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# Dynamic Planning Method for Drug Distribution in Earthquake Response Based on Sliding Time Window Series

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**ABSTRACT** Creating an effective and efficient distribution plan is a considerable challenge owing to urgency, incomplete information, and surging demands. In this study, a planning method based on a sliding time window series is designed to solve the problem of drug distribution in earthquake responses. First, this study presents a method designed to generate a series of sliding time windows considering time-varying demands. Second, a method is proposed to determine the effectiveness of the drug distribution plan according to its evaluation standards. Third, a dynamic planning model is established considering the sliding time window series and group information updates. Fourth, a simulation study is conducted to test the models and algorithms. Simulation results show that specific drug distribution plans should be provided to emergency planners in the event of an earthquake. The sliding time window series and group information updates are key factors in creating an effective drug distribution plan as part of an earthquake response.

**INDEX TERMS** Earthquake response, emergency logistics, emergency decision making, rescue drug allocation.

## I. INTRODUCTION

Earthquakes are among the most serious natural disasters that threaten human life and property. The Lisbon earthquake in 1755, San Francisco earthquake in 1906, Turkmenistan earthquake in 1948, Chimbote earthquake in 1970, Mexico earthquake in 1985, Wenchuan earthquake in 2008, Haiti earthquake in 2010, East Japan earthquake in 2011, and Mexico earthquake in 2017 each generated a considerable loss of life and property. Owing to the substantial damage caused by earthquakes, conducting an emergency rescue during a disaster is extremely difficult. In the emergency rescue process, one of the most critical problems involves matching the supply and demand of emergency rescue materials, especially the rapid transportation of emergency medicine

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(including emergency drugs and medical devices, which are primarily referred to as “emergency drugs” in this paper) to disaster sites on demand. The literature shows that the number of patients with medical conditions (e.g., wounded patients, patients with nontraumatic illness, and patients with internal disease, including acute respiratory tract infection, acute hemorrhagic enteritis, and acute enteritis) surges shortly after an earthquake, and demand for emergency medicine increases, especially that for drugs used for disinfection, antiinfection, anesthesia, and hemostasis. Any shortage or delay in medical supplies can lead to serious consequences for the victims of illnesses, threatening their lives.

In contrast to the distribution of tents and other emergency rescue materials, drugs are more important during an earthquake emergency rescue. The problem of incomplete information in earthquake-stricken areas should be solved first to achieve the on-demand distribution and rapid delivery of

drugs, specifically by improving the accuracy and reliability of information collection. Second, it is necessary to consider the urgency of the drug supply and demand distribution, as the drugs must be delivered to a site quickly to treat injured victims. Finally, owing to the constant updating of information at an earthquake site, the dynamic evolution of a disaster situation should be considered in the drug supply and demand distribution process. Hence, it is necessary to grasp the changes in postearthquake secondary disasters such as building collapses, casualties, and other situations in real-time in order to dynamically and effectively adjust to the supply and demand situation. The distribution optimization strategy is a very complex problem that is directly related to the safety of injured victims. Therefore, supply and demand dynamic optimization decisions in emergency medical logistics are crucial in a postearthquake emergency rescue. Solving the distribution problem from supply centers to disaster sites under the dynamic evolution of an earthquake situation is necessary. Moreover, determining an efficient distribution scheme for delivering adequate amounts of drugs to relevant disaster sites from supply centers at correct times is essential.

In addition, with the rapid development of UAV (unmanned aerial vehicles), AI (artificial intelligence), 5G (fifth-generation mobile communication technology), and other technologies, the acquisition of earthquake disaster information has become extremely reliable. However, despite current earthquake disaster observation technology, earthquake disasters and their impacts cannot be observed completely and accurately. Moreover, the related information for decision making in disaster situations remains inadequate. Information on earthquake intensity, secondary disasters, and drug supply and demand affecting decision making can be expressed as a vector, and group information (GI) is composed of multiple groups of vector information (Ye *et al.*, [1]). As the earthquake disaster chain evolves, GI is updated continuously over time, and prediction accuracy based on information updating improves, with the information for decisions becoming increasingly sufficient. Therefore, drug distribution decisions for earthquake rescue demonstrate obvious GI update (GIU) characteristics and time features. On the one hand, if decision making is performed early, there are fewer updates in GI, and decision-making information is lacking, then decision-making efficiency may be reduced. Early decisions can reduce the urgency of decision making, the ineffectiveness of implementation, and the complexity of problems. However, distribution costs and the risks associated with unnecessary distribution are high. On the other hand, if decisions are made late, the GI will have time to update substantially, and the decision-making information will be sufficient. Therefore, decision-making efficiency is consistently high. Although a late decision can reduce distribution costs and unnecessary distribution risks, it may delay optimal medical distribution and increase the risk of untimely distribution owing to further deterioration during an earthquake disaster.

Therefore, a decision-making method for earthquake rescue drug distribution based on a sliding time window series is presented in this study. First, when injured victims are sent to a hospital for treatment after an earthquake, the hospital's demand for relevant drugs changes with the arrival of the injured patients. In this study, the rescue cycle is divided into several time windows according to time point generation based on a hospital's demand for drugs. At the same time, based on the prediction of the time point of demand, several demand time windows are formed, and a demand time window series is created from multiple demand time windows. In addition, as rescue operations and GI updates develop continuously, the demand time window series is continuously updated (in this study, a sliding time window series is presented to describe this situation). Second, Bayesian analysis theory is applied to establish the prior and posterior probability distributions of drug demand information to update the demand information in the decision-making model. Finally, the model established in this study is applied to rescue drug distribution decision making for the Wenchuan earthquake, and the feasibility of the models is verified based on simulation analysis.

## II. LITERATURE REVIEW

Emergency management is a popular research topic for scholars. Yan *et al.* [2], Green and Kolesar [3], Özdamar [4], Craft [5], Rawls and Turnquis [6], Holguín-Veras *et al.* [7], Sheu [8], Venkat *et al.* [9], and Ye *et al.* [10] studied emergency management for platform systems, decision analysis, simulations, emergency plans, emergency disposal and top-level designs, and other aspects, obtaining rich research results. Numerous scholars have examined logistics applications in the emergency supply chain (Celik *et al.* [11]; Day [12]), emergency logistics network (Holguín-Veras *et al.* [7]; Ransikarbum and Mason [13]), emergency resource storage (Bell *et al.* [14]; Roni *et al.* [15]), selection of emergency center sites (Gutjahr and Dzibur [16]), selection of emergency distribution routes (Bozorgi-Amiri *et al.* [17]; Yang and Zhu [18]; Ye *et al.* [19]), emergency transportation (Ball and Lin [20]; Gralla *et al.* [21]), emergency resource allocation (Jacobson *et al.* [22]; Chakravarty [23]; Zhan *et al.* [24]), and other aspects. Disaster emergency resource distribution is the main focus of postdisaster emergency logistic system operations. Presently, related studies mainly report on the distribution of emergency resources, the selection of sites for transshipment centers, and distribution routes in uncertain environments. Based on the research content of this study, the related literature is summarized according to three features, that is, decision-making methods for disaster emergency resource distribution, the application of time windows and dynamic information in emergency resource distribution decisions, and decision-making methods for earthquake rescue drug distribution.

