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# Research on Railway Emergency Resources Scheduling Model under Multiple Uncertainties

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**Abstract:** This paper discusses the optimization of emergency resource scheduling for major railway emergencies under multiple uncertainties while considering the uncertainties in demand, reserve, and transportation costs of resources. We introduce a novel approach that integrates stochastic mathematical programming, interval parameter programming, and fuzzy mathematical programming to study uncertain parameter interactions and coupling. A two-stage interval fuzzy credibility-constrained model is established and solved using an interval interactive algorithm. Finally, through a case study on China Railway Nanchang Group Co., Ltd., the novelty and effectiveness of the proposed method for optimizing emergency resource scheduling strategies under multiple uncertainties are demonstrated.

**Keywords:** multiple uncertainties; railway emergency resource scheduling; interval two-stage stochastic programming; fuzzy credibility-constrained programming



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## 1. Introduction

### *1.1. Background*

The railway is crucial for the rapid development of the national economy. As the density of the railway network increases, along with higher speeds and enhanced transportation capacity, challenges to railway safety become more severe. Scientific emergency rescue and resource scheduling decisions are vital for the timely and effective management of railway emergencies, ensuring smooth operations and minimizing losses. Due to the unpredictability of accidents, factors such as resource demand, reserves, and transportation costs are uncertain. These uncertainties complicate emergency resource scheduling decisions. Insufficient consideration or improper handling may lead to ineffective scheduling, delayed responses, or even secondary disasters. Therefore, addressing the impact of multiple uncertainties on the rescue system and establishing a reasonable and scientific emergency resource scheduling program is an urgent issue that needs to be resolved in railway emergency rescue decision-making.

### *1.2. Literature Review*

Domestic and foreign scholars have researched such issues from different perspectives. For the study of the railway emergency management system, Ji et al. presented a hierarchical timed Petri net (HTPN)-based method for creating visualized, formal, and digital railway emergency plans, improving their interpretability [1]. Shi et al. proposed a scenario-response method for railway emergency management, utilizing dynamic Bayesian networks, fuzzy neural networks, and convolutional neural networks to deduce emergency states and their severity [2]. Zuo et al. introduced a space–time accessibility assessment method for railway emergency networks, utilizing the gravity model to enhance the traditional travel time budget model, ultimately providing a foundation for effective maintenance allocation strategies [3]. While a well-developed railway emergency plan in advance plays an important role in reducing casualties and property damage, resource scheduling is the key to achieving an emergency plan.

In terms of emergency resource scheduling research for emergencies, Dai et al. proposed a location-routing problem (LRP) optimization model for emergency resource distribution after disasters, taking into account the interplay between distribution center location and routing schemes [4]. Based on the characteristics and requirements of emergency resource scheduling, Tang et al. established a single-objective model with the shortest emergency resource scheduling time while constructing a dual-objective model with the shortest scheduling time and the fewest emergency rescue points [5], and then used the stratified sequencing method to solve it. Yuan et al. proposed a dual-objective resource scheduling method to optimize the resource transportation paths and reduce transportation costs [6]. In addition, based on the prospect theory, a fuzzy evaluation method is proposed to optimize the repair work. Li et al. integrated cloud computing and big data technology to study the resource scheduling problem of high-speed rail emergency services and used the virtualization of high-speed rail emergency resources as a service pool to establish a global optimal scheduling model for high-speed rail emergency resource service pools [7]. Tang et al. established a multi-objective programming model with the goal of maximizing the satisfaction degree of scheduling time and the satisfaction degree related to the pairing of relief points and emergency points, while ensuring the maximum satisfaction degree of all emergency points [8]. Fu et al. processed the road network through the network abstraction method under the premise of determining the allocation point of rescue resources [9]. Then, with the goal of minimizing the emergency response time and maximizing the resource requirements of accident spots, an emergency resource scheduling model based on phase coordination was established. Ding et al. proposed an emergency material scheduling model with multiple logistics supply points for multiple demand points based on gray interval numbers to solve the uncertainty problem of the number of emergency resources required at each disaster site [10]. Li et al. established a multi-objective mixed-integer linear programming (MILP) model with the least scheduling time and cost as the objective function, which considered the effectiveness of multiple supply sites, multiple disaster sites, multiple transportation models, uncertain demand and scheduling paths [11]. In addition, they used the augmented ε-constraint method (AUGMECON) combined with the robust optimization method to solve the model and reach the optimal scheduling scheme.

