between the vehicles volume and the total nominal demands of the medical institutions of the epidemic areas. The surplus of arrival time is the difference value between the arrival time point of vehicle k at i and ending point of the soft time window for the receiving materials.

$$\max\{\text{robustness}\} \xrightarrow{\text{transformed into}} \min\{-\text{robustness}\} \quad (4)$$

a_i^k is defined as the departure time of vehicle k from i after completing drugs support, $[RE^{1j} - (a_i^k + t_{ij})]$ denotes the time remaining for k from i to j , ϵ and $(1 - \epsilon)$ signify vehicle-borne surplus and arrival time-point surplus. Build the following model.

$$F_{RO}^2 = \left\{ \max_{ij \in N, k \in K} \{R\}, \min_{ij \in N, k \in K} \{C\} \right\} \Rightarrow \left\{ \min_{ij \in N, k \in K} \{-R\}, \min_{ij \in N, k \in K} \{C\} \right\} \quad (5)$$

Constraints are

$$\begin{cases} RE_i^l - RE_i^e \geq 0, ARE_i^l - BRE_i^e \geq 0, \forall i \in N \\ \sum_i \sum_j x_{ijk} d_i \leq B_{max}, \forall i, j \in N, \forall k \in K \end{cases}$$

3.4. Objective of cost C

(1) Sub-objective 1 of C: minimize the transportation time.

$$Z_3^{LOSE} = \begin{cases} \omega^2 \cdot 0 \\ \omega^3 x_{ijk} \left[\frac{\eta}{1 + \eta T_{1,0}^{LOSE}} (T_{1,0}^{LOSE})^2 - t_i^2 \right] \sum_{ij \in N, k \in K} [\rho_1 (1 - \xi) (T_{ijk} - T_b) + \rho_2 \xi (T_a - T_{ijk})] \\ \omega^2 \cdot 1 \end{cases}$$

$$Z_1^{ServiceT} = \omega^1 \sum_{i \neq j, i, j \in N} \sum_{k \in K} \left[t_{ij} + \frac{d_{oi} r_{ki}}{v_{oi}} + x_{ijk} (A_i^{1r} + A_i^{2r}) \right] \quad (6)$$

$$r_{ki} = \begin{cases} 1 & \text{Vehicle } k \text{ transported materials to } i \\ 0 & \text{Else} \end{cases} \quad (7)$$

$$x_{ijk} = \begin{cases} 1 & \text{Vehicle } k \text{ would leave } i \text{ to } j \\ 0 & \text{Else} \end{cases} \quad (8)$$

(2) Sub-objective 2 of C: minimize body consumption with a soft time window.

There is a certain acceptance range for time window of the materials arrival, which is to the life condition of the patients, i.e., the time deviations of the materials arrival are limited. Since the deliverymen may not guarantee to arrive at the epidemic areas within the time window in transit, certain body consumption costs of patients will be incurred.

$$Z_4^i = \begin{cases} \omega^4 \left[C_{2,0}^{Psy} - \mu_1^{Psy} E_0 - \mu_3^{Psy} t_{ri} + \mu_2^{Psy} N_2^{tou} + \mu_4^{Psy} t_4^{quar} - (T_{2,0}^{Psy} - t_i)^{\alpha_1^{Psy}} \right] & t_i \leq T_{2,0}^{Psy} \\ \omega^4 \left[C_{2,0}^{Psy} - \mu_1^{Psy} [(t_i - t_0) S_1 + E_0] - \mu_3^{Psy} t_{ri} + \mu_2^{Psy} N_2^{tou} + \mu_4^{Psy} t_4^{quar} - \vartheta_{2,2}^{Psy} (T_{2,0}^{Psy} - t_i)^{\beta_{2,1}^{Psy}} \right] & t_i > T_{2,0}^{Psy} \end{cases} \quad (11)$$

$$Z_2^{body} = \begin{cases} \omega^2 \lambda_1^{\delta(\delta > 1)} (RE^e - BRE^e) + \lambda_2 (BRE^e - t_i) & t_i \leq BRE^e \\ \omega^2 \lambda_1 (RE^e - t_i) & BRE^e < t_i \leq RE^e \\ 0 & RE^e < t_i \leq RE^l \\ \omega^2 \lambda_1 (t_i - RE^l) & RE^l < t_i \leq ARE^l \\ \omega^2 \lambda_1^{\delta(\delta > 1)} (ARE^l - RE^l) + \lambda_2 (t_i - ARE^l) & t_i > ARE^l \end{cases} \quad (9)$$

Furthermore, this paper builds a consumption cost function caused by broken line curve of the soft time window, which is shown in Fig. 2.

(3) Sub-objective 3 of C: minimize loss of efficacy for cold-chain medicine.

The loss is only related to road conditions and storage temperature.

$$\begin{cases} t_i \leq T_{1,0}^{LOSE} \\ T_{1,0}^{LOSE} < t_i < T_s^{LOSE} \\ t_i \geq T_s^{LOSE} \end{cases} \quad (10)$$

(4) Sub-objective 4 of C: minimize psychological burden of deliverymen.

The core of the distribution of emergency supplies is an arrangement of vehicle routing for the purpose of delivering various supplies to the regions of demand, apparently, the deliverymen executed it. As COVID-19 for the new virus with the fast transmission speed, respiratory infection mode, and high mortality rate, etc., these factors pose masses of great menaces to the delivery of supplies for high-risk epidemic areas and jeopardize psychological of deliverymen. The outbreak of the epidemic not only threatens the health of the public, but also affects the psychological health and mental state of people. As much as possible to reduce the psychological panic of deliverymen has become a pivotal factor during epidemic prevention and control. In the fight against psychological epidemic prevention, in addition to the medical assistance of “hardcore”, the psychological protection of “flexibility” is also indispensable.

(5) Sub-objective 5 of C: minimize carbon emissions.

Building the sub-objective 5 conforms to policies of carbon emissions and carbon trading of country, which actively responds to the environment-friendly society.

$$Z_5^{CE} = \varpi^5 \sum_{ij \in N} \sum_{k \in K} \left[\frac{\pi_{full} + \pi_0 (B_{max}^k - B_1^k)}{B_{max}^k} \right] \epsilon_{CO_2}^k d_{ijk} N_k X_{ijk} \quad (12)$$

Then, the total C is as follows (κ_i is the weight factor).

$$\begin{aligned} \min f &= \min \left\{ \kappa_1 \varpi^1 Z_1^{ServiceT} + \kappa_2 \varpi^2 Z_2^{punish} + \kappa_3 \varpi^3 Z_3^{LOSE} + \kappa_4 \varpi^4 Z_4^{Psy} + \kappa_5 \varpi^5 Z_5^{CE} \right\} \\ &= \min \left\{ \kappa_1 \varpi^1 \sum_{i \neq j, ij \in N} \sum_{k \in K} \left[t_{ij} + \frac{d_{oi} r_{ki}}{v_{oi}} + x_{ijk} (A_i^{1r} + A_i^{2r}) \right] + \kappa_2 \varpi^2 Z_2^{punish} \right. \\ &\quad + \kappa_3 \varpi^3 x_{ijk} \left[\frac{\eta}{1 + \eta T_{1,0}^{LOSE}} (T_{1,0}^{LOSE})^2 - t_i^2 \right] \sum_{ij \in N} \sum_{k \in K} [\rho_1 (1 - \xi) (T_{ijk} - T_b) + \rho_2 \xi (T_a - T_{ijk})] \\ &\quad \left. + \kappa_4 \varpi^4 \sum_{i \in N} Z_4^i + \kappa_5 \varpi^5 \sum_{ij \in N} \sum_{k \in K} \left[\frac{\pi_{full} + \pi_0 (B_{max}^k - B_1^k)}{B_{max}^k} \right] \epsilon_{CO_2}^k d_{ijk} N_k X_{ijk} \right\} \quad (13) \end{aligned}$$

3.5. Objective of robustness R

Firstly, the robust optimization is transformed into a deterministic problem, and the feasibility of the solution is limited

by (a) vehicle-borne constraints and (b) soft time window constraints. The robustness of the solution is limited by (c) vehicle-borne surplus and (d) surplus of arrival time point. Build the objective of maximum robustness.