## A. RESEARCH ON DECISION-MAKING METHODS FOR DISASTER EMERGENCY RESOURCE DISTRIBUTION

Decision-making models for disaster emergency resource distribution are created mainly to establish emergency resource distribution and scheduling models that best meet the needs of a disaster area while considering efficiency and fairness in situations such as surging demands, uncertain supplies, and damaged roads by using stochastic programming (Salmerón and Apte [25]; Sheu and Pan [26]), robust optimization (Lassiter *et al.* [27]), Bayesian analysis (Ye *et al.* [19]), time-space networks (Haghani and Oh [28]), mixed integer programming (Özdamar and Yi [29]), and other theories. From five key indicators, Gralla *et al.* [30] constructed a multiobjective emergency distribution plan evaluation method based on expert experience. Zhang *et al.* [31] promoted emergency resource distribution combining primary and secondary disasters and proposed a scenario tree based on conditional probability to define the relationship between primary and secondary disasters. In addition, the authors designed a multiobjective three-stage stochastic programming model to address transportation time and costs and minimize demand. Yu *et al.* [32] focused on resource distribution performance, including efficiency, effectiveness, and equity. These three indicators correspond to economic costs, service quality, and fairness. Moreover, by describing human suffering as a deprivation cost in a utility measure, the authors proposed a nonlinear integer model. They established an equivalent dynamic programming model to avoid the nonlinear term caused by deprivation costs. Sun *et al.* [33] presented a dual objective emergency logistic scheduling model including transportation time and costs that considered uncertain traffic and actual road conditions. Mehrotra *et al.* [34] designed a stochastic optimization model for allocating and sharing key resources during a pandemic. We examined the distribution of ventilator inventory by the Federal Emergency Management Administration in different states in the United States during the COVID-19 pandemic using this model. Chen *et al.* [35] proposed a bilevel programming model that considered problems such as road network damage, high demands, shortages in materials, and limited transportation capacity in the distribution of disaster relief materials to effectively solve uncertainty and related influencing factors during the disaster relief process.

At the same time, the distribution of disaster emergency resources is an NP-hard problem involving multiple objectives, rescue points, demand points, transportation modes, materials, and main bodies. Algorithms for solving the relevant decision model include Lagrange slack arithmetic algorithms, heuristic approaches, genetic algorithms, Bionic algorithms, ant colony algorithms, particle swarm optimization, and so on. Gillett and Miller [36] designed a heuristic algorithm to solve an emergency vehicle planning problem. Chang *et al.* [37] presented a multiobjective genetic algorithm based on a greedy search to solve a large-scale emergency resource distribution model. Zhang *et al.* [38] created a bionic algorithm focusing on the path planning

problem in emergency logistics. Yuan and Wang [39] solved a selection model in multiobjective emergency logistics by using an ant colony algorithm. In addition, Pan *et al.* [40] addressed an emergency resource distribution and scheduling model based on continuity analysis by using particle swarm optimization. Guo *et al.* [41] proposed to solve the emergency logistic open-loop vehicle routing problem with time windows by using an improved ant colony algorithm. Finally, Alencar *et al.* [42] optimized drug distribution routes by using a team ant colony system, which aims to find multiple routes of similar length to improve delivery efficiency.

## B. APPLICATION OF TIME WINDOWS AND DYNAMIC INFORMATION IN EMERGENCY RESOURCE DISTRIBUTION DECISIONS

The vehicle routing problem with time window constraints is used in the field of emergency logistics mainly to examine emergency resource distribution path selection and vehicle scheduling in emergency environments. Tuzkaya *et al.* [43] established an emergency logistics network planning model with time window constraints by using the mixed integer programming method. Liu and Zhao [44] constructed an emergency resource distribution model with time window constraints for a biological antiterrorism system. Gschwind *et al.* [45] proposed a branch-cut-and-price algorithm by using time window constraints in the field of emergency logistics. In addition, Zhu *et al.* [46] applied time window constraints to optimize emergency rescue paths. In this decision-making model, the severity of wounded victims is transformed into a time window constraint to allow early treatment for seriously injured victims.

Dynamic information is used widely in the field of decision making. Several scholars improved the estimation accuracy of information parameter distribution by using the latest sample observation information based on Bayesian analysis to increase the efficiency of relevant decision making (Azoury and Miller [47], Azoury [48]). Chen *et al.* [49], [50] applied the recursive Bayesian method in transformer tap position estimation and power system parameter estimation, significantly improving computational efficiency and robustness. This type of method provided a new way of application, although it is seldom used in emergency resource distribution. Lodree and Taskin [51] integrated continuously measured hurricane wind speed information into material reserve decision making to deal with a hurricane by using Bayesian analysis and establishing a modified Newsboy inventory model. Si and Liu [52] constructed a multiobjective stochastic programming model for emergency resource distribution under the condition of updated disaster information. Zhan *et al.* [53] established an emergency resource distribution method based on a balance between equality and efficiency under group information updating. Ye *et al.* [19] designed a decision-making model for global emergency resource distribution under demand and transportation information updating based on Bayesian decision-making technology. Finally, Zhu *et al.* [54] examined the route selection

and transportation time selection of emergency rescue material distribution under the condition of disaster information updating and proposed a multiobjective mathematical programming method for route planning.

### C. DECISION-MAKING METHODS FOR EARTHQUAKE RESCUE DRUG DISTRIBUTION

Recently, research results on postearthquake emergency logistics have become increasingly abundant, but studies on drug distribution decision-making methods during earthquake rescue are limited. Hairapetian *et al.* [55] analyzed the demands for emergency drugs after a 1988 earthquake in the United States. In addition, Thompson *et al.* [56] assessed the distribution of emergency medical and health resources, and Ardekani and Hobeika [57] analyzed emergency logistics problems after an earthquake. Fiedrich *et al.* [58] constructed a dynamic optimization decision-making model for emergency supply distribution after an earthquake. Najafi *et al.* [59] designed a dynamic model for earthquake emergency logistics and casualty transportation. Liu and Ye [60] adopted road damage information and population transfer information in decision making for emergency living material distribution after an earthquake or other disaster. Wang and Ma [61] established a fuzzy dynamic LRP (Logistics Resources Planning) optimization model with time windows in a postearthquake emergency logistics system. Cs and Kou [62] proposed a multiobjective location-routing optimization model for a postearthquake emergency logistic system and designed a hybrid heuristic algorithm to solve associated problems. Xp *et al.* [63] constructed a dynamic model for earthquake materials distribution based on a decision maker's risk perception. Ciming and Zujun [64] established a multistage optimization model to optimize emergency blood conditioning. Furthermore, Chen *et al.* [65] summarized medical rescue experiences and lessons to classify injuries and medical needs, providing a reference for improving and strengthening emergency medical rescue response after a strong earthquake. Yx [66] proposed a dynamic stochastic programming model for medical materials distribution under large-scale outbreaks of infectious diseases, examined the demand forecasting and information sharing of medical materials, and systematically solved the distribution requirements and strategies for emergency medicine, which is a special emergency resource. Taking sudden cardiac death as an example, Wang [67] investigated the impact of multistage medical logistic system optimization on the survival rate of sudden diseases to maximize the survival rate and established a survival distribution model.

### D. GAP ANALYSIS AND CONTRIBUTIONS

As we mentioned before, the humanitarian logistics problem is very complicated and creates many uncertainties. The main factors affecting the distribution of relief materials in the earthquake context include the completeness of demand information, the urgency of distribution time, and the dynamic evolution of the disaster situation. Many papers

focus on humanitarian logistics, and the time window has been widely used in operations management. However, few papers have applied time window series in humanitarian logistics. In summary, there are two gaps in the current literature. They are (1) a lack of using time window series on relief resource distribution in humanitarian logistics and (2) a lack of tailored reserve methods for drug distribution in earthquake responses.

