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Emergency medical supplies scheduling during public health emergencies: algorithm design based on AI techniques

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ABSTRACT

Based on AI technology, this study proposes a novel large-scale emergency medical supplies scheduling (EMSS) algorithm to address the issues of low turnover efficiency of medical supplies and unbalanced supply and demand point scheduling in public health emergencies. We construct a fairness index using an improved Gini coefficient by considering the demand for emergency medical supplies (EMS), actual distribution, and the degree of emergency at disaster sites. We developed a bi-objective optimisation model with a minimum Gini index and scheduling time. We employ a heterogeneous ant colony algorithm to solve the Pareto boundary based on reinforcement learning. A reinforcement learning mechanism is introduced to update and exchange pheromones among populations, with reward factors set to adjust pheromones and improve algorithm convergence speed. The effectiveness of the algorithm for a large EMSS problem is verified by comparing its comprehensive performance against a super-large capacity evaluation index. Results demonstrate the algorithm's effectiveness in reducing convergence time and facilitating escape from local optima in EMSS problems. The algorithm addresses the issue of demand differences at each disaster point affecting fair distribution. This study optimises early-stage EMSS schemes for public health events to minimise losses and casualties while mitigating emotional distress among disaster victims.

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1. Introduction

Public health emergencies inflict severe damage on public health and result in significant economic losses (Sodhi, Tang, and Willenson 2023). Emergency medical supplies scheduling (EMSS) plays a pivotal and decisive role in the effective management of disasters (Chen, Guo, and Tsui 2020; Shirazi, Kia, and Ghasemi 2021; Zhan et al. 2021). Artificial intelligence (AI) offers a novel technical solution for addressing public health emergencies (He et al. 2022; Li et al. 2021; Vishwakarma et al. 2023). Medical supply scheduling poses a significant challenge during public health emergencies. Effective allocation of medical resources is crucial in ensuring patient recovery and preventing the spread of pandemics (Boutilier and Chan 2020; Gökalp, Cakir, and Kougkoulos 2022). With the outbreak of the COVID-19 pandemic in early 2020, the emergency response of public health emergencies has become the focus of global attention (den Berg and van Essen 2019; Ding et al. 2019; Lu, Ying, and Chen 2016; Mills, Argon, and Ziya 2018), and the EMSS is particularly critical (Wang, Cui, and Fang 2023). Utilising AI in addressing the supply scheduling problem has emerged as a prominent area of research, with a particular emphasis on resolving the challenge of identifying the globally optimal solution (Chang et al. 2023a; Shrivastav 2022; Yi et al. 2022; Zhou et al. 2023).

After Wuhan announced the city's closure, people's livelihood and protective equipment relied on the government and various platforms for dispatch and distribution. How to send scarce emergency medical supplies (EMS) to the most needed places to meet the emergency needs of hospitals and citizens became the primary concern (Boutilier and Chan 2020; Ekici, Keskinocak, and Swann 2014; Jenkins, Robbins, and Lunday 2021). Emergency logistics differ from general commercial logistics, for it is a specialised activity aimed at maximising time

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benefits and minimising disaster losses caused by sudden and unpredictable factors (Wang, Yang, and Yang 2023; Wilson et al. 2016). The objective of EMSS is to accomplish prompt and efficient rescue with less emphasis on the impact of cost (Cerna et al. 2021). However, most of the disaster losses caused by the new outbreak are caused by the lack of timely and reasonable EMSS. Emergencies can lead to sudden changes in demand, insufficient stocks of medical supplies, limited transportation capacity, and shortages of raw materials (Adulyasak, Cordeau, and Jans 2014; van Lieshout, Bouman, and Huisman 2020). In order to strengthen emergency logistics management, it is necessary to optimise the rescue effect by constructing a rescue decision-making model and algorithm to help decision-makers make reasonable plans (Fukasawa et al. 2018; Nasrollahzadeh, Khademi, and Mayorga 2018). AI provides information for predictive analysis that supports complex decision-making processes (Yüksel et al. 2023).

The optimisation objective of EMSS can generally fall into the following considerations: fairness of distribution, timeliness of rescue, and economy of scheduling. As the social and economic losses in the pandemic far exceed the cost of EMSS, the impact of scheduling costs should not be emphasised. At the early stage of the pandemic, disaster relief medical supplies cannot meet the needs of all the impacted areas; the fairness of medical supplies distribution is related to the development of the disaster situation. With a focus on fairness and timeliness, we propose an algorithm to solve the multi-objective EMSS problem, where fairness is evaluated through the improved Gini coefficient, and timeliness is assessed by scheduling time. Given the varying demand for EMS in different disaster areas, this study employs the medical supply satisfaction rate to calculate the Gini index when measuring the distribution fairness of EMS (Alem, Caunhye, and Moreno 2022). The Gini coefficient is a relative index, which conforms to the principle of scale invariability and transfer, and can generally reflect the different degrees of the overall distribution. The algorithm solves the problem that the demand difference of each disaster point affects the fair distribution. The study optimises the EMSS scheme in the early stage of public health events, which can reduce the loss and casualties and appease the emotion of disaster victims. Heterogeneous ant colony algorithm (ACS-MMAS) that combines the ant colony algorithm (ACS) and max and min ant algorithm (MMAS) is used to solve the local optimal problem (Li, You, and Liu 2021). Our key finding is to show that the ACS-MMAS based on reinforcement learning mechanism is superior to ACS and MMAS in convergence speed and search efficiency and can effectively jump out of local optimum. With the increased iteration times, the HV index of ACS-MMAS has obvious advantages compared with ACS, MMAS, and NSGA-II.

The research objective of this paper is to address the optimal dispatching problem of emergency supplies. Previous vehicle path planning problems have been considered only under constrained conditions. Given the unpredictability and suddenness of emergencies, it becomes challenging to anticipate them in advance, thereby emphasising the significance of efficient emergency material dispatching. Consequently, this paper aims to investigate the following research questions:

RQ1: How can AI technology be utilized to plan the delivery vehicle route to achieve the intended goal, considering the increased complexity of medical supply scheduling, including distribution and transportation planning?

RQ2: How can AI technology be utilized to equitably allocate emergency medical resources, in conjunction with collaborative research on the distribution and routing of medical supplies, to design effective allocation strategies that minimize disaster losses?

This study contributes significantly to the literature by establishing a bi-objective optimisation model of minimum Gini coefficient and minimum scheduling time from an AI perspective while adhering to fairness and timeliness requirements. The proposed heterogeneous ant colony algorithm (ACS-MMAS) is utilised to solve the Pareto boundary. The new algorithm enhances the diversity of comprehension. Additionally, ACS-MMAS incorporates a reinforcement learning mechanism to update and exchange pheromones among populations, while reward factors are employed to adjust pheromones, thereby improving the convergence speed and search efficiency of the algorithm. Finally, the paper proposes a prioritisation-based emergency medical materials scheduling model to solve the problem of fairness and efficiency in optimising logistics. From two stages, the paper establishes a material distribution model with maximum fairness as the goal and a dual-model optimisation model with minimum dispatching time and minimum penalty cost. The two-stage model optimises EMSS protocols in the early stages of public health events, reducing losses of life and reassuring victims.

The rest of the paper proceeds as follows. Section 2 reviews prior literature on EMSS problems in emergencies. Section 3 presents our model definition and formulation. Section 4 demonstrates the proposed design of the algorithm. Section 5 shows the experimental simulation and analysis. The last section concludes the paper.

2. Literature review

EMSS can be viewed as an extension of the vehicle routing problem (VRP) in the context of emergency management. Some studies have focused on achieving a single completion of EMSS following an emergency event (Ying et al. 2023), but the demand for medical supplies is continuous for medical consumables. Lu, Ying, and Chen (2016) proposed a disaster relief supplies distribution framework based on the dynamic framework of the disaster level. The allocation of EMS resources must adhere to the principles of equity and justice while also considering the urgency of rescue operations (Liu et al. 2022).

In the early stage of an emergency, the rapid response ability and rescue effect of the emergency system mainly depends on the length of rescue time. Some studies consider the single objective optimisation of the shortest rescue time. For instance, Wan, Ye, and Peng (2023) proposed a two-pole EMS model for multi-commodity and multi-vehicle transportation, which minimises the time cost by integrating a genetic algorithm and analytic hierarchy process. Chang et al. (2023b) studied the multi-rescue point EMS model under a real-time dynamic road and realised dynamic vehicle path adjustment through an improved genetic algorithm to solve the shortest time.

Some scholars consider the shortest distance in the rescue process to improve rescue efficiency by the principle of proximity. For instance, Deng et al. (2023) examined the EMS model of a single distribution centre and multiple disaster points and proposed a concept of two-way distribution to improve the transportation efficiency of EMSS. In the early stage of the disaster, the government and the people not only care about the distribution efficiency of medical supplies but also pay attention to the fairness of rescue. Therefore, there are studies on the scheduling of EMS from a fairness perspective. For instance, Wang, Zhao, and Wu (2023) investigated a distance-based service priority strategy, which will reduce service wait times for customers farther away by giving higher service priority.

Since EMSS is a nondeterministic polynomial (NP) problem, most studies only focus on unilateral optimisation (Rautenstrauss, Martin, and Minner 2023). However, given the massive impact of emergencies, there is more than one objective to be optimised. Some studies have devoted themselves to using multi-objective optimisation technology to solve this problem. For instance, Kuo, Leung, and Yan (2023) explored three optimisation objectives: minimising driving distance, reducing delay time, and optimising vehicle utilisation. Lopes et al. (2022) combined Ant Colony Optimisation (ACO) and genetic algorithm (GA) to form a hybrid heuristic algorithm to solve a single-objective and multi-objective travelling salesman problem. Fernández Gil et al. (2023) studied the Cumulative Vehicle routing problem with time Windows (CumVRP-TW) as a variant of the vehicle routing problem that minimises the cumulative cost function while respecting customer time window constraints. Combining a saving algorithm and a 2-opt algorithm, Gao et al. (2021) developed an emergency transportation plan to achieve fairness and effectiveness. The emergency materials dispatching is summarised below, as shown in Table 1.