For the research of uncertain information in resource scheduling, conventional processing methods include stochastic mathematical programming, fuzzy mathematical programming, and interval parameter programming. As for fuzzy mathematical programming, fuzzy set theory is usually used to deal with fuzzy uncertainty in the optimization model. Bodaghi et al. proposed an emergency operation model that combined GIS and mixed-integer programming (MIP) [12]. The model facilitated the use of a variety of random scenarios to schedule and sort resources. Wu et al. divided the fire extinguishing sequence according to the severity and spreading speed of different fire locations and established a mixed-integer linear programming model for the optimization of the fire rescue vehicle path to minimize the total firefighting time [13]. Wang et al. established a multi-objective mixed-integer linear programming model and designed an iterative and fuzzy logic decision which based on the ε-constraint method to obtain the optimal emergency scheduling scheme [14]. Zhang et al. constructed a fuzzy chance-constrained programming model which considered the uncertainty in the number of evacuees in an emergency and aims to maximize evacuated victims and minimize evacuation costs [15]. Pająk proposed an AI-based computerized maintenance management system for power plants that automates power unit maintenance scheduling by using genetic algorithms and fuzzy assessment systems to enhance the maintenance management quality and generate coherent schedules while addressing complex bidirectional criteria [16]. Rivera-Niquepa et al. proposed a fuzzy multi-objective optimization method for independent power generation system programming and used the fuzzy satisfaction method to make decisions [17]. When the obtained uncertain information cannot be represented by a particular value, interval parameter programming can express the uncertain information in the interval forms of upper and lower bounds. Liu established an interval programming model with the target of time, cost, and vehicle minimization, as well as its robust optimization model, in order to improve the efficiency of emergency resource scheduling and reduce the impact of disasters [18]. Guo et al. constructed a scheduling optimization model with the least time as the objective function, which focused on the decision-making of emergency supplies scheduling in an uncertain environment and used interval numbers to describe the uncertain time parameters [19]. For stochastic mathematical programming, the amount of uncertainty is regarded as a random variable or random process, and the standard method for researching uncertain phenomena is a two-stage stochastic optimization method. Zhang et al. established a multi-objective-two-stage temporary distribution center location and emergency resource scheduling model to minimize the total cost and total time [20] and then used a relatively robust optimization method to solve the model.

A variety of research has been performed on the allocation and dispatch of emergency resources at home and abroad. However, past work has mainly focused on the development and application of models under deterministic or single uncertainty conditions. Some scholars have already started to focus on the dual uncertainty problem and have attempted to develop new methods and models to solve these more complex problems. Ren et al. proposed a multi-period dynamic transportation model based on CTM networks for large-scale emergencies, considering the dual uncertainty conditions of connectivity and travel time of transportation networks, to ensure the rapid and efficient supply of emergency resources [21]. Zhou et al. proposed an optimal scheduling strategy based on interval linear stochastic chance-constrained programming and then constructed an interval linear random chance-constrained programming model that used probability distribution functions to describe the uncertainty of renewable energy generation forecasts in the system while using interval numbers to describe the uncertainty of load forecasts [22]. Zhu et al. comprehensively considered the uncertainty of material demands and transportation times on the basis of traditional model analysis and constructed a dual-objective highway emergency resource point location determination model and robust optimization model with the smallest cost and time [23]. Wang et al. introduced interval numbers to describe the uncertainty of material demands and material transportation times on the basis of traditional linear programming and established a multi-objective linear interval programming model, taking the economy, timeliness, and fairness of emergency material distribution as the targets [24].