In a long-term earthquake response process, the demand for drugs in affected areas surges quickly. The inventories in local supply centers cannot meet the demand, but emergency workers can get more supplies from unaffected areas, even from other countries. The emergency manager must make an efficient and effective schedule to allocate and distribute the drugs from other suppliers to the local supply centers. In this study, sliding time window series are established based on GIU technology to coordinate supply and demand in multiple time windows by merging time window constraints. This method emphasizes the urgency in emergency medicine distribution and considers the dynamic updating of earthquake disaster information as it evolves. It is highly suitable for actual earthquake emergency medicine distribution situations. This study has four main contributions. (1) We define a sliding time window series for drug distribution during an earthquake response. (2) We propose a drug distribution model based on the sliding time window series for the first time. (3) We develop a tailored allocation and distribution method for drugs in an earthquake response. (4) We carry out a simulation study on drug distribution using the Wenchuan earthquake case. The results show that the proposed method can provide a specific schedule for the emergency manager. Additionally, they show that sliding time window series and group information updates are key factors in creating an effective drug distribution plan in earthquake response.

### III. DEFINITION OF THE SLIDING TIME WINDOW SERIES

First, the moment of the disaster point demand is predicted, which is used as both the starting point and endpoint in establishing a time window series. Second, after the occurrence of the subsequent demand generation time, the moment when the demand is generated is predicted once again based on new information, and a new time window series is established by sliding. Thus, this process is pushed forward repeatedly until the end of the rescue operation, as shown in Figure 1.

In this way, to distribute rescue drugs, we can establish the sliding demand time window series and supply time window series at each disaster-affected point and supply center, respectively. First, given that demand and other related information are incomplete after an earthquake disaster, by determining the actual time when the demand is generated, a new time window series can be established according to the updated samples and prediction information. Second, based on the newly observed real supply generation time and predicted supply generation time, the real supply generation time and predicted supply generation time are compared with the updated time window series. Third, the real supply generation



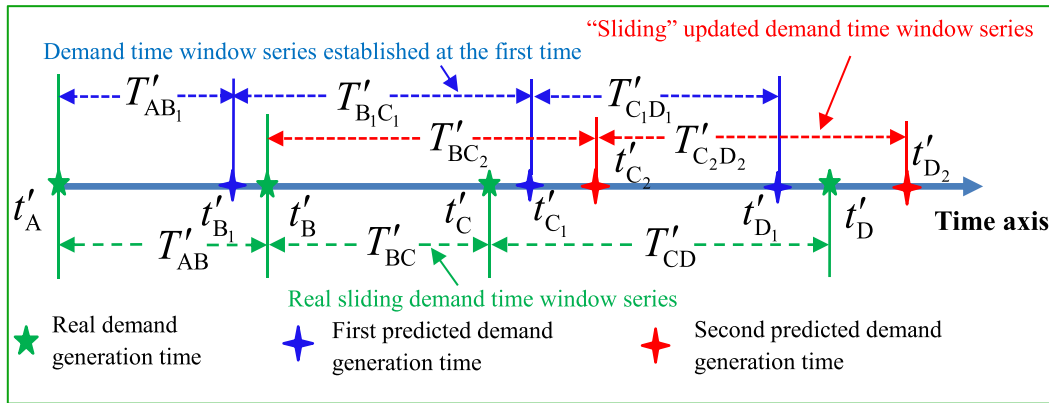


FIGURE 1. Sliding demand time window series.

time and predicted supply generation time in the demand time window of each disaster site are determined. Finally, by considering the transportation time from the supply center to the disaster site, drug distribution can be determined from the supply center supply time to the disaster site demand generation time.

#### IV. DYNAMIC DISTRIBUTION METHOD

##### A. SYMBOLS AND ASSUMPTIONS

After an earthquake, assume there are a total number of disaster-affected points and supply centers for providing drugs to these disaster-affected points. We should thus establish a new sliding time window series according to the current information, and based on this new time window series, we can get the optimal distribution scheme. This scheme contains two aspects: (1) the distribution strategy of different time windows in this time window series and (2) the distribution scheme between different supply centers and disaster-affected points in the first time window (also in this time window series). To establish a drug distribution model for earthquake rescue under the constraints of GIU and the sliding time window series, we propose the symbols shown in Table 1.

Moreover, the hypotheses are proposed as follows:

*Hypothesis 1:* After an earthquake, distributing drugs is necessary. At the same time, according to the predicted demand generation time, the decision cycle can be divided into  $l_o$  time windows for  $o$  time window series. These  $l_o$  time windows consist of a demand time window series.

*Hypothesis 2:* The resettlement rate of the victims is subject to a certain distribution; that is, its prior distribution density function  $\pi(\theta)$  is known, and the sample information concerning  $\theta$  can be obtained by continuous observation.

The Bayes decision method uses the prior information of parameters and sample information to make a decision. The prior distribution density function  $\pi(\theta)$  of disaster information can be derived from the disaster databases of various governmental departments (e.g., the National Climate Data Center, National Geophysical Data Center, and National Ocean Data Center of the United States).

*Hypothesis 3:* The demand for drugs in disaster-affected points is related to the resettlement of the affected populations (Ye et al., [19]). The disaster-affected population is an important factor affecting the demand for emergency materials. According to the resettlement rate of the affected population, the demand for emergency materials can be expressed as follows:

$$d = d(\theta) = \lambda \cdot P \cdot \theta, \quad (1)$$

where  $\lambda$  refers to the average demand for drugs by the resettlement population and  $P$  refers to the total population.

*Hypothesis 4:* The supply generated at the supply generation time can be predicted.

*Hypothesis 5:* Only the supply generated in a supply center before a time window can supply the demand for this time window.

*Hypothesis 6:* Given that the transportation resources the rescue drugs require in an earthquake rescue are not substantial, the earlier the arrival of supplies, the better. Therefore, in this study, a helicopter is used for transportation (a UAV can also be used for transportation according to the actual situation).

*Hypothesis 7:* To determine the specific distribution scheme of a certain time window, that is, to determine the specific distribution quantity from each supply center to each disaster-affected point, the most efficient distribution scheme should be obtained at this stage. In this study, the total logistics time cost is used to describe logistics efficiency.

##### B. FAIRNESS PRINCIPLE AND DEMAND SATISFACTION RATE

In addition, owing to uncertain demands and other factors, a discrepancy often exists between rescue drug distribution and actual demand. Excessive or insufficient supplies will reduce the effectiveness of the drugs. In this study, the expected demand satisfaction rate and Bayesian risk are used to express the effect of rescue drug distribution. The expected demand satisfaction rate is shown in Definition 1.

*Definition 1:* Assume that the demand and supply in each disaster-affected point at each time window are  $d(\theta)$  and  $s$ ,

TABLE 1. Symbols.

Random variable	
$\theta^t$	Resettlement rate of victims at time window $t$
$X^t$	Independent observations for $\theta^t$
$x^t$	Specific implementation value of $X^t$
$a^t$	Specific rescue drug distribution plan for each time window
$\theta_j^t$	Resettlement rate of victims in disaster-affected point $j$ at time window $t$
$X_j^t$	Independent observations for $\theta_j^t$
$x_j^t$	Specific implementation value of $X_j^t$
$a_j^t$	Specific rescue drug distribution plan for each disaster-affected point at time window $t$
Sets	
$T_o$	Time window set at $O$ time window series, where $t \in T_o$
$T_o^D$	Demand generation time set in the disaster-affected point at $O$ time window series
$T_o^S$	Supply generation time set in the supply center at $O$ time window series
$I$	Supply center set, where $i \in I$
$J$	Disaster-affected point set, where $j \in J$
$\Theta_j^t$	All possible $\theta_j^t$ sets
$\mathcal{X}_j^t$	All possible $X_j^t$ sets
$\mathcal{A}_j^t$	All possible $a_j^t$ sets
$N^+$	All positive integer sets
Parameters	
$w^0$	Unit weight of drugs
$v^0$	Unit volume of drugs
$W^0$	Total loading weight of the helicopter
$V^0$	Total loading volume of helicopter
$t_{ij}^0$	Normal transportation time of helicopter from the supply center $i$ to the disaster-affected point $j$
$d_j^t$	Demand for drug $C$ in disaster-affected point $j$ at time window $t$
$q_i^t$	Supply of drug $C$ by supply center $i$ at time window $t$
Function and equation	
$\pi(\theta_j^t)$	Prior probability density function of $\theta_j^t$
$u(x_j^t)$	Marginal probability density function of $x_j^t$
$h(x_j^t, \theta_j^t)$	Joint probability density function of $x_j^t$ and $\theta_j^t$
$f(x_j^t   \theta_j^t)$	Conditional probability density function of $x_j^t$
$\pi^*(\theta_j^t   x_j^t)$	Posterior probability density function of $\theta_j^t$

TABLE 1. (Continued.) Symbols.