Due to the limited EMS stored in the city during public health emergencies, medical supplies need to be quickly dispatched to disaster-stricken areas. The existing emergency material scheduling supply chain structure is generally a three-level supply chain network only suitable for regional material scheduling (Wang et al. 2022). To deal with the excessive data requirements and high computational complexity in the new pandemic, the 'Distribution Center-Disaster Point' mode is more suitable for large-scale EMSS, which can quickly form the emergency supply chain network among cities and respond to the unified dispatching of the government. With the continuous development of AI, big data, and other technologies, new technical support has been proposed for supply chain management (Alshurideh et al. 2022; Hasan et al. 2022). The supply chain covers the entire production and distribution channel from suppliers, manufacturers, and distributors to end customers (Helo and Hao 2022). Existing research has been conducted on supply network outages to analyse their causes and improve network resilience from different AI perspectives and techniques (Liu et al. 2016; Toorajipour et al. 2021). Therefore, it is crucial to study the optimisation of medical supplies distribution in the supply chain by using manpower.

Table 1. Emergency supplies dispatch table.

Optimisation mode	Target	Method	References	Whether to consider fairness and justice
Single object optimisation	Minimum rescue time	Genetic algorithm and analytic hierarchy process	Wan, Ye, and Peng (2023)	No
		Genetic algorithm	Chang et al. (2023a)	No
	Shortest distance	Particle swarm optimisation and a genetic algorithm	Deng et al. (2023)	No
		Discrete artificial bee colony algorithms	Wang, Zhao, and Wu (2023)	No
Multi-objective optimisation	minimising driving distance, reducing delay time, and optimising vehicle utilisation	Ant colony optimisation and genetic algorithm	Lopes et al. (2022)	No
		The Greedy randomised adaptive search procedure	Fernández Gil et al. (2023)	No
		An adaptive augmented ε-constraint method	Gao et al. (2021)	Yes

The application of AI in medical supplies optimisation scheduling has achieved remarkable results (Kumar and Dimitrakopoulos 2021; Noriega and Pourrahimian 2022; Yang et al. 2021). Using AI in multi-objective optimisation of medical supplies scheduling has become possible (Petrović et al. 2022). Reinforcement learning has a good application to resource scheduling optimisation problems. The scheduling problem can be expressed as a reinforcement learning problem, and the optimal solution is found by the simulation of the reward function (Hu et al. 2020; Lin, Chen, and Hsieh 2023). AI technology in medical (Yang et al. 2021) and intelligent factories (Hu et al. 2020; Lin, Chen, and Hsieh 2023) have made excellent progress in scheduling optimisation. Overall, on the positive side, it is agreed that the use of AI and robots in logistics and production systems can speed up operations and reduce errors (such as those caused by humans), and the use of AI will also significantly improve decision-making (Dolgui and Ivanov 2022). Against this backdrop, our paper will strengthen the learning and application to solve the problem of EMSS and improve the rationality and time of medical supplies scheduling.

Based on a comparison of existing literature on emergency management, we propose the ACS-MMAS approach to address the challenge of multi-objective EMSS. ACS-MMAS refers to the ACS-MMAS proposed in this study, which is a mixture of two adaptive ACS and MMAS. Fairness is measured by the improved Gini coefficient, and timeliness is measured by the scheduling time. ACS is responsible for the convergence speed of the algorithm. MMAS, an adaptive ant colony algorithm, is responsible for the diversity of the algorithm. The reinforcement learning mechanism (Zhou et al. 2022) has been introduced to update pheromone exchange among populations. The experimental results show that the algorithm can effectively reduce the convergence time, help jump out of local optimum in EMSS problems, and perform better than other heuristic algorithms.

3. Model

3.1. Problem definition

After the occurrence of public health emergencies, the EMS stored in the city is limited, so it is necessary to schedule medical supplies for disaster-stricken areas. The distribution of the affected areas is irregular. According to the territorial principle, medical supplies distribution centres are set up in areas with less impact of the epidemic to ensure the safety of medical supplies. The local management department selects logistics enterprises to provide medical supplies distribution services. To clarify the scope of this paper, we put forward the specific assumptions of the model as follows.

Assumption (1) In the scheduling process of emergency materials, the emergency materials are stored in the distribution centre after arriving in the affected area and then transported to each demand point by the distribution centre. The capacity of the distribution centre is large enough not to consider the situation of a warehouse explosion.

Assumption (2) Each vehicle's fuel efficiency, driving velocity, and load capacity shall remain constant and uniform, while the volume of goods transported must not exceed the maximum carrying limit.

Assumption (3) Despite the priority division of demand points, all demand points must be allocated a certain amount of emergency materials to meet basic living needs.

Assumption (4) Road transportation is only considered from the distribution centre to the demand point. Vehicles depart from the distribution centre and return to the original distribution centre after completing the transportation task. The same vehicle only serves the same demand point once, and the same demand point can be served by different vehicles, and the distribution centre has enough vehicles to complete the distribution task.

Assumption (5) The road surface between each distribution centre and the demand point is smooth, and the epidemic does not affect highway traffic. In distribution, unexpected situations such as vehicle failure and road congestion are not considered. All transport vehicles have the same speed, and the maximum carrying capacity of vehicles of the same type is the same.

Assumption (6) There are many types of emergency materials. According to the experience of previous public health events, different types of emergency materials are combined into similar materials in proportion to maximise the distribution efficiency, so this paper only considers the distribution of single materials.

The decision variables of the model are x_{ijr} and y_{bi}, which are defined as follows:

$$x_{ijr} = \begin{cases} 1, & \text{if the vehicle r moves from the disaster site } i \text{ to } j, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

$$y_{bi} = \begin{cases} 1, & \text{if the disaster site i is assigned to distribution center } b, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

The parameters list and their definitions are summarised in Table 2.

Table 2. The parameter list.

Parameter type	Parameter	Define
Model parameter	c_{ijr}	The minimum distance of vehicle *r* from demand point *i* to *j*
	S_r	Fixed vehicle speed
	s_i	Quantity delivered at disaster site *i*
	d_i	Quantity demanded at disaster site *i*
	M_r	Maximum capacity of vehicle *r*
	C	Set of disaster sites, $C = i\| i = 1, 2, \dots, N$
	B	Set of distribution centre, $B = b\| b = 1, 2, \dots, M$
	V	Emergency vehicle set, $v = r \| r = 1, 2, \dots, K$
	N	All nodes in the transportation network, $N = B \cup C$
	Q_b	Amount of medical supplies in distribution centre *b*
	γ_i	The priority of demand point i
	θ	The efficiency parameter of the vehicle, that is, the amount of material loaded per unit of time
	C_1	Penalty cost per unit time for arrivals beyond the latest tolerance time
	T	$T = (s_1, s_2, \dots, s_n)$ represents the emergency supplies allocation amount
Intermediate variable parameters	T_r^i	The point in time when vehicle r arrives at demand point *i*, $T_r^i = 0$ means the vehicle starting from the distribution centre
	t_{ijr}	The travelling time of vehicle r from demand point *i* to demand point *j*, $t_{ijr} = \frac{c_{ijr}}{V_r}$
	t_{ir}'	Vehicle *r* demand point I service time, $t_{ir}' = \frac{s_i}{\theta}$
	w_i	The satisfaction rate of demand point *i*, $w_i = \frac{s_i}{d_i \gamma_i}$
	z_{ijr}	When vehicle *r* and distribution centre *i* transport supplies to distribution centre *j*, $i, j \in B$, then $z_{ijr} = 1$, otherwise $z_{ijr} = 0$

3.2. Priority evaluation index of EMS

The priority of the demand point is affected by many factors, and different factors have different effects on the rescue priority of the demand point. According to the characteristics of the disaster information of the demand point, the influencing factors can be divided into qualitative and quantitative factors, and the determinate factors mainly include the disaster degree of the demand point, the disaster grade evaluated by the relevant departments, and the time urgency of the demand point. The quantitative factors mainly include the population density of the demand point, the shortage of supplies at the demand point, and the number of patients at the demand point. Therefore, when constructing the priority index of the demand point, the influence of each factor on the priority should be comprehensively considered. Referring to the existing research findings, we determine the priority of the demand point of EMS in public health events by two parts.

(1) Level of expected time demand γ_i^u

The demand points need an urgent degree, referring to the incident that broke out, the requirements on demand for all kinds of emergency supplies distribution time. Each demand point has a corresponding soft time Windows constraints $[l_i, ll_i]$, where l_i represents demand *i*'s expected service time at the latest. ll_i represents demand point *i*'s stand point in time, and the latest ll_{min} represents all requirements on the minimum expected service time at the latest.

(2) The time tolerance of the requirement γ_i^t

According to the time requirement and tolerance degree of the demand point for emergency materials, for the demand point with a fixed time requirement and small time tolerance, the urgency of the demand point should be appropriately increased. This paper refers to prior literature (Khishe, Orouji, and Mosavi 2023) and uses the above two accuracy indicators to measure the demand urgency. Between them, the shortage of emergency materials is positively correlated with the urgency; that is, the greater the shortage of emergency materials, the bigger the urgency of the demand point. In contrast, the time tolerance is negatively correlated with the urgency; the greater the time tolerance, the less urgent the demand point. In summary, this paper constructs linear functions to define the relationship among the three, as shown in Formula 3,

$$\Gamma_i = \bar{a}\gamma_i^{\mathrm{u}} - \bar{b}\gamma_i^{\mathrm{t}}, \tag{3}$$

where $\bar{a}$ and $\bar{b}$ are coefficients, γ_i^u represents the expected level of emergency supplies demand time at demand point i, and γ_i^t represents the demand point i's demand time tolerance. In addition, we assume that $0 \leq \bar{a} \leq 1$, $0 \leq \bar{b} \leq 1$, $\gamma_i^u \geq 1$, $0 \leq \gamma_i^t \leq 1$, and $\gamma_i \geq 1$ to ensure that the demand *i*'s urgent degree is determined by the degree of the shortage of demand and time tolerance. The values of $\bar{a}$ and $\bar{b}$ do not change according to the demand point outbreak, only on behalf of the shortage of emergency supplies demand degree and time tolerance to the influence of the priority weights. When a demand point receives distribution vehicles beyond its tolerance time, it will refuse to accept the service as its tolerance time penalty cost is more than the latest tolerance time penalty cost per unit of time C_2. The total penalty cost of the distribution network is shown in Formula 4,

$$C_1 \sum_{r\in V} \sum_{i\in C} \max[T_r^i - ll_i, 0]. \tag{4}$$

3.3. Model of equitable distribution of emergency supplies

3.3.1. Fair allocation model based on priority index

Some scholars have studied the EMSS problem from different angles. The optimisation objective can be divided into one of the following categories by considering: (i) the fairness of distribution to maximise the cumulative satisfaction rate of disaster points (Luo, Wan, and Wang 2022); (ii) the timeliness of rescue to minimise the scheduling time (Liu et al. 2022); and (iii) the economy of schedule to take the minimal scheduling cost as the goal (Kundu, Sheu, and Kuo 2022).