Although more and more scholars have focused on the practical problems under dual uncertainty and modeling studies, there remains considerable scope for research on the multiple uncertainties as compared to dual uncertainties. Moreover, the existing research primarily focuses on the dispatch of water and electricity resources, while relatively few studies have been conducted in the specific field of railway emergency rescue. This is mainly attributed to the unique characteristics of railway rescue, which include complex rescue scenarios, singular rescue routes, high rescue costs, and time constraints for effective rescue operations. Zhu [23] and Wang [24] considered the uncertainty of the demand and transportation times of road emergency rescue supplies in their study but ignored the uncertainty of the limited amount of emergency resource reserves. Although Ren's study [21] considered the uncertainty of transportation network connectivity and travel times during large-scale emergencies, it ignored the limitations of resource reserves and the critical role they played in rail emergency relief for large-scale disasters, considering only road relief. Railway emergency resources mainly use rescue trains to organize emergency materials, and most of their emergency resources are specialized materials, which may have limited emergency resources when large-scale emergencies occur. Therefore, it is important to explore the optimization of railway emergency resource dispatching under multiple uncertainties. In fact, there are many uncertainties in the process of railway emergency resource management for large-scale emergencies, and they generally manifest in different forms of different parameters, compound uncertainties of the same parameters or the existence of interactions between parameters, which eventually lead to an exceptionally complex system, introducing difficulties to emergency rescue and resource scheduling. The existing uncertainty of planning research focuses mainly on the optimization of emergency resource scheduling with a single uncertainty model, which considers only a single random, fuzzy, or interval. It is difficult to portray complex multiple uncertainty problems accurately, and the optimization results are prone to bias and even lead to poor decisions. Therefore, identifying the multiple uncertainties and complexities of the railway emergency resource management system, revealing the effects of its intrinsic components and their interactions on the railway emergency resource scheduling, constructing the corresponding optimal scheduling model, and providing the decision makers with the optimal decision solution are urgent tasks.

### *1.3. Focus for This Paper*

Based on the existing research, this paper takes the optimization problem of railway emergency resource scheduling in large-scale emergencies as the research object, analyzes the mechanism of coupling multi-dimensional uncertainties with different morphology and structure for the multiple uncertainties in the emergency rescue system, and explores the problem of characterizing and computing multiple uncertainties. The material quantities are characterized by fuzzy numbers and combined with probability distribution forms, and the transportation cost parameters are expressed in interval form. Then, the interactive coupling effect of t various uncertain parameters is studied, and the interval two-stage fuzzy credibility constraint model is constructed, which is solved by the interval interactive algorithm. We took China Railway Nanchang Group Co., Ltd. as an example for validation to ensure the feasibility of the scheduling model and scheme for railway emergency rescue under multiple uncertainties to improve the theory of emergency rescue for railway emergencies.

The main innovation points of this paper are summarized as follows:

1. In studying the optimization problem of emergency resource dispatching for major railway emergencies under multiple uncertainties, the uncertainties regarding the demand for emergency resources, reserves, and transportation costs are considered comprehensively, and fuzzy variables, probability distributions, and interval numbers are introduced to represent the multiple uncertainty parameters, respectively.
2. In this paper, by combining stochastic mathematical programming, interval parametric programming, and fuzzy mathematical programming methods, an interval two-stage fuzzy credibility constraint model is constructed for studying the interactive coupling effects of various uncertain parameters. The model is solved by using the interval interaction algorithm, and empirical analysis is conducted using the example of China Railway Nanchang Group Co., Ltd. to verify that the method and model proposed in this study are scientific and reasonable in practical applications.

## 2. Model Description and Establishment

### *2.1. Interval Two-Stage Stochastic Programming*

The interval two-stage stochastic programming method is a combination of interval parameter programming and two-stage stochastic programming. Both methods have unique advantages in solving problems with uncertain variables. The advantage of two-stage stochastic programming is to optimize the decision-making process under the probability distribution representation of different scenarios. However, the advantage of interval parameter programming is to express the uncertainty of discrete intervals and ensure that the solution interval covers the true value in the form of intervals.

The general form of two-stage stochastic planning is:

$$\min f = cx + E[Q(y,\delta)] \tag{1}$$

where $x$ is the first-stage decision made before the occurrence of the stochastic scenario; $y$ is the second-stage adaptive decision, which depends on the realization of the random variable $\delta$; $E$ denotes the mathematical expectation function; $Q(y,\delta)$ denotes the cost function of the second stage; $\delta$ is the decision variable of the second stage, and it is also a random variable whose probability distribution is difficult to determine. Considering the actual situation, the resource reserves of the emergency rescue base are treated as discrete variables, and the probability of the corresponding changes in reserves is $P_h$. The expression is as follows:

$$\sum_{h=1}^{H} P_h = 1,\ h = 1, 2, \ldots, H \tag{2}$$

$$E[Q(y,\delta)] = EQ(y) = \sum_{h=1}^{H} P_h Q(y, \delta_h) \tag{3}$$

where $h$ represents the level of material reserves in the rescue base, $h = 1$ indicates the lowest level, and $h = H$ indicates the highest level; $P_h$ represents the probability under the condition $h$ of the material reserve of the rescue base; $\delta_h$ represents the random variable corresponding to a material reserve level of $h$; each $\delta_h$ corresponds to a different second-stage decision, denoted by $y_h$.