$F^\pi(\theta_j^t)$	Cumulative distribution function of $\theta_j^t$
$R(\theta_j^t, \delta_j^t)$	Expected demand satisfaction rate of drug distribution in disaster-affected point $j$ at time window $t$
$r^*(\theta_j^t, \delta_j^t)$	Risk function of drug distribution effect in disaster-affected point $j$ at time window $t$
$F^u(x_j^t)$	Edge cumulative distribution function of $x_j^t$
$\delta_j^t(x_j^t)$	Decision making in space $\mathcal{A}$ , where $\delta_j^t(x_j^t)$ is a plan $a_j^t \in \mathcal{A}$ under the condition of $X_j^t = x_j^t$
Decision variables	
$s_{ij}^t$	Drug distribution quantity in disaster-affected point $j$ in supply center $i$ at time window $t$

respectively. The expected demand unsatisfied rate of drug distribution is

$$R(\theta, \delta) = \begin{cases} \frac{E[d(\theta)] - s}{E[d(\theta)]} & E[d(\theta)] > s \\ 0 & E[d(\theta)] \leq s. \end{cases} \quad (2)$$

The demand is the function of the random variable  $\theta$ . Thus, the accuracy of its distribution function determines the accuracy of the distribution scheme. To determine the distribution function of  $\theta$  accurately, Bayesian analysis is adopted in this study. In addition, based on the prior distribution  $\pi(\theta)$  of  $\theta$  obtained from the related historical information, the sample information observed is used to determine the posterior distribution  $\pi^*(\theta | x)$  of  $\theta$  and  $\pi^*(\theta | x)$  is used to calculate the Bayesian risk of the expected demand satisfaction rate in each disaster-affected point at each time window after the GI is updated.

*Definition 2:* Based on the formula of Bayesian risk defined by Berger (1980), the formula for the Bayesian risk of the expected demand unsatisfied rate is defined as

$$r^*(\theta, \delta) = \begin{cases} \frac{E^{\pi^*} E_\theta^x[d(\theta)] - s}{E^{\pi^*} E_\theta^x[d(\theta)]} & E^{\pi^*} E_\theta^x[d(\theta)] > s \\ 0 & E^{\pi^*} E_\theta^x[d(\theta)] \leq s. \end{cases} \quad (3)$$

To determine the specific distribution quantity, the drug distribution fairness principle considering fairness in drug distribution is defined in this study, as shown in Definition 3.

*Definition 3-1:* In the case where the total supply is determined, if the Bayesian risk of the expected demand satisfaction rate in a disaster-affected point at all time windows is the same, then this distribution scheme is considered as meeting the fairness principle. Assume that  $r^*(\theta_j^t, \delta_j^t)$  is the Bayesian risk of the expected demand unsatisfied rate in the disaster-affected point  $j$  at the time window  $t$ . According to the fairness principle, in time window series  $o$ , the Bayesian risk of the expected demand unsatisfied rate in

all disaster-affected points at time window  $t$  satisfies

$$r^*(\theta_j^t, \delta_j^t) = \frac{\sum_{j \in J} r^*(\theta_j^t, \delta_j^t)}{m}. \quad (4)$$

**Definition 3-2:** In the case where the total supply is determined, if the Bayesian risk of the total expected demand satisfaction rate in each time window is the same, then the distribution scheme is considered as meeting the fairness principle. Assume that  $r^*(\theta^t, \delta^t)$  is the Bayesian risk of the expected demand unsatisfied rate at the time window  $t$ . According to the fairness principle, in time window series  $o$ , the Bayesian risk of the expected demand unsatisfied rate in all time windows satisfies

$$r^*(\theta^t, \delta^t) = \frac{\sum_{t \in T_o} r^*(\theta^t, \delta^t)}{l_o}, \quad (5)$$

where

$$r^*(\theta^t, \delta^t) = r^*\left(\sum_{j \in J} \theta_j^t, \sum_{j \in J} \delta_j^t\right). \quad (6)$$

### C. PARTITIONING OF THE SHARED TIME WINDOW SET

In the entire time window series, not all time windows can share drugs to other time windows at will. For example, when the Bayesian risk of the expected demand unsatisfied rate of the front time windows is relatively large, while the Bayesian risk of the expected demand unsatisfied rate of the late time windows is relatively small, the drugs in the late time windows cannot be shared by the front time windows. Based on the Bayesian risk value of the expected demand unsatisfied rate at each time window, we can determine the time window set that can be shared. First, Definition 4 defines the shared time window set.

**Definition 4:** Assume that  $\mathbf{B}_1 = \{t_1, t_2, \dots, t_n\}$  is a set of  $n$  front time windows in a certain time window series, and  $t_1 < t_2 < \dots < t_n$ . In the optimal distribution scheme under the fairness principle, if  $\forall t_k \in \mathbf{B}_1, \exists t_{k'} < t_k$ , and the  $t_k$  time window shares the drugs supplied at the  $t_{k'}$  time window, then the time window set  $\mathbf{B}_1$  is called a shared time window set.

To get the partition method of the shared time window set, according to the definition of the expected demand unsatisfied rate, the average value of the Bayesian risk of the expected demand unsatisfied rate of the front  $t_0$  time windows is defined below.

**Definition 5:** Assume that  $r^*(\theta^{t_0}, \delta^{t_0})$  is the Bayesian risk of the expected demand unsatisfied rate of the time window  $t_0$ , then

$$\sum_{t_0} = \frac{\sum_{k=1}^{t_0} r^*(\theta^k, \delta^k)}{t_0}, \quad (7)$$

where  $\sum_{t_0}$  is the average value of the Bayesian risk of the expected demand unsatisfied rate of the front  $t_0$  time windows.

**Inference 1:** Assume that the total supply of the front  $t_0$  time windows cannot meet the total expected demand of the

front  $t_0$  time windows. The sufficient and necessary condition of front  $t_0$  time windows and the shared time window set is the average value of the Bayesian risk of the expected demand unsatisfied rates of the front  $t_0$  time windows and increases monotonically.