According to the experience of the new pandemic, the social and economic losses caused by public health events far exceed the cost of EMSS, so our model does not consider the impact of dispatch costs beyond the number of vehicles. At the beginning of the emergency, the medical supplies and rescue materials stored in the city can not meet the needs of all disaster areas, and the fairness of the distribution of medical supplies is related to the panic psychology of the masses and the development of the disaster situation. In this paper, the Gini coefficient (Gini) is introduced, which is a relative index that conforms to the principle of scale invariability and transfer, and can generally reflect the different degrees of the overall distribution (Gini 1912; Gini 1921). As the demand for EMS in disaster areas varies greatly, the Gini coefficient of the satisfaction rate of medical supplies is used to calculate the fairness index of EMS when measuring the fairness of EMS distribution (Zhang et al. 2023). In this paper, a distributive equity index G based on the Gini coefficient is constructed, and the calculation is shown in Formulas (5) and (6).

$$G = \frac{1}{2n^2\bar{w}} \sum_{i\in C} \sum_{j\in C} |w_i - w_j|, \tag{5}$$

$$s.t. \quad w_i = \frac{s_i}{d_i\gamma_i}, \tag{6}$$

where γ_i is the emergency degree of a medical supplies demand for the disaster site i, w_i is the satisfaction rate of each disaster point, and $\bar{w}$ is the average level of satisfaction rate of each disaster point. When the priority of a demand point γ_i ($\gamma_i \geq 1$) is larger, the material distribution is more inclined to it to some extent. In summary, γ_i is constrained to construct the fair distribution model of materials, as shown in Formula 7,

$$\min Z_1 = \frac{1}{2n^2\bar{w}} \sum_{i\in C} \sum_{j\in C} |w_i - w_j|, \tag{7}$$

$$s.t. \quad \bar{w} = \frac{\sum_{i\in C} w_i}{n}, \tag{8}$$

$$s_i \leq d_i, \forall i \in C, \tag{9}$$

$$\gamma_i > 0, \forall i \in C, \tag{10}$$

$$s_i > 0, \forall i \in C. \tag{11}$$

Formula (7) is the fairness objective function, which reflects the fairness of material distribution by minimising the fairness index. The smaller the value, the smaller the difference in demand point satisfaction rate and the better the fairness. Formula (8) represents the average satisfaction rate of all demand points in the distribution network, and Formula (9) indicates that the actual distribution quantity obtained by each demand point does not exceed its actual demand. Formula (10) denotes that the priority index of each demand point is greater than zero, and Formula (11) symbolises that each demand point is guaranteed to have emergency material distribution.

3.3.2. Emergency vehicle routing optimisation model

According to the problem description, the mathematical model is established as follows. The emergency distribution network has m distribution centres as transit points to distribute relief materials to each demand point, and each distribution centre has enough vehicles to complete the distribution task. There are n demand points, and the distribution task is carried out according to the material distribution scheme in the previous section. From the start of the distribution centre to the completion of the entire distribution network, the vehicle delivery time mainly includes two parts: the travel time and the service time of vehicles arriving at the demand point in the process of vehicle distribution. According to Assumption (5), the waiting time of vehicles in the process of distribution is not considered. For the efficiency cost problem of vehicle routing optimisation, the minimum penalty cost in the process of distribution is taken as the objective, and a dual-objective optimisation model is established as follows:

$$\min Z_2 = \sum_{i\epsilon N} \sum_{j\epsilon N} \sum_{r\epsilon V} t_{ijr} + \sum_{i\epsilon C} \sum_{r\epsilon V} {t_{ir}}', \tag{12}$$

$$\min Z_3 = C_1 \sum_{r\in V} \sum_{i\in C} \max[T_r^i - ll_i, 0], \tag{13}$$

$$s.t. \quad \sum_{i\epsilon C} s_i y_{bi} \le Q_b, \forall b\epsilon B, \tag{14}$$

$$\sum_{i\epsilon N}\sum_{j\epsilon N} s_i x_{ijr} \le M_r, \forall r\epsilon V, \tag{15}$$

$$\sum_{i\epsilon N} x_{ijr} = \sum_{i\epsilon N} x_{jir}, \forall j\epsilon N, \forall r\epsilon V, \tag{16}$$

$$\sum_{i\epsilon N}\sum_{j\epsilon N} x_{ijr} \ge 1, \forall r\epsilon V, \tag{17}$$

$$\sum_{b\epsilon B} y_{bi} \ge 1, \forall i\epsilon C, \tag{18}$$

$$\sum_{i\epsilon B}\sum_{j\epsilon B}\sum_{r\epsilon V} z_{ijr} = 0, \tag{19}$$

$$\sum_{i\epsilon C} x_{i0r} = 1, \tag{20}$$

$$\sum_{j\epsilon C} x_{0jr} = 1. \tag{21}$$

Formula (12) represents the minimum scheduling time. Formula (13) denotes the minimum penalty cost. Formula (14) indicates that the distribution volume of the distribution centre does not exceed the total distribution volume of the allocated demand point. Formula (15) specifies that the total distribution volume of a vehicle does not exceed the maximum carrying capacity. Formula (16) characterises that the scheduling process is continuous, and the path is not repeated. Formula (17) symbolises the subcircuit elimination constraint, and Formula (18) means that a demand point is served by at least one vehicle. Formula (19) shows that there are no vehicles between any two distribution centres. Formulas (20) and (21) suggest that the vehicle returns to the original distribution centre after completing the transportation task.

4. Algorithm design

Next, we analyse the research methods in detail from the perspective of AI, compare the advantages and disadvantages of other models and the ant colony algorithm based on reinforcement learning proposed in this paper, and introduce the basic principle of implementing the ant colony algorithm based on reinforcement learning.

4.1. *ε-constraint method*

There are four kinds of solving methods for multi-objective optimisation problems: (1) evaluation function method, which transforms multi-objective into a single objective by constructing an evaluation index (Petchrompo et al. 2022); (2) interactive programming method, in which decision-makers analyse the prior information in the process of optimisation and gradually generate the final solution (Tomczyk and Kadziński 2022); (3) layered solution, which is sorted according to the importance of the objective function, and then solves the single-objective optimisation problem (Deng et al. 2022); and (4) generation method (Tian et al. 2021). Decision-makers can find a satisfactory solution for solving the Pareto solution set of multi-objective functions according to the actual situation. In the bi-objective optimisation problem, the ε constraint method has a wide range of functions. Similar to the hierarchical sequence method, the optimal solution of the pre-order objective is obtained first, and then the optimal solution of the former objective is transformed into the constraint condition of the latter one. The fairness of emergency dispatch is more important in the early stage of an emergency. Firstly, the optimal value of the Gini coefficient is solved to determine the lower bound $\underline{f_1}$, supposing the Gini coefficient of initial distribution be the upper bound $\overline{f_1}$. For the objective function Z_2 increasing from the lower bound to the upper bound, a set of optimal solutions of (Z_3, ε) can be calculated for each value of ε. Let $\varepsilon = \overline{f_1}$, such that ε decreases continuously from the upper bound $\overline{f_1}$ to the lower bound $\underline{f_1}$. According to the Pareto-dominated method, the non-dominated solution is the Pareto fronts of the original problem. The bi-objective model is transformed as follows:

$$\min Z_2 = \sum_{i\epsilon N}\sum_{j\epsilon N}\sum_{r\epsilon V} t_{ijr} + \sum_{i\epsilon C}\sum_{r\epsilon V} t'_{ir}, \tag{22}$$

$$s.t. \quad C_1 \sum_{r\in V}\sum_{i\in C} \max[T_r^i - ll_i, 0] < \varepsilon, \tag{23}$$

$$\sum_{i\epsilon C} s_i y_{bi} \le Q_b, \forall b\epsilon B, \tag{24}$$

$$\sum_{i\epsilon N}\sum_{j\epsilon N} s_i x_{ijr} \le M_r, \forall r\epsilon V, \tag{25}$$

$$\sum_{i\epsilon N} x_{ijr} = \sum_{i\epsilon N} x_{jir}, \forall j\epsilon N, \forall r\epsilon V, \tag{26}$$

$$\sum_{i\epsilon N}\sum_{j\epsilon N} x_{ijr} \ge 1, \forall r\epsilon V, \tag{27}$$

$$\sum_{i\epsilon N}\sum_{j\epsilon N}\sum_{r\epsilon V} x_{ijr} \le 1, \tag{28}$$

$$\sum_{b\epsilon B} y_{bi} \ge 1, \forall i\epsilon C, \tag{29}$$

$$\sum_{i\epsilon B}\sum_{j\epsilon B}\sum_{r\epsilon V} z_{ijr} = 0, \tag{30}$$

$$\sum_{i\epsilon C} x_{i0r} = 1, \tag{31}$$

$$\sum_{j\epsilon C} x_{0jr} = 1, \tag{32}$$

where ε takes all the values of the objective function Z_3. Firstly, in the range of ε restricted domain, Formula (23) is taken as the constraint condition of the objective function Z_2, and the optimal solution of the objective function Z_2 is solved to obtain a set of Pareto optimal solutions. Then ε is reduced from the upper bound to the lower bound, and each ε value has a corresponding optimal solution Z_2, and so on to obtain many groups of Pareto solutions. Finally, the Pareto solution set and Pareto frontier are obtained.