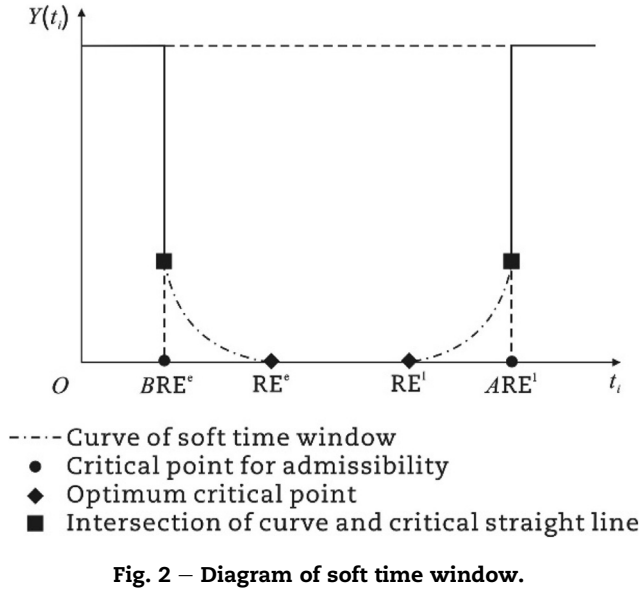
3.6. MRO modeling

In this study, the objective is to maximize the robustness and minimize the costs. To solve it simply, the objective of robust rate

was obtained by a linear transformation $\max\{R\} \rightarrow \min\{-R\}$. The uncertain sets of demand and time are transformed deterministically based on the robust optimization theory. The variation interval of the travel time for unit distance is $[t_{ij0} - \beta t_{ij}, \hat{t}_{ij}]$,

$$Z_6 = Obj_6 = \max\{R\} = \max \left\{ \epsilon \left(1 - \frac{\sum_{k \in K} \sum_{ij \in N} d_i x_{ijk}}{B_{max} \sum_{k \in K} \sum_{j \in N} x_{ojk}} \right) + (1 - \epsilon) \frac{\sum_{k \in K} \sum_{ij \in N} x_{ijk} [RE^{lj} - (a_i^k + t_{ij})]}{\sum RE^{lj}} \right\} \quad (14)$$

$$\begin{aligned} F_{RO}^3 &= \left\{ \max_{ij \in N, k \in K} \{Obj_6\}, \min_{ij \in N, k \in K} \left\{ \sum_{i=1}^5 Obj \right\} \right\} \\ &= \min_{ij \in N, k \in K} \left\{ -Obj_6, \sum_{i=1}^5 Obj \right\} = \min_{ij \in N, k \in K} \left\{ \epsilon \left(1 - \frac{\sum_{k \in K} \sum_{ij \in N} d_i x_{ijk}}{B_{max} \sum_{k \in K} \sum_{j \in N} x_{ojk}} \right) + \right. \\ &\quad \left. (1 - \epsilon) \frac{\sum_{k \in K} \sum_{ij \in N} x_{ijk} [RE^{lj} - (a_i^k + d_{ij})]}{\sum RE^{lj}}, \right. \\ &\quad \left. \sum \varpi^i \left(\kappa_1 Z_1^{ServiceT} + \kappa_2 Z_2^{body} + \kappa_3 Z_3^{LOSE} + \kappa_4 Z_4^{Psy} + \kappa_5 Z_5^{CE} \right) \right\} \\ &= \min_{ij \in N, k \in K} \left\{ \epsilon \left(1 - \frac{\sum_{k \in K} \sum_{ij \in N} d_i x_{ijk}}{B_{max} \sum_{k \in K} \sum_{j \in N} x_{ojk}} \right) + (1 - \epsilon) \frac{\sum_{k \in K} \sum_{ij \in N} x_{ijk} [RE^{lj} - (a_i^k + d_{ij})]}{\sum RE^{lj}}, \right. \\ &\quad \kappa_1 \varpi^1 \sum_{i \neq j, ij \in N} \sum_{k \in K} \left[t_{ij} + \frac{d_{oi} r_{ki}}{v_{oi}} + x_{ijk} (A_i^{1r} + A_i^{2r}) \right] + \kappa_2 \varpi^2 Z_2^{body} + \\ &\quad \sum \kappa_3 \varpi^3 x_{ijk} \left[\frac{\eta}{1 + \eta T_{1,0}^{LOSE}} (T_{1,0}^{LOSE})^2 - t_i^2 \right] \sum_{ij \in N} \sum_{k \in K} [\rho_1 (1 - \xi) (T_{ijk} - T_b) + \rho_2 \xi (T_a - T_{ijk})] \\ &\quad \left. + \kappa_4 \varpi^4 Z_4^{Psy} + \kappa_5 \varpi^5 \sum_{ij \in N} \sum_{k \in K} \left[\frac{\pi_{full} + \pi_0 (B_{max}^k - B_1^k)}{B_{max}^k} \right] \epsilon_{CO_2}^k d_{ijk} N_k X_{ijk} \right\} \quad (15) \end{aligned}$$



$t_{ij0} + \beta t_{ij} \hat{t}_{ij}$, the demand varies within $[d_{i0} - \beta d_i \hat{d}_i, d_{i0} + \beta d_i \hat{d}_i]$, assuming the maximum deviation is 8% of the nominal value.

Constraints are

$$\begin{cases} \sum_{i=1}^n \sum_{k=1}^{N_k} x_{ij}^k \geq 1, \forall i, j \in N, \forall k \in K \\ RE_i^l - RE_i^e \geq 0, ARE_i^l - BRE_i^e \geq 0, \forall i \in N \\ \sum \sum x_{ijk} d_i \leq B_{\max}, \forall i, j \in N, \forall k \in K \\ T_s^{\text{rot}} - T_{1,0}^{\text{rot}} \geq 0, T_s^{\text{rot}}, T_{1,0}^{\text{rot}}, t_i \neq 0, \forall i \in N \\ N_2^{\text{tou}}, t_4^{\text{quar}}, \alpha_1^{\text{Psy}}, \beta_{2,1}^{\text{Psy}}, \nu_{2,2}^{\text{Psy}}, \mu_1^{\text{Psy}}, \mu_2^{\text{Psy}}, \mu_3^{\text{Psy}}, \mu_4^{\text{Psy}}, \sum Z_4^i, E_1 > 0, \forall i \in N \\ B_{\max}^k - B_1^k \geq 0, \pi_{\text{full}} - \pi_0 \geq 0, \forall k \in K \end{cases}$$

4. Case study

The experimental environment is CPU 1.80 GHz, the development environment is MATLAB R2018a, and the case test is run on computer for Intel(R) Core(TM) i5-8265U CPU @ 1.80 GHz, 8 GB RAM and Windows7 platform.

4.1. Comparison with traditional algorithm

4.1.1. Experiment 1

The benchmark test data R-101 of vehicle routing problem with time window designed by Solomon (2021) is selected as

an example. The problem includes 25 demand points, horizontal and vertical coordinates (x, y) , demands, upper and lower limits of service time window and service duration. There is only one distribution center (No. 0). The number of vehicles is unlimited, and the capacity of vehicle is limited to 200. All customer points are evenly distributed in the plane coordinates of $(0, 25)^2$. The distance between distribution center and customer points and the distance between any 2 customer points are calculated by Euclidean formula, i.e., the time and distance can be converted into the same unit. According to the problem scale of 25 in this example, we set the crossover probability (p_c) of 0.9, the mutation probability (p_m) of 0.098 and the maximum iteration number of 200. Furthermore, MATLAB programming is applied to solve VRP under the broken-line soft time window and the example is tested. The comparison between the original optimal solution and the optimal solution obtained in this paper is shown in Table 2.

It can be seen from Table 2 that the optimal solution of the example dropped from 5937.2 to 4829.5, the total distribution costs decreased by 18.66%, and also, the total vehicle mileage decreased from 640.88 to 512.70, which decreased by about 20.00%. Moreover, the number of vehicles in use decreased from 7 to 5 and the number of iterations to reach the optimal solution is correspondingly reduced.

Therefore, the improved algorithm is superior to the basic algorithm in number of vehicles, road haul and total costs. In summary, the performance of the improved algorithm is superior to the traditional genetic algorithm, and the output of the algorithm is stable.

4.1.2. Experiment 2

Two examples in SET-A of CVRP test set are selected. Table 3 shows the comparison between the results of the algorithm CRO (Jiang et al., 2018) and the algorithm designed in this paper. Where bkr_{opt} represents the current optimal solution given by the standard test example, and $(bkr_{\text{opt}} - sol_{\text{best}}) / bkr_{\text{opt}} \times 100\%$ indicates the deviation.

Table 3 shows that the optimal value of one of the three calculation examples in SET-A with an average deviation of 0.48% from bkr_{opt} is calculated by CRO algorithm. However, the improved genetic algorithm designed in this paper can find two optimal solutions in three examples with an average deviation of 0.05% from bkr_{opt} .

In terms of solution accuracy, the deviation between the solution result of the improved genetic algorithm designed in this paper and bkr_{opt} is obviously small, and the algorithm can solve the optimal solution with a higher proportion, stable solution, good robustness and preferable performance.

Table 2 – Experimental result.

| Example test | Algorithm solution | Iterations to reach the optimal solution (times) | Optimal solution (sol_{best}) | Number of vehicle | Road haul | Cost gap (%) |
|--------------|-------------------------|--|--|-------------------|-----------|--------------|
| R-101 | Basic genetic algorithm | 58 | 5937.2 | 7 | 640.88 | 18.66 |
| | Improved algorithm | 37 | 4829.5 | 5 | 512.70 | |

Table 3 – Comparison of experimental result.

| Example test A-n(i)-k(j) | bkr _{opt} value | CRO (Jiang et al., 2018) | (bkr _{opt} – sol _{best})/bkr _{opt} × 100% | Improved algorithm (sol _{best}) | (bkr' _{opt} – sol' _{best})/bkr' _{opt} × 100% |
|--------------------------|--------------------------|--------------------------|---|---|--|
| A-n32-k5 | 784 | 787 | 0.38% | 784 | 0 |
| A-n33-k5 | 661 | 668 | 1.06% | 662 | 0.15% |
| A-n33-k6 | 742 | 742 | 0 | 742 | 0 |

4.2. Basic data

Owing to the disparate road conditions, the followings are the basic data of the real-world study. The coordinate values are offered in Table 4. Simultaneously, the distance and time parameters between adjacent epidemic areas are provided in Tables 5 and 6.