*Prove:* **Set C** is a set of the front  $t_0$  time windows. First, if the front  $t_0$  time windows form a shared time window set, then based on Definition 4, the late time windows inevitably share the supply of several front time windows. Next,  $\forall t_1 \in \mathbf{C}$ , and  $\exists t'_1 < t_1$ ; thus, the  $t_1$  time window shares the drugs supplied from the  $t'_1$  time window. Based on the drug distribution fairness principle, we know that the average value of the Bayesian risk of the expected demand unsatisfied rates of the front  $t_1$  time windows is smaller than that of the front  $t_1 - 1$  time windows, that is,

$$\frac{\sum_{k=1}^{t_1-1} r^*(\theta^k, \delta^k)}{t_1} < \frac{\sum_{k=1}^{t_1} r^*(\theta^k, \delta^k)}{t_1}. \quad (8)$$

Second, if the average value of the Bayesian risk of the expected demand unsatisfied rates of the front  $t_0$  time windows increases monotonically, then the front  $t_0$  time windows form a shared time window set. Otherwise,  $\exists t''_1 \in \mathbf{C}$ , and the  $t''_1$  time window does not share the supply of the time window before this time window. This outcome indicates that the demand at the  $t''_1$  time window is completely met by the supply at the  $t''_1$  time window. From the drug distribution fairness principle, we know that the Bayesian risk of the expected demand unsatisfied rate of the  $t''_1$  time window is equal to the average value of the Bayesian risk of the expected demand unsatisfied rates of the front  $t''_1 - 1$  time windows. Next,

$$\frac{\sum_{k=1}^{t''_1-1} r^*(\theta^k, \delta^k)}{t''_1 - 1} = \frac{\sum_{k=1}^{t''_1} r^*(\theta^k, \delta^k)}{t''_1}. \quad (9)$$

Formula (8) apparently contradicts the condition of assumption of a monotonic increase; thus, Inference 1 is proven.

**Inference 2:** The front  $t_0$  time windows form a shared time window set, but  $\sum_{t_0} \geq \sum_{t_0+1}$ ; thus, the front  $t_0 + 1$  time windows cannot form a shared time window set.

*Proof:* According to the drug distribution fairness principle, if the front  $t_0 + 1$  time windows form a shared time window set, then the  $t_0 + 1$  time windows share the supply with several front time windows; thus,

$$\frac{\sum_{k=1}^{t_0} r^*(\theta^k, \delta^k)}{t_0} < \frac{\sum_{k=1}^{t_0+1} r^*(\theta^k, \delta^k)}{t_0 + 1}, \quad (10)$$

which contradicts the known condition  $\sum_{t_0} > \sum_{t_0+1}$ . Therefore, Inference 2 is proven.

Based on Definition 4, Inference 1, and Inference 2, the entire time window series can be divided into several shared

time window sets. The first shared time window set is distributed in Section 4.4. For the late time window set, after the time window series slides and is updated, the specific distribution scheme is determined according to the new GI.

#### D. DISTRIBUTION MODEL

The ultimate goal of this study is to obtain the optimal distribution scheme in the current time window. For this reason, the distribution process is divided into four steps. In Step 1, the time window series is divided into several shared time window sets according to Inferences 1 and 2. In Step 2, the total distribution quantity in the current time window is obtained according to the drug distribution fairness principle in different time windows. In Step 3, the distribution quantity of each disaster-affected point is obtained according to the drug distribution fairness principle in different disaster-affected points. In Step 4, the optimal distribution scheme is determined according to the supply of each supply center and the distribution quantity of a disaster-affected point in the current time window as well as the transportation time from each supply center to a disaster-affected point.

The first  $t_1$  time windows in the  $o$  time window series are set to the first shared time window set. Based on the drug distribution fairness principle in different time windows, the distribution quantity of each time window in the first shared time window set can be obtained.

*Inference 3:*  $\mathbf{B}_2$  is set as a shared time window set composed of the front  $t_1$  time windows of this time window series. Thus,  $\forall t'_1 \in \mathbf{B}_2$ , and the distribution quantity in the  $t'_1$  time window is

$$s^{t'_1} = K \cdot d(\theta^{t'_1}), \quad (11)$$

where

$$K = 1 - \frac{\sum_{k=1}^{t'_1} r^*(\theta^k, \delta^k)}{t'_1}. \quad (12)$$

$$r^*(\theta^k, \delta^k) = \begin{cases} \frac{E^{\pi^*} E_{\theta}^x[d(\theta^k)] - s^k}{E^{\pi^*} E_{\theta}^x[d(\theta^k)]} & E^{\pi^*} E_{\theta}^x[d(\theta^k)] > s^k \\ 0 & E^{\pi^*} E_{\theta}^x[d(\theta^k)] \leq s^k. \end{cases} \quad (13)$$

$$\begin{aligned} E^{\pi^*} E_{\theta}^x[d(\theta^k)] &= \sum_{j \in J} E^{\pi^*} E_{\theta}^x[\lambda \cdot P \cdot \theta_j^k] \\ &= \lambda \cdot P \cdot \sum_{j \in J} \int_{\Theta_j^k} \int_{\mathbf{X}_j^k} \theta_j^k dF^{X_j^k} \\ &\quad \times (x_j^k | \theta_j^k) dF^{\pi^*}(\theta_j^k | x_j^k) \end{aligned} \quad (14)$$

$$F^{\pi^*}(\theta_j^k | x_j^k)(\theta_j^k) = \frac{h(x_j^k, \theta_j^k)}{m(x_j^k)}. \quad (15)$$

$$h(x_j^k, \theta_j^k) = \pi(\theta_j^k) \cdot f(x_j^k | \theta_j^k). \quad (16)$$

$$m(x_j^k) = \int_{\Theta_j^k} f(x_j^k | \theta_j^k) dF^{\pi}(\theta_j^k). \quad (17)$$

Inference 3 can be derived directly from the definition of the drug distribution fairness principle. Similarly, we can deduce Inference 4.

*Inference 4:*  $S^1$  is set as the distribution quantity of the first time window in this time window series. Next,  $\forall j \in \mathbf{J}$ , and the distribution quantity of the disaster-affected point  $j$  is

$$s_j^1 = K^1 \cdot d(\theta_j^1), \quad (18)$$

where

$$K^1 = 1 - \frac{\sum_{k=1}^m r^*(\theta_k^1, \delta_k^1)}{m}. \quad (19)$$

$$r^*(\theta_k^1, \delta_k^1) = \begin{cases} \frac{E^{\pi^*} E_{\theta}^x[d(\theta_k^1)] - s_k^1}{E^{\pi^*} E_{\theta}^x[d(\theta_k^1)]} & E^{\pi^*} E_{\theta}^x[d(\theta_k^1)] > s_k^1 \\ 0 & E^{\pi^*} E_{\theta}^x[d(\theta_k^1)] \leq s_k^1. \end{cases} \quad (20)$$

$$\begin{aligned} E^{\pi^*} E_{\theta}^x[d(\theta_k^1)] &= E^{\pi^*} E_{\theta}^x[\lambda \cdot P_k \cdot \theta_k^1] \\ &= \lambda \cdot P_k \cdot \int_{\Theta_k^1} \int_{\mathbf{X}_k^1} \theta_k^1 dF^{X_k^1} \\ &\quad \times (x_k^1 | \theta_k^1) dF^{\pi^*}(\theta_k^1 | x_k^1). \end{aligned} \quad (21)$$

$$F^{\pi^*}(\theta_k^1 | x_k^1)(\theta_k^1) = \frac{h(x_k^1, \theta_k^1)}{m(x_k^1)}. \quad (22)$$

$$h(x_k^1, \theta_k^1) = \pi(\theta_k^1) \cdot f(x_k^1 | \theta_k^1). \quad (23)$$

$$m(x_k^1) = \int_{\Theta_k^1} f(x_k^1 | \theta_k^1) dF^{\pi}(\theta_k^1). \quad (24)$$

Inference 4 can get the distribution quantity of each disaster-affected point in the first time window of this time window series. Based on this step, determining the distribution quantity from each supply center to each disaster-affected point is necessary. Model M is established, aiming for the highest distribution efficiency, that is, the shortest distribution time.