The process of the algorithm is as follows.

Step 1: Initialisation parameters, according to the proportion of demand to determine the initial value of the distribution $T_0 = \{s_1, s_{2....}s_n\}$, and calculate the initial Gini coefficient G_0. As the upper bound $\overline{f_1}$, let $\varepsilon = \overline{f_1}$, and current iterations $iter = 1$.

Step 2: Calculate the satisfaction rate of each disaster site w_i. Find out the maximum disaster point $w_i^{\max}$ and the minimum disaster point $w_i^{\min}$. Adjust the ζ% of the distribution volume of the disaster-hit point with the maximum satisfaction rate to the disaster point with the minimum satisfaction rate; ζ is a constant and meets the condition of $s_i < d_i$. Otherwise, adjust to the disaster point with the secondary low satisfaction rate.

Step 3: If $iter < iter_{max}$, $iter = iter + 1$, return to step 2; otherwise, the algorithm ends. When the Gini coefficient is the minimum, output the optimal solution of distribution quantity T_{best} and Minimum Gini coefficient as the lower bound of the objective function $Z_1 : \underline{f_1}$.

Step 4: Let $\varepsilon = \overline{f_1}$, calculate the minimum path L_b of the single objective function Z_2 under this constraint, and substitute L_b into the objective function Z_2 to determine whether it is a Pareto solution.

Step 5: Determine the step size of upper and lower bounds $\Delta\varepsilon = (\overline{f_1} - \underline{f_1})/n$. If $\varepsilon > \underline{f_1}$, $\varepsilon = \varepsilon - \Delta\varepsilon$, return to Step 2; otherwise, end the algorithm, output Pareto solution $(\varepsilon,\ L_b)$.

4.2. ACS algorithm

4.2.1. Path choice

The ant colony system was proposed by Dorigo and Gambardella (1997). Based on the ant colony algorithm, three improvements have been made: (1) state transition with pseudo-random probability; (2) updating pheromone only on the optimal ant path; (3) adding local update rules to adjust the amount of information in each path. State transition rules of ants moving from i to j in ACS:

$$S = \begin{cases} \underset{j \in \text{allowed}}{\operatorname{argmax}} [\tau_{ij}(t) \times \eta_{ij}{}^{\beta}], & q \le q_0 \\ s, & q > q_0 \end{cases}, \tag{33}$$

where S stands for the ant to choose the next point to go, and q is a random number evenly distributed on [0,1]. q_0 is a certain value, and the parameter Q can be changed q_0 to adjust the ant's ability to explore new paths. s represents a roulette choice, and the formula is as follows:

$$\mathrm{P}_{ij}(\mathrm{t}) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}(\eta_{ij})^{\beta}}{\sum_{u \in \text{allowed}} [\tau_{iu}(t)]^{\alpha}(\eta_{iu})^{\beta}}, & j \in \text{allowed} \\ 0, & j \notin \text{allowed} \end{cases}, \tag{34}$$

in which $\tau_{ij}(t)$ is the pheromone concentration between points i and j after t iterations, η_{ij} is the reciprocal of the distance between points i and j, α and β are the information heuristic factor and the expected heuristic factor respectively, and 'allowed' is the current ant feasible point set.

4.2.2. Pheromone update

In the ACS algorithm, when all ants complete a path exploration, only the optimal ant is selected to release a pheromone, which speeds up the convergence speed and reduces the complexity of the algorithm. In the global update of pheromone, ACS update rules are as follows :

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij}, \tag{35}$$

$$\Delta\tau_{ij} = \begin{cases} \dfrac{1}{L_b}, & if\,(i,j) \in \text{Bestpath} \\ 0, & \text{otherwise} \end{cases}, \tag{36}$$

where ρ $(0 \le \rho \le 1)$ is the Volatilisation Coefficient of global pheromone, pheromone increment $\Delta\tau_{ij}$ is the reciprocal of L_b, and L_b is the current optimal path length. After the ant cycle, ACS updates the pheromone of each ant's path to narrow the gap between the pheromone and the optimal path pheromone. In the local updating of pheromone, ACS update rules are as follows:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\tau_0, \tag{37}$$

in which τ_0 is the initial pheromone concentration on each path.

4.3. MMAS algorithm

MMAS algorithm was proposed by Stützle and Hoos (1997) to solve Travelling Salesman Problem (TSP) and Quadratic Assignment Problem (QAP) (Stützle and Hoos 1997). The biggest improvement of the algorithm is to set a threshold to limit the maximum and minimum pheromone to avoid falling into the local optimum due to the large difference in pheromone concentration. In the initial stage, all pheromones are initially τ_{max} to increase the exploratory ability of the algorithm. After all, ants have explored the path, and only pheromones on the optimal solution path are updated; the pheromone of each path is limited to $[\tau_{\min}, \tau_{\max}]$. MMAS also uses roulette for the next selection of ants, such as Formula 34. The pheromone update rule is as follows:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}^{\text{best}}, \tag{38}$$

$$\Delta\tau_{ij}^{\text{best}} = \frac{1}{L_{\text{best}}}, \tag{39}$$

$$\tau_{ij}(t+1) = \begin{cases} \tau_{\max}, \mathit{if}\, \tau_{ij}(t+1) > \tau_{\max} \\ \tau_{ij}(t+1), \mathit{if}\, \tau_{ij}(t+1) \in [\tau_{\min}, \tau_{\max}] \\ \tau_{\min}, \mathit{if}\, \tau_{ij}(t+1) < \tau_{\min} \end{cases}, \tag{40}$$

$$\tau_{\max} = \frac{1}{1-\rho} \times T_{\text{best}}, \tag{41}$$

$$\tau_{\min} = \frac{\tau_{\max}}{\frac{n}{2} - 1}, \tag{42}$$

where L_{best} is the current optimal or global optimal length and T_{best} is the globally optimal path length. According to Stützle and Hoos (1997), the values of $\tau_{\min}$ and $\tau_{\max}$ are set such that$\tau_{\min}$ ensures the exploratory of the ant colony and $\tau_{\max}$ ensures the heuristic of the ant colony.

4.4. Heterogeneous ant colony under reinforcement learning

4.4.1. Communication mechanism

The multi-colony ant colony algorithm can be divided into two types: isomorphic ant colony and heterogeneous ant colony. Chen et al. (2022) demonstrate that heterogeneous performance outperforms isomorphism. However, the optimal path of the two ant colonies is different before communication. If the optimal solution is exchanged, the pheromone gap may be too large and fall into the local optimal solution. Therefore, this paper chooses to exchange pheromones to exchange information between populations A and B, as shown in Formula (43).

$$\text{Pheromone}_A \rightleftharpoons \text{Pheromone}_B. \tag{43}$$

Because of the complementary relationship between ACS and MMAS, MMAS has a pheromone threshold limit, so the pheromone gap of each path is not obvious. ACS has a global and local pheromone update mechanism, which leads to the pheromone accumulation of some paths in the early stage. When the two populations exchange pheromone matrix, ACS obtains a more uniform pheromone of MMAS, which increases the diversity of solution in the process of ant search. MMAS uses the pheromone with a larger difference in ACS with τ_{max} and τ_{min} initialisation to avoid falling into local optimum prematurely and causing algorithm stagnation. The frequency of communication between the two populations is set according to different data sizes. Assuming that the total number of iterations is '*iter*'; the more data points, the more total iterations, and the more communication times. If the pheromone communication is too frequent, the diversity of search solutions will be reduced; if the interval of pheromone interaction is too long, the efficiency of the learning mechanism between populations will be affected. Let E be the number of population communication, where

$$E = \begin{cases} \left\lceil \frac{n}{20} \right\rceil, & \text{if } t \in \left[0, \frac{\text{iter}}{2}\right] \\ \left\lceil \frac{n}{8} \right\rceil, & \text{if } t \in \left(\frac{\text{iter}}{2}, \text{iter}\right] \end{cases}. \tag{44}$$

In the first half of the iteration process, the communication frequency between the two populations is reduced, the search space in the early stage of the population is expanded, and the diversity of solutions is improved. In the second half of the iteration, due to the accumulation of pheromones, the algorithm may fall into local optimisation. At this time, increasing the communication frequency between populations can effectively avoid algorithm stagnation.

4.4.2. Reward mechanism

In the context of AI, the reward mechanism of reinforcement learning can regulate the communication between ant colonies. After the interaction between population A and population B, the reinforcement learning reward mechanism (Karimi, Dowlatshahi, and Hashemi 2023) is introduced to promptly evaluate their communication. Using the Q-learning reward mechanism for reference, the pheromone concentration of the dominant population is increased, and that of the inferior population is reduced. By subtracting the optimal path searched by population A (or B) before communication from the optimal path found after communication, the evaluation operator r^A of population A is defined as follows:

$$r^A = \frac{L_{\text{best}}^A(t') - L_{\text{best}}^A(t'+1)}{L_{\text{best}}^A(t')}, \tag{45}$$

where pheromone exchange occurs in the t' iteration, $L_{\text{best}}^A(t')$ is the optimal path length of the population before communication, and $L_{\text{best}}^A(t'+1)$ is the optimal path length of the population after communication. If the

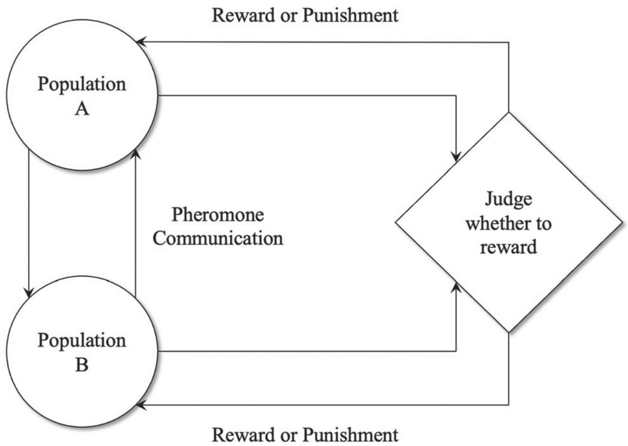


Figure 1. Reinforcement learning mechanism.

evaluation operator r^A is greater than 0, the pheromone of the optimal ant in population A is rewarded. The reward rules are as follows:

$$\tau_{ij}(t'+1) = \begin{cases} (1-\rho)\tau_{ij}(t') + \rho\Delta\tau_{ij} + \Delta\tau_r, & r^A > 0 \\ (1-\rho)\tau_{ij}(t') + \rho\Delta\tau_{ij}, & \text{otherwise} \end{cases}, \tag{46}$$

$$\Delta\tau_r = r^A e^{-t'}. \tag{47}$$

The reinforcement learning mechanism is shown in Figure 1. In the parallel iteration process of the double ant colony, due to the positive feedback effect of pheromones, more pheromones are rewarded, which speeds up the convergence speed of the algorithm. As shown in Formula 47, the reward operator $\Delta\tau_r$ decreases with the increase of the number of iterations, and the influence on the pheromone gradually weakens in the later stage to ensure the diversity of solutions in the later stage of the algorithm.