The linear form of the model is expressed as:

$$\min f = cx + \sum_{h=1}^{H} P_h Q(y_h, \delta_h) \tag{4}$$

The constraint condition is shown as follows:

$$Ax \le b \tag{5}$$

$$x \ge 0 \tag{6}$$

$$y_h \ge 0 \tag{7}$$

$$T(\delta_h)x + W(\delta_h)y_h = g(\delta_h) \quad \forall h = 1, 2, \ldots, H \tag{8}$$

where $A$ is the constant coefficient matrix of the first-stage decision variable $x$; $b$ is a constant matrix; $T(\delta_h)$, $W(\delta_h)$, and $g(\delta_h)$ are the stochastic model parameters with reasonable dimensions, which are functions of the random variable $\delta_h$.

The decision variables of the system are usually represented as interval parameters with upper and lower bounds; therefore, the interval parameters are introduced into the model to obtain the interval two-stage stochastic planning model (ITSP), which is represented as follows:

$$\min f^{\pm} = c^{\pm}x^{\pm} + \sum_{h=1}^{H} P_h Q\left(y^{\pm}, \delta_h\right) \tag{9}$$

where $x$ is a closed and bounded set of real numbers; $x^{\pm}$ is an interval with known upper and lower bounds, while the distribution information for $x$ is unknown.

The constraint condition is shown as follows:

$$A^{\pm}x^{\pm} \le b^{\pm} \tag{10}$$

$$x^{\pm} \ge 0 \tag{11}$$

$$y_h^{\pm} \ge 0 \tag{12}$$

$$T\left(\delta_h^{\pm}\right)x^{\pm} + W\left(\delta_h^{\pm}\right)y_h^{\pm} = g\left(\delta_h^{\pm}\right) \quad \forall h = 1, 2, \ldots, H \tag{13}$$

In research on the optimization of emergency resource scheduling for railway emergencies, full consideration should be given to the various railway emergencies that may occur in the future and the influence of the uncertain variables in them. The railway emergency scheduling model, constructed through interval two-stage programming, can scientifically and effectively respond to the various scenarios of railway emergencies that may occur in the future, thus providing feasible and reliable solutions. However, it is not enough to characterize the reserves of emergency rescue bases only through a probability distribution; a combination of fuzzy numbers and probability distribution should characterize it. When there are fuzzy features in the constraints and these features are represented by probability distributions, fuzzy credibility constraint programming should be introduced to transform the model into linear programming to facilitate the solution.

*2.2. Fuzzy Credibility Constraint Programming*

The form of fuzzy credibility constraint programming is as follows:

$$\max f = \sum_{j=1}^{n} c_j \mathrm{x}_j \tag{14}$$

The constraint condition is shown as follows:

$$Cr(\sum_{j=1}^{n} a_{ij}x_{ij} \leq \widetilde{A}) \geq \lambda_i,\ i = 1, 2, \ldots, m \tag{15}$$

$$x_j \geq 0, j = 1, 2, \ldots, n \tag{16}$$

where $c_j$ and $a_{ij}$ are real number parameters. $\widetilde{A}$ represents fuzzy numbers, $x_j$ represents the decision variables, $Cr$ is the credibility measure, $\lambda_i$ is the credibility confidence level.