*Objective:*

$$z = \min x_{ij}^1 \cdot t_{ij}^0. \quad (25)$$

*Meet*

$$\sum_{i \in \mathbf{I}} \sum_{j \in \mathbf{J}} s_{ij}^1 = S^1. \quad (26)$$

$$\sum_{i \in \mathbf{I}} s_{ij}^1 = s_j^1, \quad \forall j \in \mathbf{J}. \quad (27)$$

$$\sum_{j \in \mathbf{J}} s_{ij}^1 \leq q_i^1, \quad \forall i \in \mathbf{I}. \quad (28)$$

$$x_{ij}^1 = \max \left\{ \left[ \frac{s_{ij}^1 \cdot w^0}{W^0} \right], \left[ \frac{s_{ij}^1 \cdot v^0}{V^0} \right] \right\}, \quad \forall i \in \mathbf{I}, j \in \mathbf{J}. \quad (29)$$

$$s_{ij}^1 \in Z^+, \quad \forall i \in \mathbf{I}, j \in \mathbf{J}, \quad (30)$$

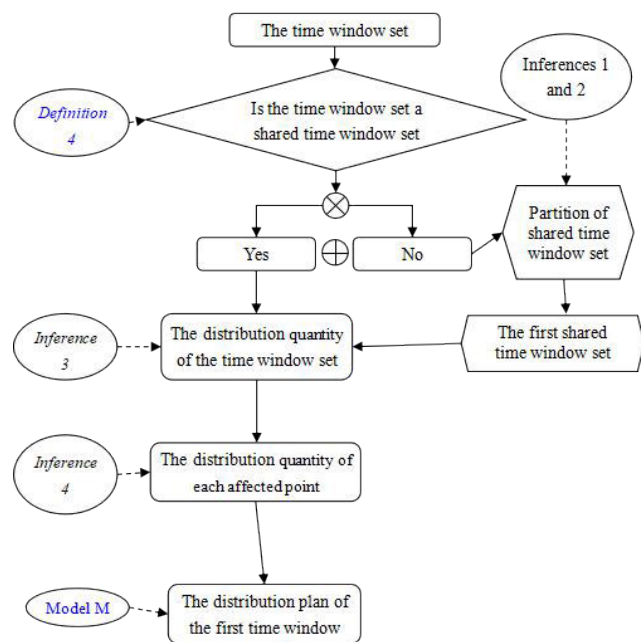
where Formula (25) shows the objective function, and the goal is to minimize the total transportation time.



Formula (26) demonstrates the total supply constraint, Formula (27) exhibits the distribution quantity constraint of each disaster-affected point, Formula (28) displays the supply constraint of each supply center, and Formula (29) illustrates the transport sorties from each supply center to each disaster-affected point. That is,  $x_{ij}^1$  refers to the helicopter sorties required for distributing drugs from the supply center  $i$  to the disaster-affected point  $j$ , where 1 sortie refers to a round trip. Given that the drug distribution unit is in boxes, Formula (30) shows the positive integer constraint of the decision variables.

**E. THE PROCESS FOR SOLVING THE PROPOSED METHOD**

After defining the fairness principle and demand satisfaction rate, we give the method of partitioning for the shared time window set. Then, we propose a programming model to get the first time window scheduling plan. Fig. 2 gives the process of solving the proposed method.



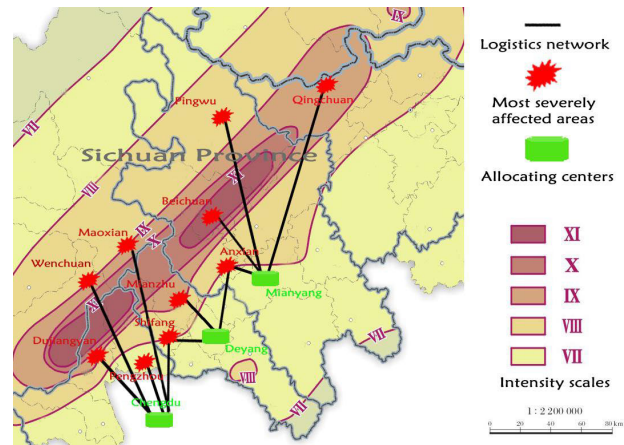
**FIGURE 2.** The process of solving the proposed method.

**V. NUMERICAL SIMULATION ANALYSIS**

**A. SIMULATION BACKGROUND**

In 2008, an intensity 8.0 earthquake occurred in Wenchuan, China, killing 69,227 people and injuring 374,643. Moreover, 17,923 people were never found. This earthquake was the most destructive disaster in the People’s Republic of China since the country was founded. The Wenchuan earthquake caused serious damage in Wenchuan (WCX), Beichuan County (BCX), Mianzhu city (MZS), Shifang city (SFS), Qingchuan County (QCX), Maoxian County (MX), Anxian County (AX), Dujiangyan city (DJYS), Pingwu County (PWX), and Pengzhou city (PZS). With the Wenchuan earthquake as the background, and Chengdu (CDS), Deyang (DYS), and Mianyang (MYS) as the supply centers,

a simulation analysis is conducted on the drug distribution in 10 extremely severe disaster areas. The locations of the three supply centers and 10 extremely severe disaster areas are shown in Fig. 3. The helicopter transport timetable is presented in Table 2. The flying speed of the helicopter is 170 km/h, the maximum carrying capacity is 4 t, and the maximum carrying volume is 35 m<sup>3</sup>.



Source: China Seismological Bureau

**FIGURE 3.** Locations of three supply centers and 10 extremely severe disaster areas for the Wenchuan earthquake simulation analysis.

**TABLE 2.** Transport time from supply centers to extremely severe disaster areas (unit: minute).

Description	WCX	BCX	MZS	SFS	QCX	MX	AX	DJYS	PWX	PZS
CDS	65	78	57	49	115	71	68	50	101	44
DYS	60	58	41	38	94	58	47	57	80.	46
MYS	66	46	47	52	78	59	35	71	67	60

Note: Ranging tool: Google Earth; speed of helicopter: 170 km/h

At the same time, assume that the demand time window series in the 10 extremely severe disaster areas are determined based on the time the victims from all disaster-affected areas are relocated to resettlement sites. Table 3 shows the predicted time to relocate the victims from the 10 extremely severe disaster areas to resettlement sites, starting from the occurrence of the earthquake. Therefore, the overall demand time window series can be given by taking the earliest arrival time of the victims from each disaster area to a resettlement site as the end of a time window, as shown in Table 4. Table 4 also shows the supply volume of the three supply centers in the related time windows. Assume that 100 samples are observed in each extremely severe disaster area. Table 5 lists the population of each extremely severe disaster area, the transfer number of victims for the first time window, and the predicted transfer number of victims for the subsequent four time windows, and  $\lambda = 0.1$ .