5. Experimental simulation and analysis

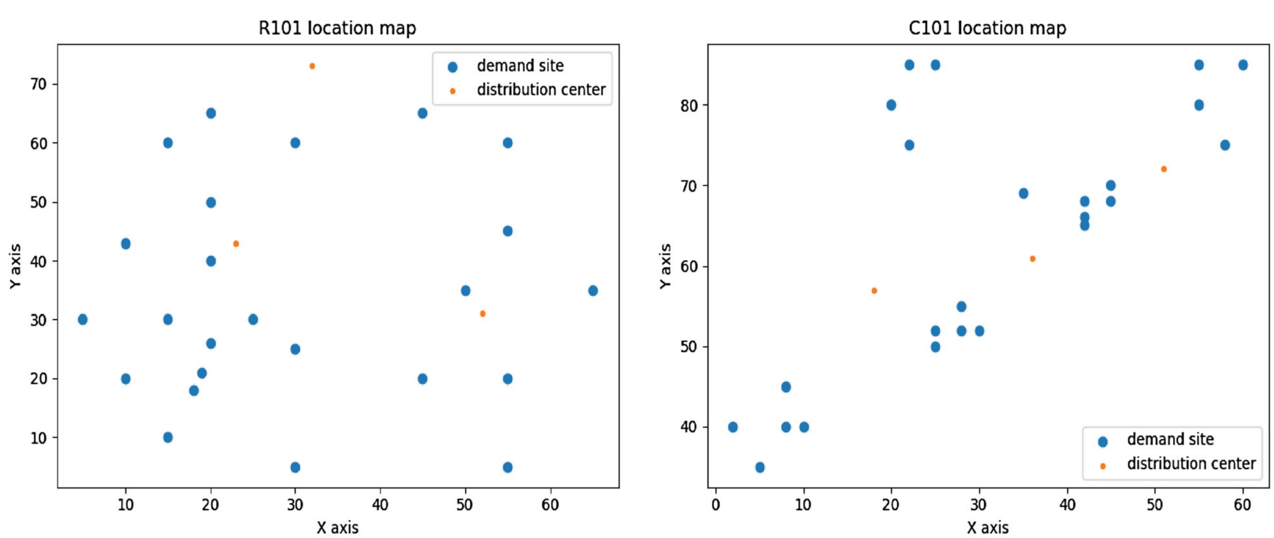
5.1. Algorithm design paradigm

To validate the efficacy and feasibility of the equitable distribution and multi-objective path optimisation models proposed in this study, two examples were constructed using selected data from Solomon datasets R101 and C101. Each example comprises 24 supplies demand points and 3 distribution centres, as illustrated in Figure 2. Each distribution centre is equipped with two distinct types of vehicles for task scheduling. This model considers the priority of transportation demand points and the penalty cost of emergency scheduling and adjusts the traditional Solomon dataset to fit the research problem addressed in this paper. Tables 3–8 lists the information about the demand point, distribution centre, and distribution vehicle for the R101 and C101 examples.

5.2. Numerical simulation and results

5.2.1. Analysis of optimal results of emergency materials distribution

It can be seen from the above that the first-stage model of the emergency scheduling problem is solved in this section, namely the fair distribution model of emergency materials. Due to the great impact of the epidemic and the shortage of the originally stored medical materials, the medical materials are in short supply for a short period, so they cannot meet all the demands of all demand points.



(a) Example R101

(b) Example C101

Figure 2. Location distribution diagram of the example: (a) Example R101: (b) Example C101.

Table 3. R101 example demand point information table.

Demand point number	X coordinates (km)	Y coordinates (km)	Demand quantity (units)	Latest service time l_i (min)	Latest tolerance time ll_i (min)
1	55	45	13	116	126
2	55	20	19	149	159
3	15	30	26	34	44
4	25	30	3	99	109
5	20	50	5	81	91
6	10	43	9	95	105
7	55	60	16	97	107
8	30	60	16	124	134
9	20	65	12	67	77
10	50	35	19	63	73
11	30	25	23	159	169
12	15	10	20	32	42
13	30	5	8	61	71
14	10	20	19	75	85
15	5	30	2	157	167
16	20	40	12	87	97
17	15	60	17	76	86
18	45	65	9	126	136
19	45	20	11	62	72
20	55	5	29	68	78
21	65	35	3	153	163
22	18	18	17	185	195
23	20	26	9	83	93
24	19	21	10	58	68

Table 4. R101 example distribution centre information table.

Distribution centre number	X coordinates	Y coordinates	Material total
1	23	43	60
2	32	73	80
3	52	31	110

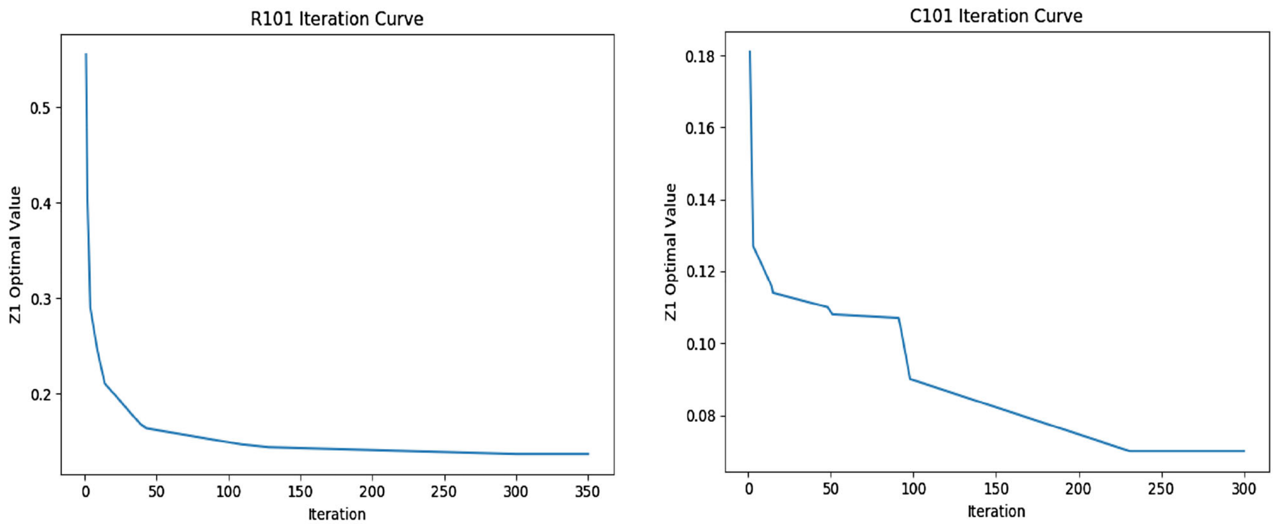
Table 5. R101 example distribution vehicle information table.

Type of delivery vehicle	Maximum capacity (units)	Ground speed (km/min)	Vehicle efficiency parameters (units/min)
1	50	1	8
2	30	1	5

Combined with the number of patients at the demand points and the urgency of the demand for emergency materials published by the local government, the priority calculation formula of the demand points in Formula (7) was used to determine the priority of the demand points. When the demand for emergency supplies exceeds the supply in the early stage of an epidemic, it is assumed

Table 6. C101 example demand point information table.

Demand point number	X coordinates (km)	Y coordinates (km)	Demand quantity (units)	Latest service time l_i (min)	Latest tolerance time ll_i (min)
1	45	68	10	912	967
2	45	70	30	825	870
3	42	66	10	65	146
4	42	68	10	727	782
5	42	65	10	15	67
6	35	69	10	448	505
7	25	85	20	652	721
8	22	75	30	30	92
9	22	85	10	567	620
10	20	80	40	384	429
11	10	40	30	31	100
12	8	40	40	87	158
13	8	45	20	751	816
14	5	35	10	283	344
15	2	40	20	383	716
16	30	52	20	914	965
17	28	52	20	812	883
18	28	55	10	732	777
19	25	50	10	65	144
20	25	52	40	169	224
21	60	85	30	561	622
22	58	75	20	30	84
23	55	80	10	743	820
24	55	85	20	647	726



(a) R101 iterative graph of fair index optimization

(b) C101 iterative graph of fair index optimization

Figure 3. Iteration diagram of fair index optimisation: (a) R101 iterative graph of fair index optimisation: (b) C101 iterative graph of fair index optimisation.

Table 7. C101 example distribution centre information table.

Distribution centre number	*X* coordinates	*Y* coordinates	Material total
1	40	50	80
2	26	33	110
3	52	21	170

Table 8. C101 example distribution vehicle information table.