Suppose $\xi$ is the triangular fuzzy variable $(a, b, c)$, $a$,$b$, and $c$ are all real numbers greater than 0, $a$ is the lower limit of the fuzzy number $\xi$, $c$ is the upper limit of the fuzzy number $\xi$, and $b$ is the possible value of the fuzzy number $\xi$. Then, the expression of the membership function $\mu_{\widetilde{A}}(x)$ is shown as follows:

$$\mu_{\widetilde{A}}(x) = \begin{cases} 0 & (x \leq a) \\ \frac{x-a}{b-a} & (a \leq x \leq b) \\ \frac{c-x}{c-b} & (b \leq x \leq c) \\ 0 & (x \leq c) \end{cases} \tag{17}$$

Then, based on this membership function, the credibility of $x \leq \xi$ is expressed as follows:

$$Cr(x \leq \xi) = \begin{cases} 1 & (x \leq a) \\ \frac{2b-a-x}{2(b-a)} & (a \leq x \leq b) \\ \frac{x-c}{2(b-a)} & (b \leq x \leq c) \\ 0 & (c \leq x) \end{cases} \tag{18}$$

Using $U$ instead of $\sum\limits_{j=1}^{n} \mathrm{a}_{ij}x_j$, the constraints of the model can be transformed into:

$$Cr\left\{U \leq \widetilde{A}\right\} \geq \lambda_i, i = 1, 2, \ldots, m \tag{19}$$

The model can be converted as follows:

$$\max f = \sum_{j=1}^{n} c_j x_j \tag{20}$$

The constraint condition is shown as follows:

$$Cr\left\{U \leq \widetilde{A}\right\} \geq \lambda_i, i = 1, 2, \ldots, m \tag{21}$$

$$x_j \geq 0,\ j = 1, 2, \ldots, m \tag{22}$$

The general confidence level should take a value greater than 0.5; therefore, based on the above definition of confidence, $\lambda_i$ will be expressed as

$$1 \geq \mu_A(\widetilde{x}_i) \geq \lambda_i \geq 0.5 \tag{23}$$

$$\frac{2b - a - U}{2(b-a)} \geq \lambda_i \rightarrow U \leq b + (1 - 2\lambda_i)(b - a) \tag{24}$$

The above constraints are substituted into the model to find the optimal solution. From the above model, it can be seen that the fuzzy credibility-constrained programming model is transformed into a linear planning model, which can be solved according to the solution method of the linear programming mode.

### 2.3. Interval Two-Stage Fuzzy Credibility Constraint Programming

By synthesizing the above models, this paper establishes the interval two-stage fuzzy credibility constraint programming model for optimizing emergency resource scheduling in railway emergencies. The objective function is to achieve the minimum cost under the premise of satisfying the various constraints. The constraints include constraints on the total amount of supplies in the rescue base, pre-decision-making constraints, constraints on the amount of aid-assisted materials, and non-negative constraints. The model is shown as follows:

The objective function is:

$$min\ f^{\pm} = \sum_{i=1}^{I} n_i k + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{n=1}^{N} a_j^{\pm} l_i^n x_{ijn}^{\pm} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{h=1}^{H}\sum_{n=1}^{N} P_h c_j^{\pm} l_i^n y_{ijhn}^{\pm} \tag{25}$$

where $f^{\pm}$ is the system cost; $A_n$ represents the $n_{th}$ accident demand point; $R_i$ is the $i_{th}$ emergency rescue base; $h$ represents the level of material reserves in the rescue base, where $h = 1, 2, 3$, respectively, refers to three different levels: low, medium and high; $P_h$ represents the probability under the condition $h$ of the material reserve of the rescue base; $n_i$ represents whether the $i_{th}$ rescue base provides rescue, $n_i = 0, 1$, where 1 means providing rescue, 0 means not providing rescue; $k$ represents the basic start-up costs of the emergency rescue base; $a_j^{\pm}$ represents the unit dispatch cost of the category $j$ relief supplies; $c_j^{\pm}$ represents the additional penalty cost for other related departments to provide category $j$ materials; $l_i^n$ represents the distance between the emergency rescue base $R_i$ and the accident spot $A_n$.