4.2.1. Nominal demand analysis with TFN-PERT

Wuhan, Hubei Province was one of the epidemic cities under COVID-19. Therefore, taking 14 days after the sealing city

(2020.2.8), i.e., the end node of the first incubation period of NCP, as the observation data to study.

The cold-chain emergency drugs needed in Hubei Province are shown in Table 7. To solve the mathematical model in this study, defuzzification is the first problem to be solved. As there are a mass of fuzzy indexes in this paper, the TFN theory (Triangular Fuzzy Number, a method to convert fuzzy and uncertain linguistic variables into certain values) is involved to solve the model, and the triangular fuzzy numbers are comprised of the most pessimistic value, the most probable value, and the most optimistic value. Simultaneously, PERT method is used for estimation (Taking ξ_1, ξ_0, ξ_2 as triangular fuzzy number) of nominal demands, those are shown in Table 8. The triangular fuzzy numbers are comprised of the most pessimistic value, the most probable value and the most optimistic value. PERT method is used for estimation and formula is $D_i = \frac{\xi_1 a_1 + \xi_0 a_0 + \xi_2 a_2}{6}$. a_1 almost always takes 1/6, a_0 almost always takes 4/6, and a_2 almost always takes 1/6 for defuzzification. Therefore, the nominal demand $d_{i0} = \frac{1 \times \xi_1 + 4 \times \xi_0 + 1 \times \xi_2}{6}$. It hereby, the final nominal values are acquired.

4.2.2. Urgency determination with IGRA

Combination of IGRA method based on vectorial angle cosine and Delphi method, the objective weights, and the subjective weights will be obtained. And then, the linear weighted $W_k = pC_k + (1-p)E_k$ is adopted so as to the final weights are gained (Initial matrix is as follows). Lastly, the urgency coefficient ψ_i of 17 epidemic areas shall be gained.

Table 4 – Coordinate values of the epidemic areas.

| Area i [A. i] | (X, Y) |
|---------------|------------|
| [A.1] | (473, 75) |
| [A.2] | (438, 123) |
| [A.3] | (524, 75) |
| [A.4] | (277, 61) |
| [A.5] | (540, 46) |
| [A.6] | (267, 244) |
| [A.7] | (525, 67) |
| [A.8] | (385, 209) |
| [A.9] | (474, 12) |
| [A.10] | (187, 100) |
| [A.11] | (275, 136) |
| [A.12] | (142, 310) |
| [A.13] | (17, 40) |
| [A.14] | (365, 98) |
| [A.15] | (339, 69) |
| [A.16] | (390, 60) |
| [A.17] | (129, 206) |

Table 5 – Distance between two adjacent areas (km) (Source of data: Baidu Map API open platform).

| i | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1 | – | 73 | 74 | 222 | 98 | 313 | 78 | 170 | 93 | 322 | 240 | 441 | 519 | 141 | 155 | 101 | 536 |
| 2 | 73 | – | 139 | 247 | 163 | 258 | 143 | 115 | 146 | 320 | 220 | 386 | 518 | 121 | 181 | 127 | 481 |
| 3 | 74 | 139 | – | 307 | 46 | 379 | 14 | 237 | 131 | 408 | 313 | 507 | 605 | 214 | 241 | 187 | 603 |
| 4 | 222 | 247 | 307 | – | 303 | 204 | 278 | 262 | 237 | 115 | 91 | 364 | 313 | 126 | 73 | 126 | 411 |
| 5 | 98 | 163 | 46 | 303 | – | 403 | 34 | 260 | 98 | 412 | 333 | 531 | 609 | 257 | 245 | 191 | 626 |
| 6 | 313 | 258 | 379 | 204 | 403 | – | 384 | 169 | 397 | 251 | 132 | 171 | 448 | 264 | 266 | 319 | 287 |
| 7 | 78 | 143 | 14 | 278 | 34 | 384 | – | 240 | 119 | 396 | 317 | 511 | 593 | 218 | 229 | 175 | 606 |
| 8 | 170 | 115 | 237 | 262 | 260 | 169 | 240 | – | 254 | 320 | 220 | 289 | 518 | 157 | 198 | 213 | 391 |
| 9 | 93 | 146 | 131 | 237 | 98 | 397 | 119 | 254 | – | 340 | 302 | 525 | 537 | 186 | 173 | 119 | 620 |
| 10 | 322 | 320 | 408 | 115 | 412 | 251 | 396 | 320 | 340 | – | 122 | 352 | 241 | 225 | 172 | 225 | 367 |
| 11 | 240 | 220 | 313 | 91 | 333 | 132 | 317 | 220 | 302 | 122 | – | 291 | 323 | 149 | 151 | 204 | 355 |
| 12 | 441 | 386 | 507 | 364 | 531 | 171 | 511 | 289 | 525 | 352 | 291 | – | 552 | 408 | 425 | 463 | 187 |
| 13 | 519 | 518 | 605 | 313 | 609 | 448 | 593 | 518 | 537 | 241 | 323 | 552 | – | 427 | 373 | 423 | 564 |
| 14 | 141 | 121 | 214 | 126 | 257 | 264 | 218 | 157 | 186 | 225 | 149 | 408 | 427 | – | 61 | 75 | 486 |
| 15 | 155 | 181 | 241 | 73 | 245 | 266 | 229 | 198 | 173 | 172 | 151 | 425 | 373 | 61 | – | 62 | 472 |
| 16 | 101 | 127 | 187 | 126 | 191 | 319 | 175 | 213 | 119 | 225 | 204 | 463 | 423 | 75 | 62 | – | 525 |
| 17 | 536 | 481 | 603 | 411 | 626 | 287 | 606 | 391 | 620 | 367 | 355 | 187 | 564 | 486 | 472 | 525 | – |

$$I = \begin{pmatrix} 9 & 5 & 7 & 3 & 1 & 3 & 7 & 5 & 3 & 5 & 7 & 1 & 3 & 7 & 5 & 5 & 1 \\ 1121 & 492 & 633 & 557 & 271 & 568 & 106 & 222 & 255 & 414 & 290 & 340 & 402 & 125 & 97 & 153 & 7.6 \\ 1498 & 2436 & 2141 & 997 & 760 & 988 & 639 & 984 & 493 & 711 & 663 & 467 & 379 & 171 & 82 & 379 & 171 \\ 4 & 1 & 2 & 1 & 0.3 & 0.7 & 3.3 & 0.9 & 0.8 & 1.1 & 2.9 & 0 & 0 & 5 & 2.4 & 1.3 & 0 \\ 9 & 7 & 7 & 7 & 3 & 7 & 7 & 5 & 3 & 5 & 5 & 3 & 3 & 5 & 3 & 3 & 1 \\ 5 & 7 & 7 & 7 & 5 & 3 & 5 & 7 & 5 & 5 & 7 & 7 & 7 & 5 & 3 & 5 & 3 \end{pmatrix}^T \tag{16}$$

For the sake of reflecting fully the epidemic situation in various cities of Hubei Province and ensuring the efficiency of distribution tasks, severity of the epidemic, number of NCP infections, death rate of NCP, degree of shortage and difficulty for transportation are all regarded as the evaluation indexes (Table 9) of the urgency. The permanent resident population is acquired from the demographic analysis network. The number of infections and the mortality rate (%) are obtained from the announcement of the Hubei Provincial Health Commission and relevant news reports.

The crucial parameters of the code and the running results (Table 10) are as follows.

$$(a) r_{jk} = uo_{jk} / \left\{ \max_j \{uo_{jk}\} - \min_j \{uo_{jk}\} \right\}$$

% % Ratio of the deviation.

(b) O is the normalized matrix, and the normalized method is shown below.

$$o_{jk} = i_{jk} / \max_j \{i_{1k}, i_{2k}, \dots, i_{mk}\}$$

$$(c) m_{jk} = lo_{jk} / \left\{ \max_j \{uo_{jk}\} - \min_j \{uo_{jk}\} \right\}$$

% % Deviation rate of inferior quality.

$$(d) \maxuo = \max\{\max\{UO\}\}$$

% % Optimal maximum deviation of two-stage Δ_{\max}^u .

$$(e) \minuo = \min\{\min\{UO\}\}$$

% % The two-order minimum of the optimal deviation Δ_{\min}^u .

$$(f) \maxlo = \max\{\max\{LO\}\}$$

% % The two-order maximum of the inferiority deviation Δ_{\max}^l .

$$(g) \minlo = \min\{\min\{LO\}\}$$

% % The two-order minimum of the inferior deviation Δ_{\min}^l .

$$(h) qq = \minuo + p \times \maxuo$$

% % The molecular of coefficient of superior correlation λ_{uj} .

$$(i) ww = UO + p \times \maxuo$$

% % The denominator of coefficient of superior correlation λ_{uj} .

$$(j) qq_1 = \minlo + p \times \maxlo$$

% % The molecular of coefficient of inferior correlation λ_{ij} .

$$(k) ww_1 = LO + p \times \maxlo$$

% % The denominator of coefficient of inferior correlation λ_{ij} .

The priority distribution shall be known for some areas with high urgency coefficient ψ_i and it is $1 \rightarrow 3 \rightarrow 7 \rightarrow 2 \rightarrow 11 \rightarrow 4 \rightarrow 14 \rightarrow 13 \rightarrow 10 \rightarrow 8 \rightarrow 6 \rightarrow 12 \rightarrow 16 \rightarrow 15 \rightarrow 9 \rightarrow 5 \rightarrow 17$.