Type of delivery vehicle	Maximum capacity (units)	Ground speed (km/min)	Vehicle efficiency parameters (units/min)
1	60	1	15
2	50	1	10

that demand urgency at the point of need outweighs time tolerance at said point, i.e. a > b, and satisfies the following conditions: $\gamma_i^u \geq 1$, $0 \leq \gamma_i^t \leq 1$ and $\bar{a}\gamma_{\mathrm{i}}^{\mathrm{u}} - \bar{b}\gamma_{\mathrm{i}}^{\mathrm{t}} \geq 1$. Let the parameters $a = 0.8$ and $b = 0.2$ be utilised to calculate the priority of demand points, maximise life-saving efforts, and enhance rescue efficiency. The genetic algorithm's iteration number is set at 1000, with a population size of 100 and a penalty factor $C_1 = 10$ for vehicles that exceed their tolerance time.

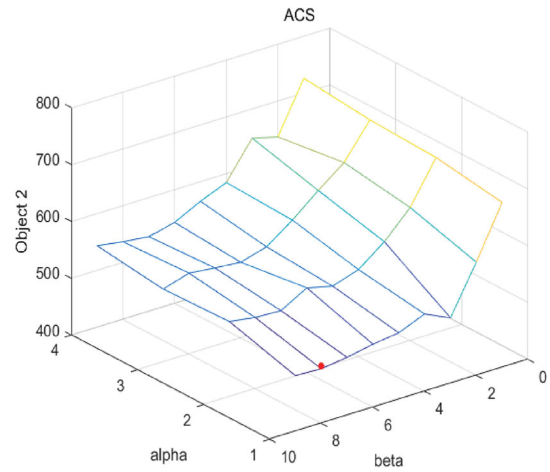
In this paper, Pycharm2020.1.1 is used for programming solutions. First, R101 and C101 example data are inputted, and then the fair distribution model of the first stage is solved. Second, we run 10 times to take the average value as the objective function Z_1; the iterative process of the optimisation results is shown in Figure 3. Finally, we obtain the optimal objective function value $Z_1 = 0.083$, for example, R101 and $Z_1 = 0.054$, for example, C101.

5.2.2. Analysis of emergency vehicle routing optimisation results

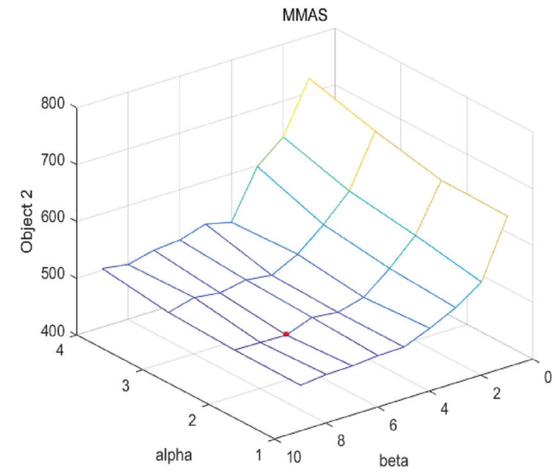
In the first phase of the material assigned based on solving the second stage of the vehicle routing optimisation problem, optimising the parameters of the ant colony algorithm largely determines the algorithm's convergence. So, first of all, through the control variable method, we find the optimal parameter of the ant colony algorithm by running 10 times the optimal result; the run results are shown in Figure 4.

Since both ACS and MMAS adopt adaptive parameters in the process of dual population communication, the parameters greatly influence the experimental results. The number of ants will affect the trend of the average pheromone tends to average. The information heuristic factor α and the expected elicitation factor β control the exploration and convergence of the population, so it is necessary to adjust the parameters before the experiment. Under the minimum Gini coefficient constraint, each group of parameters is substituted into the algorithm and run 10 times to take the average value. The experimental results are shown in Figure 4. For ACS, information heuristic factor $\alpha = 1$, expected heuristic factor $\beta = 8$, pheromone volatilisation factor $\rho = 0.2$; for MMAS, information heuristic factor $\alpha = 2$, expected heuristic factor $\beta = 7$, pheromone volatilisation factor $\rho = 0.8$, and Ant $= 24$.

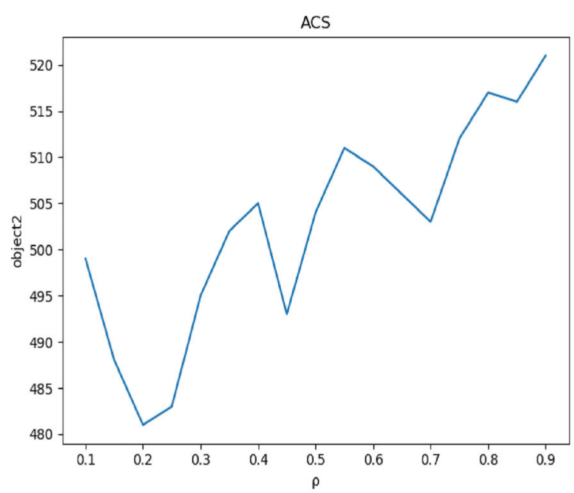
The material distribution scheme obtained in the previous section is substituted into the path optimisation model for the solution. The specific vehicle distribution scheme is shown in Tables 9 and 10, and the obtained



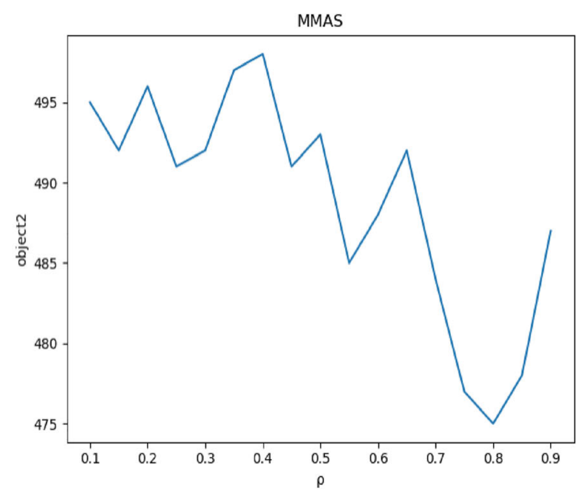
(a) ACS algorithm and parameter



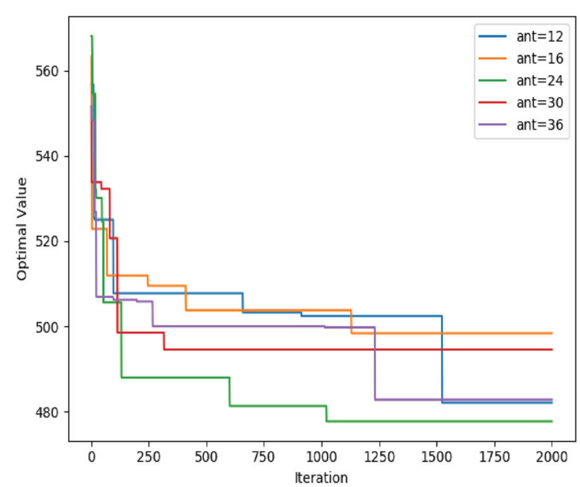
(b) MMAS algorithm and parameter



(c) ACS algorithm parameter selection

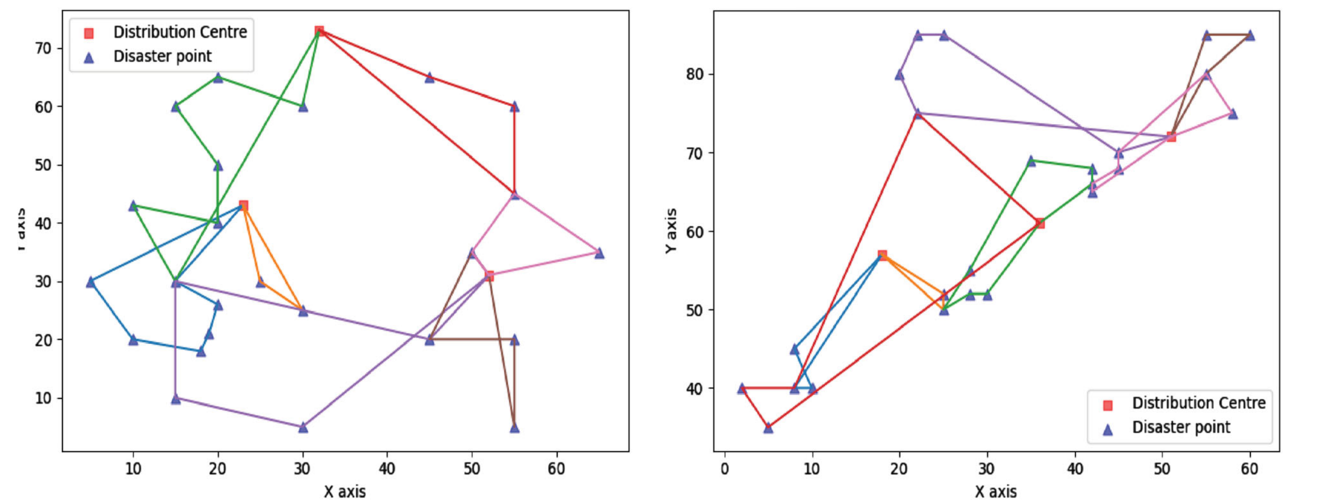


(d) MMAS algorithm parameter selection



(e) Ant Quantity

Figure 4. Ant colony parameter tuning: (a) ACS algorithm and parameter: (b) MMAS algorithm and parameter: (c) ACS algorithm parameter selection: (d) MMAS algorithm parameter selection: (e) Ant Quantity.



(a) R101 Vehicle distribution roadmap

(b) C101 Vehicle distribution roadmap

Figure 5. Roadmap of vehicle distribution: (a) R101 Vehicle distribution roadmap: (b) C101 Vehicle distribution roadmap.

Table 9. R101 is an example of a vehicle distribution route.

Distribution centre	Vehicle number	Distribution line
1	1,2	(15,14,22,24,23,3),(4,11)
2	3,4	(8,9,17,5,16,6,3),(18,7,1)
3	5,6,7	(13,12,3,11,19),(20,2,19,10),(10,1,21)

Table 10. C101 is an example of a vehicle distribution route.