The constraint condition is:

$$C_r\left\{x_{ijn}^{\pm} - y_{ijhn}^{\pm} \leq \widetilde{S}_{ijh}\right\} \geq \lambda_i \tag{26}$$

The above constraint represents the limitations imposed on the total amount of materials available at the rescue base. Where $x_{ijn}^{\pm}$ represents the amount of type $j$ materials that are required to be provided by accident spot $A_n$ as the pre-decision rescue point $i$; $y_{ijhn}^{\pm}$ represents the number of emergency rescue materials of type $j$ provided by other relevant departments at the rescue point of $i$ to the accident spot of $A_n$ under the reserve level $h$; $\widetilde{S}_{ijh}$ represents the quantity of emergency rescue materials of category $j$ at the $i_{th}$ rescue base in the reserve status $h$; $Cr$ is the credibility measure; $\lambda_i$ is the credibility confidence level.

$$\sum_{i=1}^{I} x_{ijn}^{\pm} \geq Q_{qj}^{n} \tag{27}$$

The above constraint represents that the sum of the amount of pre-decision is not less than the number of materials required for emergencies. Where $Q_{qj}^{n}$ represents the total amount of emergency rescue materials of category $j$ that are required by accident spot $A_n$ in an emergency with a scenario level of $q$. $q$ represents the scale of emergencies, $q = 1, 2, 3, 4$, respectively, refers to four different levels of scenarios from low to high.

$$y_{ijhn}^{\pm} > 0,\ \sum_{n=1}^{N} x_{ijn}^{\pm} - \sum_{n=1}^{N} y_{ijhn}^{\pm} \geq S_{ijha} \tag{28}$$

The above constraint indicates that the amount of materials for the auxiliary rescue is provided when the supply is insufficient. Where $S_{ijha}$, $S_{ijhb}$ and $S_{ijhc}$ are all real numbers greater than 0, which are, respectively, the lower limit value, the maximum value, and the upper limit value of $\widetilde{S}_{ijh}$.

$$x_{ijn}^{\pm} \leq S_{ijhc} + S_{rjc} \tag{29}$$

The above constraint represents the interval range of the pre-decision quantity. Where $S_{rja}$, $S_{rjb}$ and $S_{rjc}$ are all real numbers greater than 0, which are, respectively, the lower limit value, the maximum value, and the upper limit value of $\widetilde{S}_{rj}$.

$$\sum_{n=1}^{N} y_{ijhn}^{\pm} \leq \widetilde{S}_{rj} \tag{30}$$

The above constraint indicates that the amount of auxiliary relief materials does not exceed the reserve amount of the relevant departments. Where $\widetilde{S}_{rj}$ represents the reserve of the category $j$ emergency relief materials of other relevant departments.

$$\sum_{j=1}^{J} x_{ij}^{\pm} > 0,\ n_i = 1, n_i \in \{0, 1\} \tag{31}$$

The above constraint indicates whether the emergency rescue base provides rescue.

$$\sum x_{ija} x_{ijb} = 0,\ a \neq b,\ \text{and } a, b \in N \tag{32}$$

The above constraint indicates that when there are multiple accident points, since there is only one rescue train, the materials in the rescue base can only attend to one accident point.

$$\sum_{h=1}^{H} P_h = 1 \tag{33}$$

The above constraint represents the probability distribution constraints of different levels of reserves.

$$x_{ijn}^{\pm}, y_{ijhn}^{\pm} \in N \tag{34}$$

The above constraint represents the rounding of the material quantity.

$$x_{ijn}^{\pm}, y_{ijhn}^{\pm} \geq 0,\ \forall j, h \tag{35}$$

The above constraint represents the non-negativity constraint.

In constraint (26), $\lambda_i$ is the level of confidence, and the constraint of the confidence level in the model is the material quantity constraint for a single emergency rescue base. In the macro decision-making of dealing with simple problems, according to the needs of the decision makers, it is possible to consider converting the constraints into restrictions on the total amount of emergency relief supplies and then broaden the constraints to obtain decision schemes of leniency. The confidence levels are represented in the model, as shown in Table 1.

**Table 1.** Confidence level and its signification.

| Confidence Level | Level of Satisfaction |
|---|---|
| $\lambda = 1$ | Rescue base reserves fully meet constraints |
| $\lambda = 0.9$ | Rescue base reserves mostly meet constraints |
| $\lambda = 0.8$ | Rescue base reserves basically meet constraints |

## 3. Model Application and Solution

The interval interaction algorithm is commonly used to solve multi-objective planning with models containing heterogeneous data (i.e., real numbers, interval numbers, fuzzy numbers, sequence numbers, etc.) [25]. The method is able to identify the decision maker's preferred solution based on reliable information through a rational data iteration process. It also shows the level of risk that matches each solution and helps the decision makers anticipate the possible risks [26]. Therefore, in this paper, the interval interaction algorithm is used to solve the constructed interval two-stage fuzzy credibility constraint programming model.