Table 6 – Arrival time between two adjacent areas (min) (Source of data: Baidu Map API open platform).

| i | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1 | – | 68 | 73 | 188 | 87 | 220 | 73 | 132 | 90 | 257 | 179 | 303 | 431 | 119 | 144 | 102 | 445 |
| 2 | 68 | – | 122 | 196 | 137 | 183 | 125 | 94 | 117 | 243 | 179 | 266 | 417 | 119 | 147 | 116 | 408 |
| 3 | 73 | 122 | – | 226 | 63 | 271 | 30 | 178 | 119 | 298 | 228 | 355 | 474 | 168 | 183 | 151 | 494 |
| 4 | 188 | 196 | 226 | – | 209 | 141 | 199 | 185 | 166 | 90 | 73 | 253 | 264 | 95 | 54 | 89 | 361 |
| 5 | 87 | 137 | 63 | 209 | – | 283 | 42 | 192 | 94 | 289 | 239 | 370 | 467 | 186 | 174 | 142 | 507 |
| 6 | 220 | 183 | 271 | 141 | 283 | – | 286 | 128 | 286 | 186 | 107 | 134 | 363 | 187 | 188 | 223 | 282 |
| 7 | 73 | 125 | 30 | 199 | 42 | 286 | – | 175 | 100 | 280 | 226 | 356 | 467 | 165 | 162 | 129 | 496 |
| 8 | 132 | 94 | 178 | 185 | 192 | 128 | 175 | – | 188 | 231 | 164 | 213 | 417 | 126 | 150 | 160 | 351 |
| 9 | 90 | 117 | 119 | 166 | 94 | 286 | 100 | 188 | – | 240 | 208 | 360 | 426 | 135 | 122 | 90 | 501 |
| 10 | 257 | 243 | 298 | 90 | 289 | 186 | 280 | 231 | 240 | – | 107 | 281 | 222 | 166 | 126 | 161 | 341 |
| 11 | 179 | 179 | 228 | 73 | 239 | 107 | 226 | 164 | 208 | 107 | – | 214 | 286 | 110 | 113 | 148 | 329 |
| 12 | 303 | 266 | 355 | 253 | 370 | 134 | 356 | 213 | 360 | 281 | 214 | – | 456 | 294 | 296 | 321 | 208 |
| 13 | 431 | 417 | 474 | 264 | 467 | 363 | 467 | 417 | 426 | 222 | 286 | 456 | – | 332 | 289 | 323 | 525 |
| 14 | 119 | 119 | 168 | 95 | 186 | 187 | 165 | 126 | 135 | 166 | 110 | 294 | 332 | – | 57 | 66 | 406 |
| 15 | 144 | 147 | 183 | 54 | 174 | 188 | 162 | 150 | 122 | 126 | 113 | 296 | 289 | 57 | – | 48 | 400 |
| 16 | 102 | 116 | 151 | 89 | 142 | 223 | 129 | 160 | 90 | 161 | 148 | 321 | 323 | 66 | 48 | – | 438 |
| 17 | 445 | 408 | 494 | 361 | 507 | 282 | 496 | 351 | 501 | 341 | 329 | 208 | 525 | 406 | 400 | 438 | – |

Table 7 – Cold-chain emergency drugs of Hubei Province (list four).

| Name of drug | Category | Storage condition (°C) |
|--|--------------------------|------------------------|
| c ₁ (recombinant bovine basic fibroblast growth factor eye gel) | Etology drugs/skin drugs | 2–8 |
| c ₂ (intravenous injection of human immunoglobulin (pH4)) | Biological products | 2–8 |
| c ₃ (bifidobacterium and Lactobacillus triple live tablet) | Microecological medicine | 2–8 |
| c ₄ (insulin injection) | Insulin | 2–8 |

Table 8 – Nominal demand (units) based on TFN-PERT (turn uncertainty into certainty by β_{d_2} , \hat{d}_i).

| Area i [A. i] | \hat{d}_{i0} (units) |
|---------------|------------------------|
| [A.1] | 14.36 |
| [A.2] | 5.93 |
| [A.3] | 5.01 |
| [A.4] | 2.37 |
| [A.5] | 2.10 |
| [A.6] | 2.01 |
| [A.7] | 2.18 |
| [A.8] | 2.19 |
| [A.9] | 2.20 |
| [A.10] | 2.21 |
| [A.11] | 1.99 |
| [A.12] | 1.92 |
| [A.13] | 2.10 |
| [A.14] | 1.52 |
| [A.15] | 1.39 |
| [A.16] | 1.68 |
| [A.17] | 0.18 |
| Sum | 51.43 |

Table 9 – Fuzzy evaluation index.

| Epidemic area site i | Severity of epidemic (level) | Permanent resident population (10 ⁴) | Number of infections | Mortality rate (%) | Material shortage degree | Difficulty of material transportation |
|----------------------|------------------------------|--|----------------------|--------------------|--------------------------|---------------------------------------|
| Wuhan | Very serious | 1121.20 | 14,982 | 4.06 | Very serious | General |
| Xiaogan | General | 492.10 | 2436 | 1.19 | Serious | Difficult |
| Huanggang | Serious | 633.30 | 2141 | 2.01 | Serious | Difficult |
| Jingzhou | Slight | 557.01 | 997 | 1.30 | Serious | Difficult |
| Huangshi | Very slight | 270.83 | 760 | 0.26 | Slight | General |
| Xiangyang | Slight | 568.00 | 988 | 0.71 | Serious | Easy |
| Ezhou | Serious | 105.97 | 639 | 3.29 | Serious | General |
| Suizhou | General | 222.1 | 984 | 0.91 | General | Difficult |
| Xianning | Slight | 254.84 | 493 | 0.81 | Slight | General |
| Yichang | General | 413.79 | 711 | 1.13 | General | General |
| Jingmen | Serious | 289.75 | 663 | 2.87 | General | Difficult |
| Shiyan | Very slight | 339.80 | 467 | 0.00 | Slight | Difficult |
| Enshi | Slight | 402.10 | 379 | 0.00 | Slight | Difficult |
| Tianmen | Serious | 124.74 | 171 | 5.08 | General | General |
| Qianjiang | General | 96.61 | 82 | 2.44 | Slight | Easy |
| Xiantao | General | 152.92 | 379 | 1.32 | Slight | General |
| Shennongjia | Very slight | 7.61 | 10 | 0.00 | Very slight | Easy |

4.3. Algorithm

GA was first proposed by Professor Holland from University of Michigan in 1975. In order to solve the non-inferior solution set of multi-objective optimization, NSGA came into being. The grey system was first proposed by Julong Deng, a professor of control science and engineering, the GRA is a method to measure the correlation degree between factors according to the similarity or difference degree of the development trend among factors, i.e., the “grey correlation degree”. In this study, a hybrid algorithm NSGA-IGRA was adopted to solve the model, which combined with multi-objective genetic algorithm and improved grey relative analysis method, and the optimization process was realized with two stages.

a) Phase 1 ($\psi_i = 0$ /same)

STEP 1: Set initial parameters and initialize the population
 STEP 2: $\psi_i = 0$, $n = 1$, the initial Pareto non-inferior solution set is obtained

b) Phase 2 (different ψ_i)

STEP 1: The new $\psi_i = a$ were obtained.
 STEP 2: A new nondominated solution set was gained by running.

GA is a heuristic algorithm, which is more suitable for practical problems. Therefore, this paper uses genetic algorithm to solve the VRP of CEM. The universality and robustness of this algorithm are superior, and the process of multi-objective genetic algorithm is shown in Fig. 3.

4.4. Results and discussion

4.4.1. Robust optimization solution without considering the urgency

Fig. 4 shows the distribution curve when the model is iterated 200 times. It clearly can be seen that robustness and cost are negatively correlated, i.e., provided the robustness increases, the optimality decreases. Also, the total costs are generally between 22,000 units and 34,000 units. In this paper, the

Table 10 – ψ_i coefficient value.

| Area i [A. i] | ψ_i value |
|---------------|----------------|
| [A.1] | 0.846 |
| [A.2] | 0.515 |
| [A.3] | 0.594 |
| [A.4] | 0.467 |
| [A.5] | 0.195 |
| [A.6] | 0.294 |
| [A.7] | 0.525 |
| [A.8] | 0.303 |
| [A.9] | 0.237 |
| [A.10] | 0.330 |
| [A.11] | 0.509 |
| [A.12] | 0.274 |
| [A.13] | 0.349 |
| [A.14] | 0.418 |
| [A.15] | 0.238 |
| [A.16] | 0.265 |
| [A.17] | 0.114 |

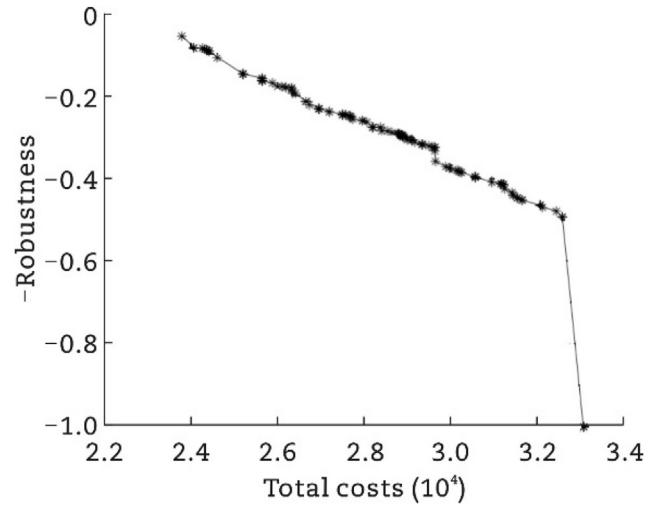


Fig. 4 – Two-dimensional display of Pareto solution.

maximization of robustness and the minimization of total costs are regarded as objective function plus the opposite change directions. The representative Pareto solutions are used for discussing as follows in Fig. 5, and the optimal distribution routes obtained from each solution with high

costs or high robustness are selected, respectively. Different colors in Fig. 5 present routes of different vehicles.