Distribution centre	Vehicle number	Distribution line
1	1,2	(13,11,12),(20,19)
2	3,4	(16,17,19,18,6,4,3),(14,15,12,8)
3	5,6,7	(8,10,9,7,2),(24,21,23),(5,3,1,2,23,22)

optimal route diagram is shown in Figure 5, with each colour line representing the distribution route of each vehicle.

To verify the impact of the priority index on fairness, a control group is set up in this subsection, the priority of the demand point is not considered, and the material quantity is allocated only according to the proportion of demand point to demand point. The Pareto solution set of minimum scheduling time is used for comparison, and the penalty cost is calculated according to the penalty factor set above. The comparison results are shown in Table 11. The difference in scheduling time between the distribution scheme without considering the priority and the distribution scheme considering the priority is small, but the difference in scheduling penalty cost is large. It can be found that the distribution scheme considering the priority of the demand point is better in fairness, which ensures the balance between fairness and efficiency of emergency rescue to a certain extent.

Table 11. Comparison of the results of two allocation schemes.

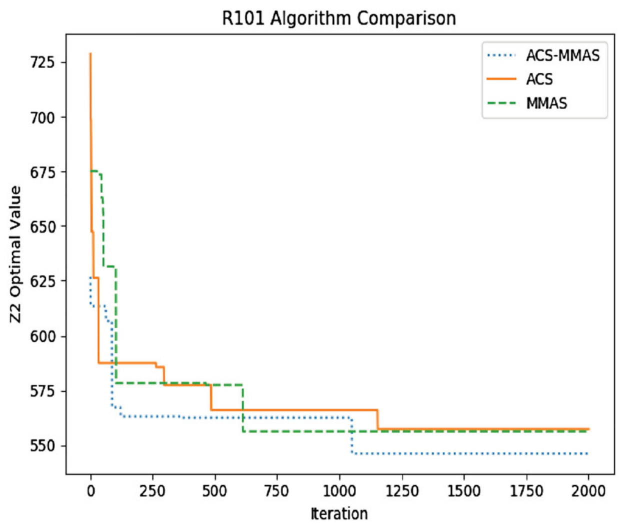
Solution result	Priority is considered	Priority is not considered
R101 Dispatch time	531	522
R101 Penalty costs	1020	1760
C101 Dispatch time	377	380
C101 Penalty costs	440	690

5.2.3. Algorithm performance analysis

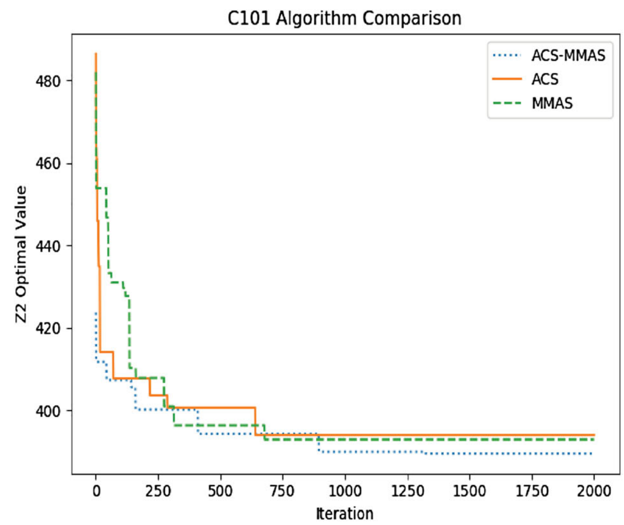
(1) Algorithm convergence

Comparing the allocation algorithm in this paper with the traditional binary coding genetic algorithm, as shown in Tables 12 and 13, the population number of the traditional genetic algorithm is 100, the number of iterations is 1000, the mutation probability is 0.07, and the crossover probability is 0.8. It can be seen from the tables that the convergence of the algorithm in this paper is better and has a faster convergence speed. In the optimisation of an objective function Z_1, the solution algorithm of this model can find the minimum value more accurately, which indicates that real-valued coding is more suitable for genetic algorithms with high accuracy requirements. At the same time, it optimises the computational complexity, improves the search speed of the algorithm, can deal with complex multi-decision variable constraints, obtains a fairer distribution scheme to ensure the fairness principle of emergency rescue operations, and provides a reasonable material distribution scheme for the subsequent emergency vehicle routing optimisation problem.

Then, the parameters of the ant colony algorithm optimised in the previous subsection were put into the model and ran 10 times to obtain the optimal solution. The convergence of the ACS-MMAS algorithm, ACS algorithm, and MMAS algorithm was compared, and ε was set equal



(a) Comparison of algorithm convergence in R101 example



(b) Comparison of algorithm convergence in C101 example

Figure 6. Comparison of algorithm convergence: (a) Comparison of algorithm convergence in R101 example: (b) Comparison of algorithm convergence in C101 example.

Table 12. R101 example algorithm comparison results.

Evaluation index	The algorithm in this paper	Traditional genetic algorithm
Objective function Z_1	0.083	0.087
Convergent iteration number	300	456
Run time	218 s	240 s

Table 13. C101 example algorithm comparison results.

Evaluation index	The algorithm in this paper	Traditional genetic algorithm
Objective function Z_1	0.054	0.063
Convergent iteration number	500	527
Run time	203 s	224 s

to its upper bound value for constraint, and the solution with minimum scheduling time was compared and analysed. It can be seen from Figure 6 that the ACS-MMAS algorithm can effectively jump out of the local optimal solution, avoid the premature of the algorithm, and have better convergence for the operations optimisation problem.

(2) Pareto frontier

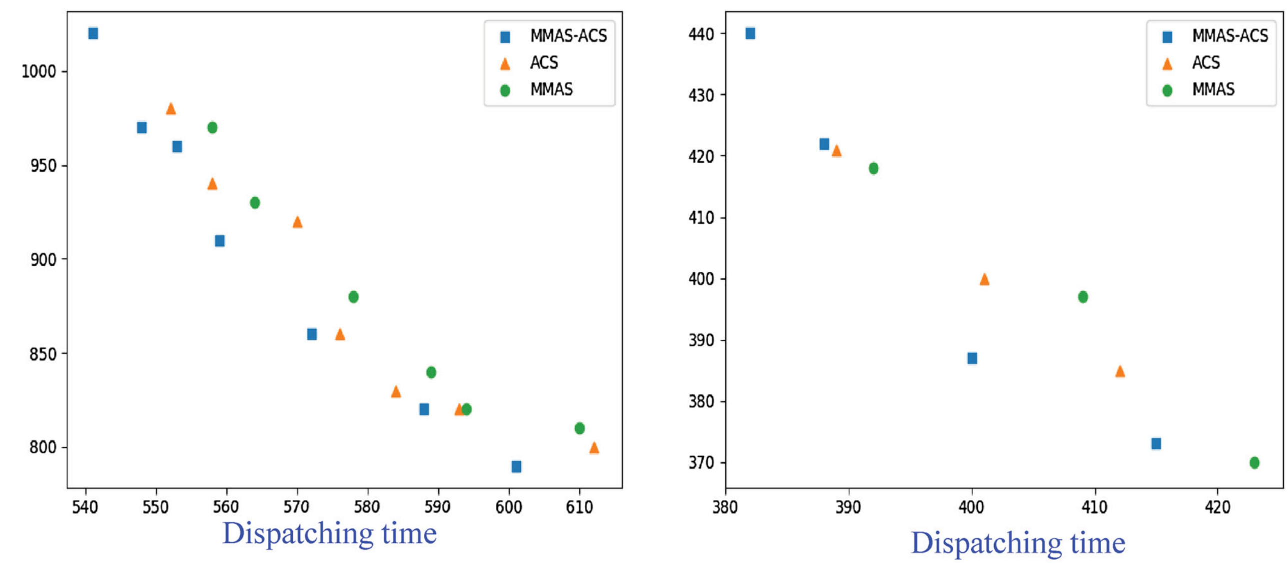
According to the aforementioned epsilon constraint method will double objectives into a single target at the beginning of the incident to rescue the wounded as soon as possible. To reduce casualties, priority will be given in this paper, double the target model of scheduling time optimisation, the minimum penalty cost as constraint conditions $Z_3 < \varepsilon$, the minimum penalty cost constraint ε is continuously reduced from the upper bound to the lower bound, and each value corresponds to a set of optimal solutions to solve (Z_2, ε), to obtain the non-dominated solution of the original problem, that is, the Pareto solution set, as shown in Figure 7. The ACS-MMAS algorithm obtains more Pareto solution sets in the Pareto front curve. Moreover, the controllable space of the ACS-MMAS algorithm is larger than that of the ACS algorithm and MMAS algorithm, so the ACS-MMAS algorithm has better convergence.

(3) Oervolume index

To comprehensively evaluate the algorithm's performance, the solution set's advantages and disadvantages are assessed based on the hypervolume (HV) index (Khishe, Orouji, and Mosavi 2023). HV index is a comprehensive performance evaluation method of the solution set, which can simultaneously evaluate the convergence, uniformity, and universality of the solution set (Yang et al. 2019). The HV calculation formula of solution set s is as follows:

$$HV(S) = Leb(\cup_{x \in S}[f_1(x), Z_1] \times [f_2(x), Z_2] \ldots \times [f_k(x), Z_k]), \tag{48}$$

where k is the dimension of multi-objective and Lebesgue measurement method is Lebesgue, reference point Ref $= (Z_1 \ldots Z_k)$, $[f_1(x), Z_1] \times [f_2(x), Z_2] \ldots \times [f_k(x), Z_k]$ represents a hypercube composed of a Pareto front and reference points (Raimundo, Ferreira, and Von Zuben 2020).



(a) R101 example Pareto frontier (b) C01 example Pareto frontier

Figure 7. Pareto frontier comparison of algorithms: (a) R101 example Pareto frontier: (b) C01 example Pareto frontier.

The hypervolume index is in line with Pareto dominance; that is, the Pareto front is strictly equal to the maximised HV. The larger the HV value corresponding to the solution set S, the larger the dominating space of the solution set, and the quality is better.