Introduce a new decision variable $Z_{ijn}$,$Z_{ijn} \in [0,1]$ make the $x_{ijn}^{\pm} = x_{ijn}^{-} + z_{ijn}\Delta x_{ijn}$, $\Delta x_{ijn} = x_{ijn}^{+} - x_{ijn}^{-}$. When $Z_{ijn} = 0$, $x_{ijn}^{\pm}$ takes the minimum value; when $Z_{ijn} = 1$, $x_{ijn}^{\pm}$ takes the maximum value. For constraint Equation (26), import Equation (24) and transform the constraint into linear programming. Because the objective function is the lowest system cost, it is necessary to perform model calculations conforming to $f^{-}$ first, obtain the optimized decision variable $Z_{ijnopi}$ by solving, and further expand the decision-making space.

### 3.1. Lower Bound Submodel

The first step is to calculate the objective function as follows:

$$\min f^{-} = \sum_{i=1}^{I} n_i k + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{n=1}^{N} a_j^{-} l_i^{n} (x_{ijn}^{-} + z_{ijn}\Delta x_{ijn}) + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{h=1}^{H}\sum_{n=1}^{N} P_h c_j^{-} l_i^{n} y_{ijhn}^{-} \tag{36}$$

The constraint condition is shown as follows:

$$x_{ijn}^{-} + z_{ijn}\Delta x_{ijn} - y_{ijhn}^{-} \le S_{ijhb} + (1 - 2\lambda_i)(S_{ijhb} - S_{ijha}) \tag{37}$$

$$\sum_{i=1}^{I} \left( x_{ijn}^{-} + z_{ijn}^{-}\Delta x_{ijn} \right) \ge Q_{qj}^{n} \tag{38}$$

$$\text{When the } y_{ijhn}^{-} > 0\text{ , } \sum_{n=1}^{N} (x_{ijn}^{-} + z_{ijn}\Delta x_{ijn}) - \sum_{n=1}^{N} y_{ijhn}^{-} \ge S_{ijha} \tag{39}$$

$$x_{ijn}^{\pm} \le S_{ijhc} + S_{rjc} \tag{40}$$

$$\sum_{n=1}^{N} y_{ijhn}^{-} \le \widetilde{S}_{rj} \tag{41}$$

$$\text{When the } \sum_{j=1}^{J} x_{ij}^{\pm} > 0 \text{ , } n_i = 1, n_i \in \{0,1\} \tag{42}$$

$$\sum x_{ija}x_{ijb} = 0, \ a \neq b, \text{ and } a, b \in N \tag{43}$$

$$\sum_{h=1}^{H} P_h = 1 \tag{44}$$

$$x_{ijn}^{\pm}, y_{ijhn}^{-} \in N \tag{45}$$

$$x_{ijn}^{\pm}, y_{ijhn}^{\pm} \geq 0, \ \forall j, h \tag{46}$$

### 3.2. Upper Bound Submodel

Substitute $Z_{ijnopi}$ and calculate the objective function as follows:

$$\min f^{+} = \sum_{i=1}^{I} n_i k + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{n=1}^{N} a_j^{+} l_i^{n} (x_{ijn}^{-} + z_{ijn}\Delta x_{ijn}) + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{h=1}^{H}\sum_{n=1}^{N} P_h c_j^{+} l_i^{n} y_{ijhn}^{+} \tag{47}$$