Based on the above results, the Pareto solution set is classified into the optimal (a), the suboptimal (b), the second suboptimal (c) and the third suboptimal (d) solutions

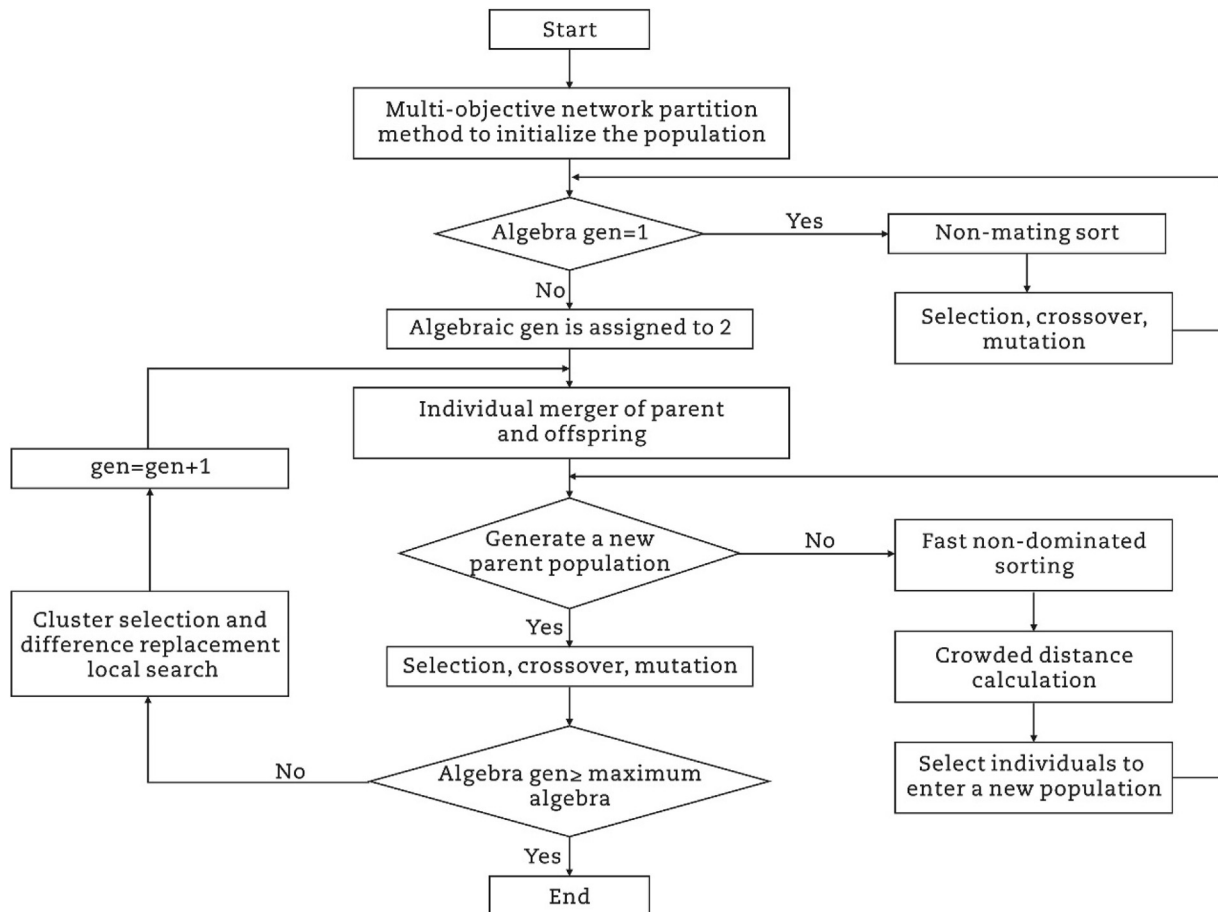


Fig. 3 – Operation process of NSGA to solve MOP.

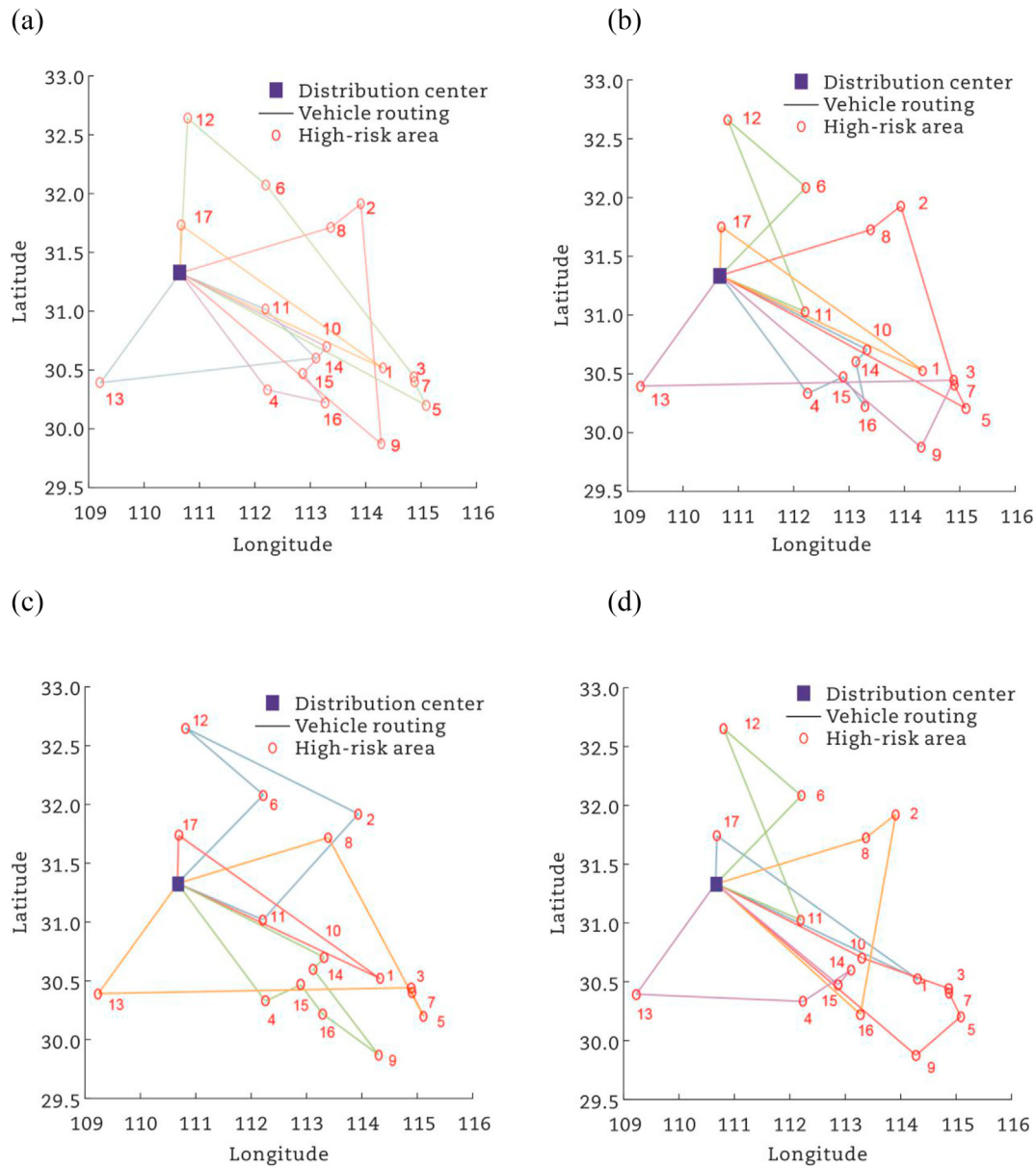


Fig. 5 – Dispatching routes. (a) Path of optimal delivery solution, scheme (a), $C = 24,337$, $-R = -0.0161$. (b) Path of optimal delivery solution, scheme (b), $C = 27,580$, $-R = -0.2554$. (c) Path of optimal delivery solution, scheme (c), $C = 29,224$, $-R = -0.3502$. (d) Path of optimal delivery solution, scheme (d), $C = 28,825$, $-R = -0.3090$.

respectively for the perspective of $\min\{C\}$, also, the corresponding C values and distribution routings are analyzed in Tables 11 and 12. All of (a), (b), (c) schemes use 5 vehicles, and the total driving time are 20,758, 20,804 and 20,400 min, respectively. For scheme (d), the total driving time is 23,598 min when 7 vehicles are in use, whereas, 20,818 min when 5 vehicles are in use.