**TABLE 3. Predicted transfer time of victims from the extremely severe disaster areas to resettlement sites.**

	Arrival time 1	Arrival time 2	Arrival time 3	Arrival time 4	Arrival time 5
WCX	300 min	520 min	850 min	1310 min	1550 min
BCX	280 min	500 min	910 min	1320 min	1530 min
MZS	330 min	510 min	830 min	1300 min	1520 min
SFS	250 min	520 min	880 min	1290 min	1500 min
QCX	350 min	550 min	950 min	1330 min	1570 min
MX	330 min	540 min	880 min	1280 min	1510 min
AX	310 min	530 min	860 min	1330 min	1560 min
DJYS	290 min	500 min	910 min	1340 min	1580 min
PWX	300 min	530 min	920 min	1320 min	1550 min
PZS	340 min	550 min	950 min	1300 min	1530 min

**TABLE 4. Total supply in different time window series and supply centers (unit: box).**

	Time window 1	Time window 2	Time window 3	Time window 4	Time window 5
Time window series with surging demand	0–250 min	251–500 min	501–830 min	831–1280 min	1281–1500 min
CDS	10600	8000	11000	6300	8500
DYS	5700	4000	5400	3100	4300
MYS	3800	2600	3600	2100	2800
Total supply	20100	14600	20000	11500	15600

**TABLE 5. Observed and predicted victim transfer numbers from the extremely severe disaster areas to resettlement sites.**

Descriptions	WCX	BCX	MZS	SFS	QCX	MX	AX	DJYS	PWX	PZS
Total population	1120	1610	5160	4330	2500	1040	4840	6220	1860	7700
Time window 1	12	8	9	10	8	9	9	7	9	8
Time window 2	13	10	6	8	5	10	7	5	7	5
Time window 3	10	9	7	9	6	8	7	4	8	6
Time window 4	8	7	8	7	7	7	8	6	6	7
Time window 5	11	9	7	8	5	9	9	5	8	6

**B. POSTERIOR DISTRIBUTION OF POPULATION TRANSFER RATE**

The relevant data for population transfer after historical earthquake disasters can be obtained from relevant databases of governmental departments. Ye *et al.* [19] tested historical data by using the Kolmogorov–Smirnov test for a single sample, with SPSS as the solution tool. The authors concluded that the population transfer rate  $\theta_j^t$  is distributed as follows:

$$\theta_j^t \sim N(0.5991, 0.27748^2). \tag{31}$$

At the same time, to determine the distribution of the independent observation  $X_j^t$ , the population transfer rate of each disaster-affected site can be observed. Specifically,  $X_j^t$  is set as the transfer population.  $X_j^t$  obeys the binomial distribution  $B(n_j^t, \theta_j^t)$ , where  $\theta_j^t$  refers to the proportion of the population transferred from disaster-affected site  $j$ . Thus,

$X_j^t$  is distributed as follows:

$$X_j^t \sim B(100, \theta_j^t). \tag{32}$$

According to the central limit theorem, when the sample size reaches 100,  $X_j^t$  can be distributed as follows:

$$X_j^t \sim N(x_j^t \cdot \theta_j^t, x_j^t \cdot \theta_j^t \cdot (1 - \theta_j^t)). \tag{33}$$

In addition, the variance of the population transfer sample  $X_j^t$  is the total sample variance, and the following inference can be concluded.

*Inference 5:* When  $\theta_j^t \sim N(0.5991, 0.27748^2)$ , and  $X_j^t \sim N(x_j^t \cdot \theta_j^t, 1.8309^2)$ , after  $x_j^t$  is observed, the posterior distribution of  $\theta_j^t$  is

$$N(0.69998 + 0.17707 \cdot x_j^t, 0.1051). \tag{34}$$

*Proof:* First,  $\mu(x_j^t)$  and  $\rho_j^t$  are defined as follows:

$$\mu(x_j^t) = \frac{1}{\rho_j^t} \left[ \frac{\mu_0}{\sigma_0} + \frac{x_j^t}{\sigma_j^t} \right]. \tag{35}$$

$$\rho_j^t = \frac{1}{\sigma_0^2} + \frac{1}{(\sigma_j^t)^2}, \tag{36}$$

where  $\mu_0 = 0.5991$ ,  $\sigma_0 = 0.27748$ , and  $\sigma_j^t = 1.8309$ . Thus, we can easily obtain

$$h(x_j^t, \theta_j^t) = \pi(\theta_j^t) \cdot f(x_j^t | \theta_j^t) = (2\pi \cdot \sigma_0 \cdot \sigma_j^t)^{-1} \cdot \exp \left\{ -\frac{1}{2} \left[ \frac{(\mu_j^t - \mu_0)^2}{\sigma_0^2} + \frac{(x_j^t - \mu_j^t)^2}{(\sigma_j^t)^2} \right] \right\}. \tag{37}$$

There is

$$\begin{aligned} & \frac{1}{2} \left[ \frac{(\mu_j^t - \mu_0)^2}{\sigma_0^2} + \frac{(x_j^t - \mu_j^t)^2}{(\sigma_j^t)^2} \right] \\ &= \frac{1}{2} \left[ \left( \frac{1}{\sigma_0^2} + \frac{1}{(\sigma_j^t)^2} \right) \cdot \mu_j^t - 2 \left( \frac{\mu_0}{\sigma_0} + \frac{x_j^t}{(\sigma_j^t)^2} \right) \cdot \mu_j + \left( \frac{\mu_0^2}{\sigma_0^2} + \frac{x_j^{t2}}{(\sigma_j^t)^2} \right) \right] \\ &= \frac{1}{2} \rho_j^t \cdot \left[ \mu_j^t - \frac{1}{\rho_j^t} \left( \frac{\mu_0}{\sigma_0} + \frac{x_j^t}{(\sigma_j^t)^2} \right) \right]^2 + \frac{(\mu_0 - x_j^t)^2}{2(\sigma_0^2 + (\sigma_j^t)^2)}. \end{aligned} \tag{38}$$

Therefore,

$$h(x_j^t, \theta_j^t) = (2\pi \cdot \sigma_0 \cdot \sigma_j^t)^{-1} \cdot \exp \left\{ -\frac{1}{2} \rho_j^t \cdot v_j^{t2} \right\} \cdot \exp \left\{ \frac{(\mu_0 - x_j^t)^2}{2(\sigma_0^2 + (\sigma_j^t)^2)} \right\}, \tag{39}$$

where  $v_j^t = \mu_j^t - \frac{1}{\rho_j^t} \left( \frac{\mu_0}{\sigma_0^2} + \frac{x_j^t}{(\sigma_j^t)^2} \right)$ . In addition,

$$m(x_j^t) = (2\pi \cdot \rho_j^t)^{-1/2} \cdot (\sigma_0 \cdot \sigma_j^t)^{-1} \exp \left\{ -\frac{(\mu_0 - x_j^t)^2}{2(\sigma_0^2 + (\sigma_j^t)^2)} \right\}, \tag{40}$$

Therefore,

$$\begin{aligned} \pi^*(\theta_j^t | x_j^t) &= \frac{h(x_j^t, \theta_j^t)}{m(x_j^t)} \\ &= \left( \frac{\rho_j^t}{2\pi} \right)^{1/2} \\ &\cdot \exp \left\{ -\frac{1}{2} \rho_j^t \cdot \left[ \mu_j^t - \frac{1}{\rho_j^t} \left( \frac{\mu_0}{\sigma_0^2} + \frac{x_j^t}{(\sigma_j^t)^2} \right) \right]^2 \right\}. \end{aligned} \tag{41}$$

Hence, when  $\mu(x_j^t) = 0.69998 + 0.17707 \cdot x_j^t$ , and  $\rho_j^t = 3.0844$ , the posterior distribution of the  $\theta_j^t$  of the given  $x_j^t$  is  $N(\mu(x_j^t), 0.1051)$ . Thus, the proof is complete.

**C. SIMULATION RESULT AND DISCUSSION**

Genetic algorithms and other heuristic algorithms have been used to solve many scheduling models for humanitarian logistics. However, in this paper we propose four inferences to get the distribution quantity of each disaster-affected point in the first time window of the time window series. In addition, a programming model is established to get a distribution plan. Therefore, we can use Matlab 2012a and Lingo 14 as the solution engines to get the distribution plan. According to Inference 5, we can obtain the expected demand for each time window in each extremely severe disaster area based on the calculation after GIU, as shown in Table 6.