This subsection further comprehensively verifies the convergence, diversity, and universality of the proposed algorithm from the hypervolume index. The hypervolume values of the ACS-MMAS algorithm, ACS algorithm, and MMAS algorithm are respectively calculated by selecting appropriate reference points in the dominant region of the Pareto front. Super volume value is surrounded by several hypercube areas to make the problem of two-dimensional target hypervolume value calculation easier, assuming a non-dominated solution set $S' = \{a_1, a_2, a_3\}$, where $a_1, a_2,$ anda_3 represent three groups of Pareto solutions, and the super volume value is the sum of several hypercube volumes. In a two-dimensional space solution set S', super value is equal to the volume of the area of the shaded part, as shown in Figure 8's non-dominated solution set of the area. The greater the quality of the solution set, the better it is. The average value of the optimal solution is taken by running the different algorithms 10 times, and the value range of the two objective functions is scaled down to [0,1] to calculate the hypervolume value. Table 14 shows that the hypervolume value of the ACS-MMAS algorithm proposed in this paper is larger than that of other heuristic algorithms, indicating that the solution set obtained by the algorithm is closer to the real Pareto front. It is a better non-dominant solution set.

Table 14. Algorithm HV value comparison.

Example/ Algorithm	ACS algorithm	MMAS algorithm	ACS-MMAS algorithm
R101	0.698	0.712	0.731
C101	0.725	0.737	0.754

6. Discussion

This paper proposes a novel algorithm for optimising medical supplies scheduling, ACS-MMAS, based on a reinforcement learning mechanism. The experimental results demonstrate that the convergence speed and search effectiveness of ACS-MMAS are superior to those of both ACS and MMAS algorithms, and they can escape from local optima during the search process. As the number of iterations increases, the HV index of ACS-MMAS exhibits a significant advantage over that of ACS, MMAS, and NSGA-II. The proposed ACS-MMAS algorithm outperforms other heuristics in terms of performance. Integrating AI algorithms and traditional heuristic algorithms can enhance algorithmic efficiency and improve rationality and timeliness in medical supply allocation.

Specifically, We propose a bi-objective optimisation model that prioritises fairness and timeliness in emergency medical services (EMS) during the pre-disaster period of major public health events. Our approach utilises ACS-MMAS, a reinforcement learning mechanism that balances EMS distribution and dispatching efficiency. The ε-constraint method is introduced in this study to solve the Pareto solution of a conflicting

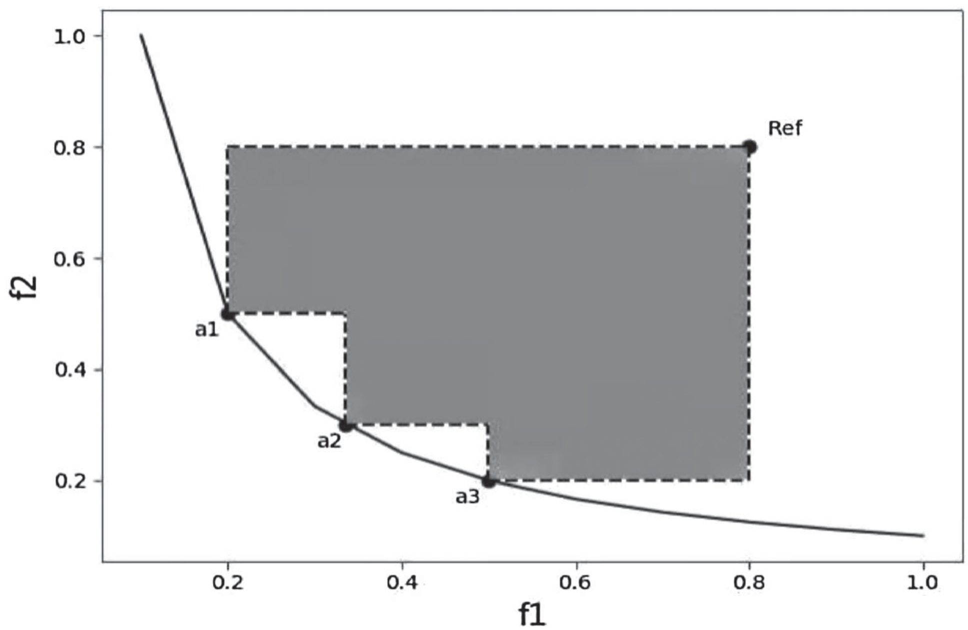


Figure 8. Shadow area is the HV value of the solution set S'.

bi-objective function, and an optimal vehicle dispatching route is obtained through simulation experiments. The research on the emergency logistics scheduling problem of public health emergencies is insufficient. Many studies discuss the theoretical management methods of emergency logistics and explore emergency response at a theoretical level, but there is a lack of specific material distribution schemes and path planning schemes that are combined with practical applications. Most scholars tend to examine the issues of emergency supplies' distribution and transportation in isolation. However, considering the practical scenario, when scheduling emergency supplies, distribution and transportation problems are closely intertwined and should be studied together to ensure a comprehensive emergency plan.

From an AI perspective, advanced technologies are utilised to optimise EMSS. The theoretical significance of our research results lies in providing a superior research methodology for addressing the problem of EMSS before major public health events. In terms of practical significance, our study considers both timeliness and fairness, effectively resolving issues related to unequal distribution due to varying demand at each disaster point and minimising losses. For the assessment of equity in EMS, most existing studies fail to fully consider the influencing factors and rely solely on a single index or factor to evaluate distribution equity. Additionally, current literature only employs convergence or Pareto front as verification indices when assessing model or algorithm effectiveness and practicality, lacking comprehensive comparative research. The paper incorporates the hypervolume index to comprehensively evaluate algorithmic performance, thereby offering sound theoretical support for actual disaster relief efforts through optimised scheduling of MES.

7. Conclusion

7.1. Theoretical contribution

(1) The ACS-MMAS model of EMSS based on AI is constructed

Against the backdrop of research into major public health crises, this study devises a reinforcement learning heterogeneous ant colony algorithm based on AI to tackle the two-objective optimisation problem of EMS. The issue is resolved through ACS-MMAS utilising a reinforcement learning mechanism that takes into account both equitable distribution and scheduling efficiency of emergency supplies. The study introduces the ε-constraint method to solve the Pareto solution of a bi-objective function conflict and obtains an optimal vehicle scheduling route through simulation experiments. This paper combines reinforcement learning in AI technology with a traditional heuristic algorithm to design a reward mechanism for communication between ant colonies, enabling local optima to escape from the search process (Fernández Gil et al. 2023; Kuo, Leung, and Yan 2023; Lopes et al. 2022). The model proposed in this paper enhances the equity and promptness of medical materials scheduling, achieves the optimisation objective of medical materials scheduling, and opens up a new avenue for future research on medical supplies scheduling.

(2) A bi-objective optimisation model is formulated to balance the fairness and timeliness of EMS

Given the initial shortage of emergency materials, this paper examines the impact of demand point prioritisation, measures it by urgency and time tolerance, and constructs an equity index based on the Gini coefficient to ensure fair distribution of resources. To address the dual-objective emergency vehicle routing optimisation problem, a constraint-based approach was employed to transform the original problem into a single-objective optimisation. Subsequently, we proposed a heterogeneous ant colony algorithm that leverages reinforcement learning mechanisms to tackle this optimisation challenge. Through the mechanism of reinforcement learning, the exchange of pheromones between heterogeneous ant colonies was effectively controlled. The Pareto frontier and hypervolume index was utilised to verify the comprehensive performance of the algorithm.

7.2. Practical contribution

The distribution of medical supplies during public health events and the application scope of the accurate model proposed in this research have significant implications for practitioners in the field. The following will be analysed from three dimensions of human, organisation, and technology. For decision-makers, the impact of priority on scheduling schemes is analysed by comparing the models, and suggestions are provided for decision-makers to balance the fairness and efficiency of scheduling schemes. For the affected people, the distribution of medical supplies according to this model can reduce the mortality rate of the population, meet the basic medical supplies and treatment, and enable them to lead a happier and better new life as soon as possible.

For management, it can reasonably manage medical materials in major public health events, effectively control the impact of events, and contribute to the prevention and emergency decision-making of public health events. In response to a public health outbreak, emergency medical rescue prevention and control measures have exposed the disordered, chaotic, and inefficient logistics of medical supplies. Meanwhile, the difference between multiple demand points and supply points of medical supplies is prominent, significantly reducing the effect of medical treatment services and the prevention and control efficiency of major public health emergencies. Therefore, suitable locations and selection of material warehouses for suppliers of medical supplies can meet the needs of medical supplies in disaster areas with different priorities in the event of public health events.

Advanced technologies can improve the ability to deal with major public health emergencies. New technologies such as 5G, blockchain, the Internet of things, AI, and big data should be fully utilised to monitor and warn about public health events more accurately and effectively, strengthen the monitoring mechanism for unexplained diseases and abnormal public health events, and improve the sensitivity and accuracy of assessment and monitoring. Moreover, a multi-point trigger mechanism is established for intelligent early warning.

7.3. Limitations and future research directions

To sum up, it is necessary to optimise the EMSS scheme in the early stage of public health events, which can reduce the loss and casualties and appease the emotion of disaster victims. However, there are still several limitations in this paper. First, the impact of public health events on traffic roads is not considered. Second, we have not taken into consideration the inventory problem of a distribution centre, vehicle transportation cost, and service time of picking up and delivering goods. These factors also affect the medical supplies scheduling problem. Future models also need to take into account dynamic variables. In the process of transportation of medical supplies, the path optimisation problem of this paper does not consider the changes in road capacity, and the transportation modes and constraints of different kinds of EMS are different. Such dynamic factors will also impact the transportation process, and integrating more dynamic factors into the scheduling model is the main goal of subsequent research.

Disclosure statement

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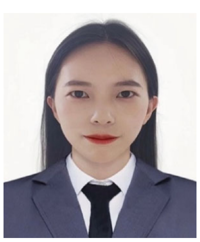

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Management, Industrial Management & Data Systems, Journal of Information & Knowledge Management, Journal of Knowledge Management, Knowledge & Process Management, Knowledge Management Research & Practice.

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Data availability statement

Data available on request from the authors.

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