Analysis of a_i^k (take k_1 of scheme (a) as an example) vehicle k_1 starts from the distribution center O , which unloads and rests after arriving at epidemic area 13, and the departure time from 13 to 14 is 468 min. After arriving at epidemic area 14, the

vehicle unloads and rests again, the departure time from 14 to 15 is 852 min. Then, the vehicle also unloads and rests after arriving at epidemic area 15 and the starting time from 15 to 11 is 1007 min. After arriving at epidemic area 11, the vehicle unloads and rests as well, ultimately, the departure time of returning to the distribution center O from point 11 is 1289 min.

It can be seen from Table 12, the scheme (c) and scheme (d) with higher robustness are regarded as the optimal scheme and suboptimal scheme, which the robustness are 0.3502 and 0.3090, respectively. Nevertheless, the robustness of

Table 11 – Pareto solution analysis 1 for perspective of min{C} (no priority distribution).

| Level of scheme | Total cost value C | Path selection (i→j) | Departure time from each epidemic site a_i^k (min) |
|-----------------------|--------------------|----------------------|---|
| Optimal (a) | 24,337 | 0 → 13→14 → 11→0 | 468 ₁₃ ¹ ⇒ 852 ₁₄ ¹ ⇒ 1007 ₁₁ ¹ ⇒ 1289 ₀ ¹ |
| | | 0 → 8→2 → 9→0 | 381 ₈ ² ⇒ 534 ₂ ² ⇒ 732 ₉ ² ⇒ 1255 ₀ ² |
| | | 0 → 5→7 → 3→6 → 12→0 | 683 ₅ ³ ⇒ 776 ₇ ³ ⇒ 864 ₃ ³ ⇒ 1212 ₆ ³ ⇒ 1402 ₁₂ ³ ⇒ 1976 ₀ ³ |
| | | 0 → 17→1 → 0 | 409 ₁₇ ⁴ ⇒ 894 ₁ ⁴ ⇒ 1700 ₀ ⁴ |
| | | 0 → 4→16 → 15→10 → 0 | 417 ₄ ⁵ ⇒ 560 ₁₆ ⁵ ⇒ 655 ₁₅ ⁵ ⇒ 825 ₁₀ ⁵ ⇒ 1083 ₀ ⁵ |
| Suboptimal (b) | 27,580 | 0 → 4→15 → 16→ | 417 ⇒ 525 ⇒ 617 ⇒ 730 ⇒ 941 ⇒ 1199 |
| | | 14 → 10→0 | |
| | | 0 → 5→7 → 2→8 → 0 | 683 ⇒ 776 ⇒ 959 ⇒ 1134 ⇒ 1515 |
| | | 0 → 6→12 → 11→0 | 536 ⇒ 726 ⇒ 991 ⇒ 1273 |
| | | 0 → 17→1 → 0 | 409 ⇒ 894 ⇒ 1700 |
| Second suboptimal (c) | 29,224 | 0 → 13→3 → 9→0 | 468 ⇒ 994 ⇒ 1190 ⇒ 1713 |
| | | 0 → 6→12 → 2→11 → 0 | 536 ⇒ 726 ⇒ 1043 ⇒ 1303 ⇒ 1585 |
| | | 0 → 17→1 → 0 | 409 ⇒ 894 ⇒ 1700 |
| | | 0 → 4→15 → 16→9 | 417 ⇒ 525 ⇒ 617 ⇒ 754 ⇒ 940 ⇒ 1151 ⇒ 1409 |
| | | →14 → 10→0 | |
| Third suboptimal (d) | 28,852 | 0 → 8→5 → 7→3 → 13→0 | 381 ⇒ 632 ⇒ 725 ⇒ 813 ⇒ 1364 ⇒ 1832 |
| | | 0 → 6→12 → 11→10 → 0 | 536 ⇒ 726 ⇒ 991 ⇒ 1150 ⇒ 1408 |
| | | 0 → 4→14 → 16→15 → 0 | 417 ⇒ 566 ⇒ 677 ⇒ 772 ⇒ 1072 |
| | | 0 → 17→1 → 0 | 409 ⇒ 894 ⇒ 1700 |
| | | 0 → 2→3 → 8→0 | 621 ⇒ 824 ⇒ 1079 ⇒ 1460 |
| | | 0 → 13→5 → 1→7 → 0 | 468 ⇒ 987 ⇒ 1080 ⇒ 1238 ⇒ 1761 |

scheme (a) is the lowest as the third suboptimal scheme. The best transportation routings can be chosen for preference decision-makers with maximizing robustness.

In summary, the optimality of schemes (a) and (b) is more superior and the robust rate is lower, the optimality of schemes (c) and (d) is more inferior, yet, the robust rate is higher. Therefore, the optimal plan should be chosen for the decision-makers with the lowest cost or the highest robustness, and the robust optimization model can be used to realize the allocation scheme with high robustness when only the range information of factors is known.

4.4.2. Robust optimization solution considering the urgency

Fig. 6(a) shows the distribution curve when the model is iterated to 200 times with consideration of the demand urgency, which also shows that there is a negative correlation between robustness and costs, and the costs are almost always between 22,000 units and 33,000 units. As shown in Fig. 6(b), scheme (b) is the optimal distribution plan when priority distribution is considered plus the robust rate of 0.4813, which has strong robustness. Different colors in Fig. 6(b) present routes of different vehicles. The total

costs are 27,289, which are lower, i.e., the robustness rate increases with the reduction of the cost. The number of vehicles in use is 5, and the total driving time is 20,489 min. The routings are shown in Table 13.

As the distribution order has been determined in the case of taking into consideration of the demand urgency for epidemic areas, all the running results corresponding to Pareto solutions are the same, and the distribution path is unique.

4.4.3. Comparison of considering urgency or not

The results in Table 14 above, the average costs are 28,911.26 units without taking into consideration of the demand urgency for epidemic areas and 27,609.85 units under the circumstances of considering the priority distribution, respectively, the value declines 4.51%. And the average robustness is 0.25706 without taking into account the demand urgency of epidemic areas and 0.28710 in the case of considering the priority distribution, respectively, the value rises 11.69%. The cost reduced slightly and the robustness rate increased due to the pre-estimation of the difference in demands of the epidemic areas and the attention to the difference in demands of different regions in the case of priority distribution, i.e., the total costs of the distribution scheme decrease and the robustness increases when the demand urgency of each epidemic area is taken into account.

In simple terms, the solution considering the emergency degree is better and more robust. The robustness rate R is the main objective of this study and the minimizing the transportation time T is the most urgent factor of materials support during the epidemic period under COVID-19. Accordingly, the

Table 12 – Pareto solution analysis 2 for perspective of max{R} (no priority distribution).

| Level of scheme | Robustness value R |
|-----------------------|--------------------|
| Optimal (c) | 0.3502 |
| Suboptimal (d) | 0.3090 |
| Second suboptimal (b) | 0.2554 |
| Third suboptimal (a) | 0.0161 |

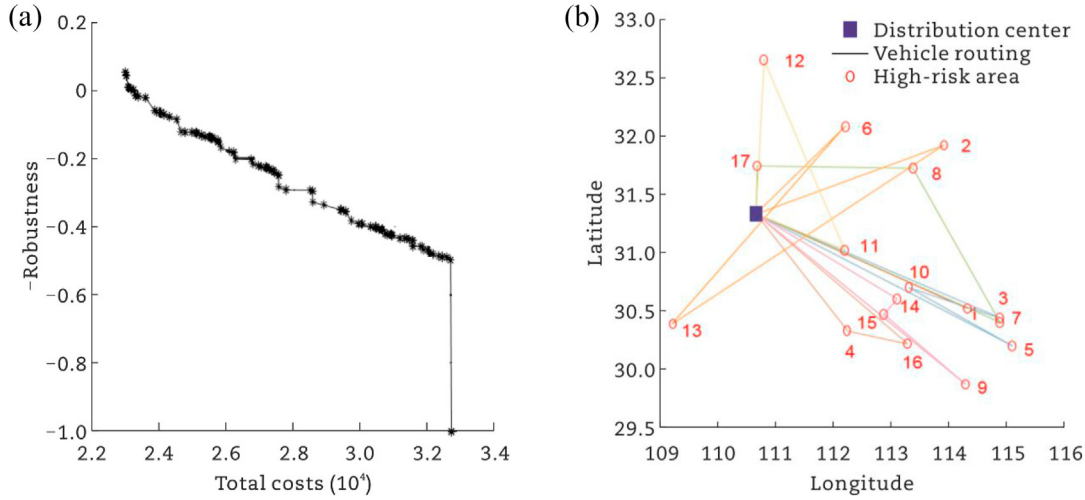


Fig. 6 – Pareto solution (priority delivery) and routing. (a) Pareto solution, Pareto front (priority delivery). (b) Optimal path (with urgency), scheme (b), $C = 27,289$, $-R = -0.4813$.

relationship of R-T and other four sub-costs are visually shown by laying out the three-dimensional graphs in Fig. 7. The physical consumption cost of patients W, the psychological burden of deliverymen when entered high-risk areas B, the additional carbon trading costs generated by carbon emissions P and the efficacy loss value V, namely the relationship between the three sub-objective functions R-T-W, T-R-P, V-T-R, T-B-R, respectively.

4.4.4. Objective function results without considering robustness

The running result of the optimal solution of the CEM scheduling and distribution scheme in MATLAB under the condition that without considering priority distribution is as follows.