**TABLE 6. Expected demand of each time window in each extremely severe disaster area after GIU.**

Descriptions	W	BC	M	SF	QC	M	A	DJ	PW	PZ	Total
	CX	X	ZS	S	X	X	X	YS	X	S	
Time window 1	149 3	14 31	51 60	48 11	22 22	10 40	48 40	483 8	186 0	68 44	345 39
Time window 2	161 8	17 89	34 40	38 49	13 89	11 56	37 64	345 6	144 7	42 78	261 86
Time window 3	124 4	16 10	40 13	43 30	16 67	92 4	37 64	276 4	165 3	51 33	271 02
Time window 4	996	12 52	45 86	33 67	19 44	80 9	43 02	414 7	124 0	59 89	286 32
Time window 5	136 9	16 10	40 13	38 48	13 89	10 40	48 40	345 6	165 3	51 33	283 51

According to Definition 3-1 and Definition 3-2, we can calculate and obtain the Bayesian risk of the expected demand unsatisfied rate in each time window after GIU, and the Bayesian risk of the average expected demand unsatisfied rate

of the front  $t$  time windows  $\sum^t$ , as shown in Table 7. According to Table 7, the Bayesian risk of the average expected demand unsatisfied rate from Time window 1 to Time window 2 increases monotonically, whereas the Bayesian risk of the expected demand unsatisfied rate in Time window 3 decreases. In addition, the Bayesian risk of the average expected demand unsatisfied rate from Time window 3 to Time window 5 increases monotonically. Therefore, based on Inference 1 and Inference 2, Time window 1 and Time window 2 can form a shared time window set, and Time window 3, Time window 4, and Time window 5 can form a shared time window set.

**TABLE 7. Bayesian risk of expected demand unsatisfied rate in each time window.**

Time window	1	2	3	4	5
Risk value (%)	41.80	44.25	26.20	59.84	44.98
$\sum^t$ (%)	41.8	42.86	37.72	43.16	43.51

Next, based on Inference 3, the distribution quantity and expected demand satisfaction rate in each time window can be calculated, as shown in Table 8.

**TABLE 8. Distribution quantity and expected demand satisfaction rate in each time window (unit: box).**

Time window	1	2	3	4	5
Distribution quantity	19737	14963	15181	16038	15881
Expected demand satisfaction rate (%)	57.14	57.14	56.01	56.01	56.01

After obtaining the specific distribution quantity in Time window 1 based on Inference 4, we can obtain the distribution quantity and expected demand satisfaction rate in Time window 1 for each extremely severe disaster area, as shown in Table 9.

**TABLE 9. Distribution quantity and expected demand satisfaction rate in Time window 1 (unit: box).**

Description	W	BC	MZ	SFS	QC	M	AX	DJ	PW	PZ
	C	X	S	S	X	X	AX	YS	X	S
Distribution quantity	85 3	81 8	294 9	274 9	127 0	59 4	276 6	276 5	106 3	39 11
Expected demand satisfaction rate (%)	57. 13	57. 16	57.1 5	57.1 4	57.1 6	57. 1	57.1 5	57. 15	57. 15	57. 14

Based on these data, we can obtain the specific distribution scheme through Model M, as shown in Table 10.

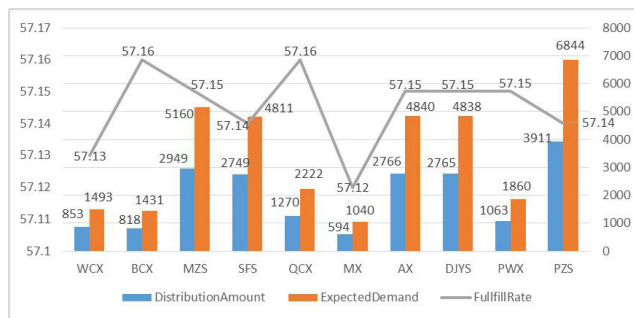
As shown in Fig. 4, different shared time window distribution sets have different Bayesian risks for the expected demand unsatisfied rate, and the total supply of the first shared time window set is relatively more than that of the second shared time window set. Therefore, the expected demand satisfaction rate of Time window 1 and Time window 2 is higher than that of Time window 3, Time window 4, and Time window 5. Moreover, according to Fig. 5, the rounding rule is

**TABLE 10. Specific distribution scheme in time window 1 (unit: box).**

Descrption	WCX	BCX	MZS	SFS	QCX	MX	AX	DJYS	PWX	PZS
CDS	853	0	0	2709	0	0	0	2765	0	3911
DYS	0	818	2949	40	0	594	1299	0	0	0
MYS	0	0	0	0	1270	0	1467	0	1063	0



**FIGURE 4. Comparison of distribution situations in different time windows (UNIT: BOX).**



**FIGURE 5. Comparison of distribution situations in extremely severe disaster areas in the first time window (UNIT: BOX).**

adopted for the distribution quantity of each extremely severe disaster area. Thus, slight differences can be observed in the expected demand satisfaction rate of each extremely severe disaster area in the first time window. In addition, the total distribution quantity in each extremely severe disaster area is 19738, which is 1 more than the distribution quantity in the first time window, which is 19737. This result is obtained because of the rounding rule adopted for the distribution quantity of each extremely severe disaster area.

Just as we mentioned before, in the current literature, many models focused on the uncertainties, and they just distributed all the supplies at hand. They did not consider the coordination of the demand and supply in different time windows. However, in this paper, we consider the uncertainty of demand and the coordination of demand and supply in different time windows. In reality, the emergency manager must consider the coordination of the demand and supplies in a different time window. If all supplies were distributed at the present time window, the following time window might have no drugs to distribute; this would severely increase the total Bayesian risks of the whole response process.

Moreover, the above results are based on the fairness principle. Decision makers can choose other distribution strategies based on actual needs. For example, when decision makers pursue the highest distribution efficiency and choose the lowest Bayesian risk of the expected demand satisfaction rate of each disaster-affected point or time window as the distribution strategy, different distribution schemes can be obtained. Generally, the fairness principle and efficiency priority in the distribution of rescue drugs cannot be achieved simultaneously. Thus, decision makers must balance fairness and efficiency. At the same time, in practical applications, certain weight should be placed on fairness and efficiency to balance the two principles.

## VI. CONCLUSION

After major earthquakes, such as the Mexico earthquake, establishing several resettlement sites around disaster areas to relocate the victims is necessary. Some victims transferred to resettlement sites require medical treatment owing to injuries. As the number of victims in resettlement sites rises, the number of wounded victims likewise increases, and vast amounts of rescue drugs are needed. However, the occurrence and development of earthquake disasters are highly uncertain, and relevant decision-making information is typically incomplete. Therefore, the demand for rescue drugs is also uncertain. At the same time, the demand for drugs in earthquake disaster rescue increases substantially by the time the victims arrive at a resettlement site, which can be described as a demand time window series.

In this study, the concept of a sliding time window series for rescue medicine demand is proposed. Moreover, Bayesian analysis theory is applied to establish a decision-making method for rescue medicine distribution under demand GIU by comprehensively applying historical information, sample information, and predictive information. The effectiveness and feasibility of the proposed method are verified through numerical simulations. The following conclusions are presented. (1) The drug demand time window for earthquake rescue can be divided according to the time when victims arrive at a resettlement site, and the time window series of the demand generation can be defined. In addition, the time window series is updated continuously as earthquake rescue action develops. (2) Relevant decision-making information for drug distribution in earthquake rescue is incomplete. Bayesian analysis theory can be applied to construct GIU technology to cope with the challenges generated by incomplete information. (3) Specific strategies for rescue drug distribution have a considerable impact on distribution schemes. Choosing an appropriate distribution strategy according to actual situations is necessary for decision makers to attain balance between distribution efficiency and fairness. In future research, different distribution strategies can be adopted to expand drug distribution methods for earthquake rescue. In addition, other uncertain factors in demand GIU can be considered to improve the accuracy of demand analysis.



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