(a) Results without considering robustness and urgency

The total objective function value

$$\begin{aligned}
 f_{\text{Total Object}} &= Z_1^{\text{ServiceT}} + Z_2^{\text{punish}} + Z_3^{\text{LOSE}} + Z_4^{\text{Psy}} + Z_5^{\text{CE}} \\
 &= \sum_{i \neq j, i, j \in N, k \in K} \left[t_{ij} + \frac{d_{oi} r_{ki}}{v_{oi}} + x_{ijk} (A_i^{1r} + A_i^{2r}) \right] + Z_2^{\text{punish}} \\
 &+ x_{ijk} \left[\frac{\eta}{1 + \eta T_{1,0}^{\text{LOSE}}} (T_{1,0}^{\text{LOSE}})^2 - t_i^2 \right] \sum_{i, j \in N, k \in K} [\rho_1 (1 - \xi) (T_{ijk} - T_b) + \rho_2 \xi (T_a - T_{ijk})] \\
 &+ \sum_{i \in N} Z_4^i + \sum_{i, j \in N, k \in K} \left[\frac{\pi_{\text{full}} + \pi_0 (B_{\text{max}}^k - B_1^k)}{B_{\text{max}}^k} \right] \epsilon_{\text{CO}_2}^k d_{ijk} N_k x_{ijk} \\
 &= 31,267.2020 \text{ units}
 \end{aligned} \tag{17}$$

$$\begin{aligned}
 f_{\text{Total Object}} &= \left\{ \sum_{i \neq j, i, j \in N, k \in K} \left[t_{ij} + \frac{d_{oi} r_{ki}}{v_{oi}} + x_{ijk} (A_i^{1r} + A_i^{2r}) \right] + \sum_{i, j \in N, k \in K} \left[\frac{\pi_{\text{full}} + \pi_0 (B_{\text{max}}^k - B_1^k)}{B_{\text{max}}^k} \right] \epsilon_{\text{CO}_2}^k d_{ijk} N_k x_{ijk} \right\} \\
 &+ x_{ijk} \left[\frac{\eta}{1 + \eta T_{1,0}^{\text{LOSE}}} (T_{1,0}^{\text{LOSE}})^2 - t_i^2 \right] \sum_{i, j \in N, k \in K} [\rho_1 (1 - \xi) T_{ijk} - T_b + \rho_2 \xi (T_a - T_{ijk})] \\
 &+ Z_2^{\text{punish}} + \sum_{i \in N} Z_4^i \\
 &= 29,432.61 \text{ units}
 \end{aligned} \tag{18}$$

(b) Results with considering urgency but not robust

The total objective function value is shown as Eq. (18).

It can be seen from Table 15 that the results of the two functions without considering the robustness are obviously different. The dispatching scheme with considering the urgency is better than the dispatching scheme under the condition of not considering it, i.e., the cost will be reduced to a certain extent.

4.4.5. Comprehensive comparison

Table 16 is a comparative analysis of the scheduling schemes under various computing scenarios with respect to cost. To sum up, the scheduling scheme of considering the demand urgency under the premise of robust optimization is the optimum with the lowest cost and high robustness, i.e., the scheme [1'1''] is the optimal solution. However, the scheduling scheme without considering robust optimization and the urgency is the inferior, which cost is the highest, i.e., the scheme [2'2''] is the inferior.

4.4.6. Scheduling scheme of more vehicles

As the severity of the epidemic rises and the number of infection increases, the demand for cold-chain medical

Table 13 – Pareto solution analysis 2 for optimal scheme (e) (with urgency).

| Path selection (i → j) | Departure time from each epidemic site a_i^k (min) |
|---|--|
| 0 → 6 → 12 → 14 → 8 → 0 (k_1) | 536 ⇒ 726 ⇒ 1071 ⇒ 1242 ⇒ 1623 |
| 0 → 13 → 11 → 0 (k_2) | 468 ⇒ 806 ⇒ 1088 |
| 0 → 4 → 16 → 2 → 10 → 0 (k_3) | 417 ⇒ 560 ⇒ 723 ⇒ 1047 ⇒ 1305 |
| 0 → 17 → 1 → 0 (k_4) | 409 ⇒ 894 ⇒ 1700 |
| 0 → 9 → 7 → 3 → 5 → 15 → 0 (k_5) | 523 ⇒ 674 ⇒ 762 ⇒ 902 ⇒ 1127 ⇒ 1427 |

Table 14 – Comparison discussion.

| Objective function | No priority delivery (no urgency) | Consider priority delivery (with urgency) | Rate of change (%) |
|--------------------|-----------------------------------|---|--------------------|
| Average value of C | 28,911.26 | 27,609.85 | -4.51 |
| Average value of R | 0.25706 | 0.28710 | 11.69 |

materials in various medical institutions will continuously augment so that more vehicles are needed to provide support for material distribution to the risk areas. Therefore, the following results is obtained with the scheduling scheme for more vehicles. The results are shown in Fig. 8.

Fig. 8(a) shows the distribution curve when the model is iterated to 200 times without demand urgency, which shows that there is a negative correlation between robustness and costs. As shown in Fig. 8(b), the scheme is the optimal distribution plan when priority distribution is not considered, plus the robustness of 0.4256, which has strong robustness. The number of vehicles in use is 10, and the total driving time is 24,638 min. Then, Fig. 8(c) also presents the distribution curve when the model is iterated to 200 times with demand urgency. The scheme in Fig. 8(d) is the optimal distribution plan when priority distribution is considered plus the robustness of 0.4961, which has strong robustness. Different colors in Fig. 8(b) and (d) present routes of different vehicles. The number of vehicles in use is 10, and the total driving time is 23,194 min. In summary, the scheduling scheme is better when the demand urgency of each epidemic area is considered from the perspective of robustness.

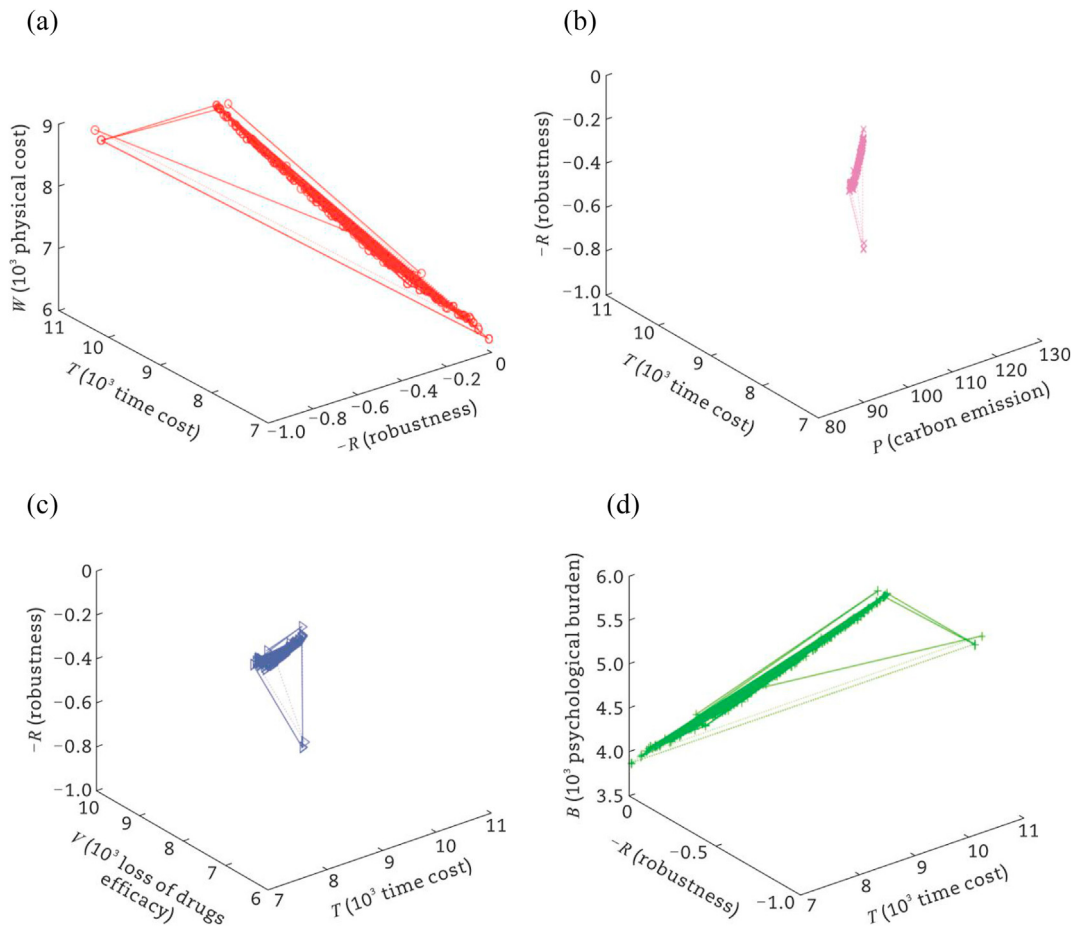


Fig. 7 – Relationship of sub-objectives. (a) R-T-W. (b) T-R-P. (c) V-T-R. (d) T-B-R.

Table 15 – Comparison discussion.

| Situation | No robustness or urgency | No robustness but urgency | Rate of change (%) |
|--------------------------|--------------------------|---------------------------|--------------------|
| Objective function value | 33,267.2020 | 29,432.6100 | -11.53 |

Table 16 – Cost comparison in different computing scenarios.

| Scenario of solution | [1'] consider robustness | [2'] no robustness | Amplitude of variation (%) |
|-----------------------------|--------------------------|--------------------|----------------------------|
| [1'] consider urgency | [1'1'] 27,609.8500 | [2'1'] 29,432.6100 | -6.6018 |
| [2'] no urgency | [1'2'] 28,911.2604 | [2'2'] 33,267.2020 | -15.0666 |
| Proportion of variation (%) | -4.5014 | -13.0284 | - |

5. Conclusions and limitations

In this study, the problems exposed in emergency logistics system of China and the shortcomings of dispatching for the cold-chain emergency medicine under the COVID-19 were summarized. For VRP with a soft time window, the authors

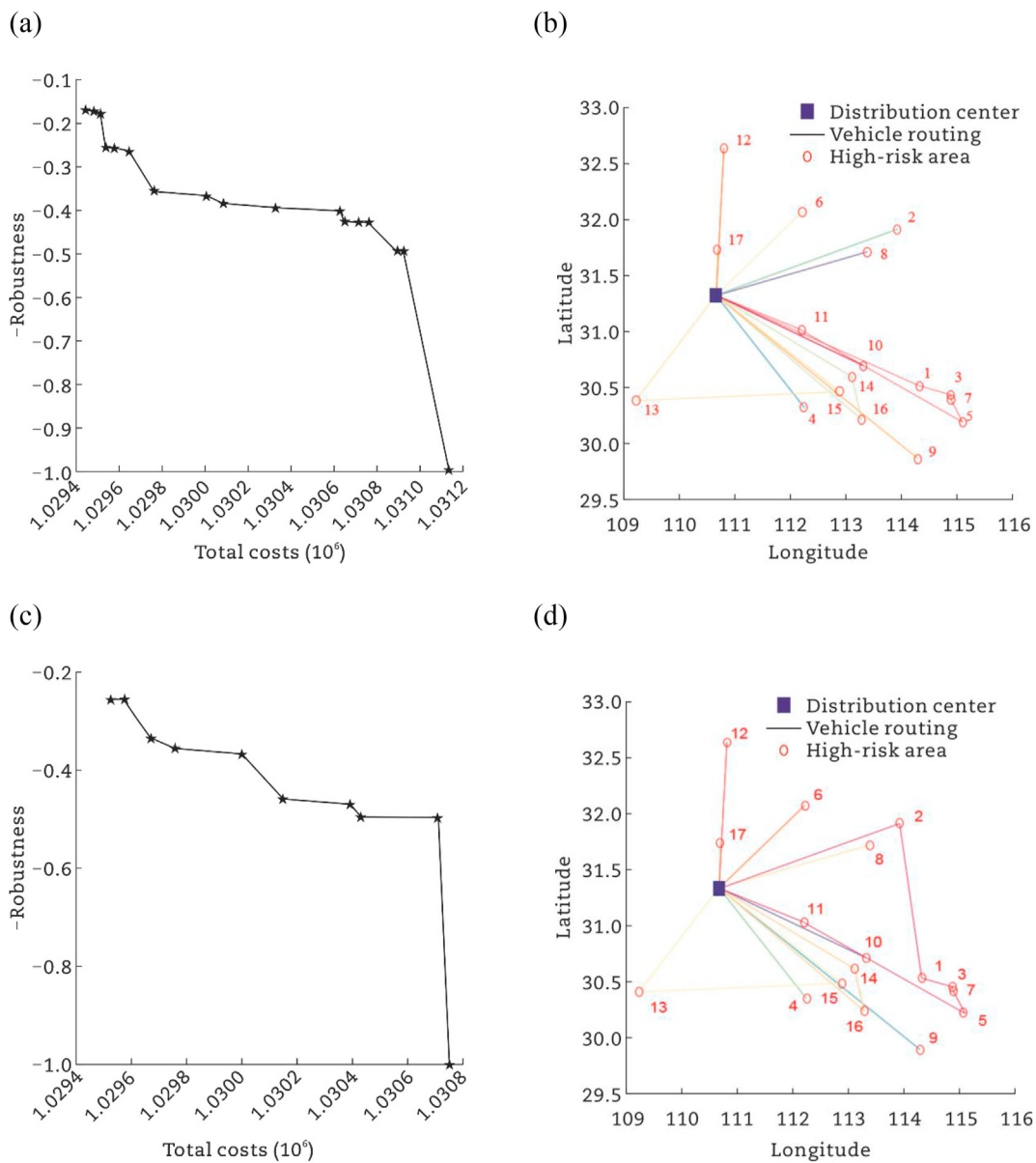


Fig. 8 – Pareto solution and routing (10 vehicles). (a) Pareto front (no urgency). (b) $-R = -0.4256$ (overall time is 24,638 min). (c) Pareto front (with urgency). (d) $-R = -0.4961$ (overall time is 23,194 min).

have comprehensively considered such factors as the psychological burden and panic of deliverers entering the epidemic area of high-risk infectious diseases, the uncertainty of cold-chain drug delivery time and demand, the deviation of efficacy caused by emergencies in distribution process, the robustness of the solution and other characteristics, etc., with the goal of maximizing the robustness rate and minimizing the total costs. The robust optimization scheduling model and distribution system for urban CEM under major public health emergencies were redesigned and verified, and the results has shown both the effectiveness and applicability of model. Also, the initial optimal schemes were compared with the optimal route scheme with considering priority distribution, and the consequence demonstrates that the total costs with considering demand urgency are lower and the robustness rate is stronger.

- (1) The timeliness (minimum time), robustness (maximum robust rate), high-efficiency (psychological burden of deliverymen), economy (total costs), environmental protection (policy of carbon emission reduction) and precision of distribution (demand urgency) were taken into account synthetically in the abovementioned model, and the minimization of carbon costs conforms to policies of carbon emissions and carbon trading of country, which actively responds to the environment-friendly society. Also, the psychological panic burden of deliverymen entering high-risk areas has been a momentous research objective with the high infectivity of COVID-19.
- (2) The robustness of Pareto solution is limited by the surplus of vehicle-borne and the surplus of arrival time, also, the robustness is redefined based on the uncertainty of factors. The results verify the accuracy.
- (3) NSGA-IGRA is designed as a hybrid algorithm to solve the robust optimization model for cold-chain emergency supplies scheduling, which can find out the robust solution of Pareto solution set comprised of the optimal and sub-optimal, the research results demonstrate that the average costs of the distribution schemes considering the demand urgency is slightly reduced by 4.51% compared with the initial scheme, and robustness increases by 11.69%. Accordingly, considering the priority distribution can not only reduce the cost slightly, but also make the robustness stronger and avoid the blindness and misalignment of the distribution effectively in practice. The findings of this study provide insights into the distribution path for CEM, the model and the joint-hybrid algorithm can be directly applied to the robust optimization of distribution path for CEM.

In summary, the dispatching of emergency supplies is regarded as a pivotal and momentous work in responding to emergencies. After all, whether the materials can be transported promptly to the needed areas directly determines the efficiency of the rescue, therefore, time is urgent, and it is of the essence. At a large-scale epidemic disease context, i.e., a COVID-19 pandemic, which is susceptible extraordinarily to infection, the psychological burden of deliverymen also is a crucial research object as well. Also, the uncertainty of

distribution time and demand of materials, the deviation of efficacy caused by emergencies in distribution process and the robustness of the solution and other characteristics, these sub-objectives are of a great research significance. Without loss of generality, the blindness and misalignment of distribution will likewise reduce the overall achievement of rescue. Consequently, it is supremely critical to conduct the reasonable and scientific dispatching for conformance to the quantity of emergency supplies and the maximum load capacity of vehicles on account of the priority distribution is considered or not. Considering the above, the model optimizes the distribution time, life consumption of patients, robustness of solution, and psychological burden of deliverymen when entering infectious regions simultaneously to research the CEM with massive demands. Therefore, not only the costs can be slightly reduced and heighten robustness, but also the blindness and misalignment of the distribution can be avoided effectively with the factor of urgency being considered. Both the model and hybrid algorithm can better complete the robust optimization for the CEM distributing. Solved by virtue of a hybrid algorithm combined Pareto genetic algorithm and the improved grey relative analysis, the numerical results manifest the viability and superiority of it, which could save computing time and iteration times than an unimproved genetic algorithm. Affirmatively, the study shall furnish promising applications for the cold-chain emergency supply and render a resultful practical decision support in case of emergency.

However, some limitations should be addressed in future work. First, the location and inventory of distribution center for CEM are not considered in order to realize a numerical model, for example, methods and algorithm of location are neglected in the current analysis, that is, a complete analysis for integration of site selection-distribution is not well presented in the literature, so one possible future goal is to apply the new frameworks to build a system for the integration of site selection-distribution, which will realize the integrity of logistics chains. In addition, the current literature also lacks algorithm comparison analysis, thus, different algorithms will be used to contrast differences as another possible goal. These are the preliminary plans and the research contents of the next stage. In simple terms, our hope is that research in this direction will help bridge the gap between theoretical soundness and the practical usefulness of the robust optimization of distribution path for CEM.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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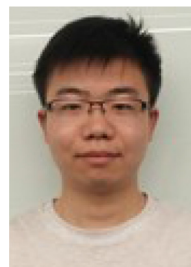
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