The constraint condition is shown as follows:

$$x_{ijn}^{-} + z_{ijn}\Delta x_{ijn} - y_{ijhn}^{+} \leq S_{ijha} + (1 - 2\lambda_i)(S_{ijhb} - S_{ijha}) \tag{48}$$

$$\sum_{i=1}^{I} (x_{ijn}^{-} + z_{ijn}\Delta x_{ijn}) \geq Q_{qj}^{n} \tag{49}$$

$$\text{When the } y_{ijhn}^{+} > 0, \ \sum_{n=1}^{N} (x_{ijn}^{-} + z_{ijn}\Delta x_{ijn}) - \sum_{n=1}^{N} y_{ijhn}^{+} \geq S_{ijha} \tag{50}$$

$$x_{ijn}^{\pm} \leq S_{ijhc} + S_{rjc} \tag{51}$$

$$\sum_{n=1}^{N} y_{ijhn}^{+} \leq \widetilde{S}_{rj} \tag{52}$$

$$\text{When the } \sum_{j=1}^{J} x_{ij}^{\pm} > 0, \ n_i = 1, n_i \in \{0,1\} \tag{53}$$

$$\sum x_{ija}x_{ijb} = 0, \ a \neq b, \text{and} a, b \in N \tag{54}$$

$$\sum_{h=1}^{H} P_h = 1 \tag{55}$$

$$x_{ijn}^{\pm}, y_{ijhn}^{+} \in N \tag{56}$$

$$x_{ijn}^{\pm}, y_{ijhn}^{+} \geq 0, \ \forall j, h \tag{57}$$

Here, when $y_{ijhn}^{+}$ is the decision variable, then solve for optimal solutions $f_{opt}^{+}$ and $y_{ijhn}^{+}$. Finally, obtain the desired result:

$$f_{opt}^{\pm} = [f_{opt}^{-}, f_{opt}^{+}] \tag{58}$$

$$x_{ijnopt} = x^{-}_{ijn} + z_{ijnopi}\Delta x_{ijn} \tag{59}$$

Based on the demand for emergency resource scheduling solutions, the above model can be used to calculate and obtain decisions for different scenarios and to minimize emergency rescue costs while ensuring the completion of rescue tasks. In the results, $x_{ijnopt}$ represents the optimal supply of various emergency rescue materials at each emergency rescue point to the accident point, and a reference interval $f^{\pm}_{opt} = [f^{-}_{opt}, f^{+}_{opt}]$ is given for the total cost of the emergency rescue to assist the decision makers in making their decisions.

## 4. Instance Analysis

### 4.1. Basic Information

The jurisdiction of Nanchang Railway (China Railway Nanchang Group Co., Ltd., Nanchang, China) includes the whole of the Jiangxi and Fujian provinces and parts of the Hunan and Hubei provinces and mainly includes two major railway lines: Beijing-Kowloon and Shanghai-Kunming. Additionally, it is located in the core area of the central railway network of China, with an operating mileage of more than 7700 km. It occupies a significant position in the national railway's eight vertical and eight horizontal high-speed railway networks. It connects east and west, running through the north and south as well, and it is also the critical link connecting the Yangtze River Delta in the east and the Pearl River Delta in the south. Moreover, there are 14 emergency rescue bases belonging to Nanchang Railway, and each base is equipped with a rescue train and related rescue materials.

This paper takes the Nanchang Railway (China Railway Nanchang Group Co., Ltd.) as an example, assuming that the railway lines in the area under the jurisdiction of Nanchang Railway are affected by severe weather and that several natural disasters have occurred, such as a location between Zixi Railway Station and Guangze Railway Station and another location between Dongxiang Railway Station and Jinxian Railway Station being greatly affected by a natural disaster. Therefore the experts of the emergency management department of Nanchang Railway have to assess the level of possible emergencies between a major accident $q_2$ and an extraordinarily serious accident $q_1$. The emergency rescue base is needed to dispatch emergency rescue trains to repair the damaged lines. Then obtain the transportation distance from the emergency base to the accident spot through the ArcGIS software calculation, choose the emergency bases to include Xiangtang, Yingtan, Shangrao, Jingdezhen, Laizhou, and Shaowu as the rescue points, and then represent these as $R_1$ to $R_6$. The distances of the rescue bases from the accident spot are shown in Table 2.

**Table 2.** The length of the rescue path from each emergency rescue base to the accident spot (m).

| | $R_1$ | $R_2$ | $R_3$ | $R_4$ | $R_5$ | $R_6$ |
|---|---|---|---|---|---|---|
| $l_i^1$ | 214,684 | 99,756 | 205,955 | 252,863 | 220,267 | 44,637 |
| $l_i^2$ | 64,315 | 49,790 | 158,363 | 201,934 | 368,307 | 193,807 |

Extraordinarily serious accidents ($q_1$) and major accidents ($q_2$) require three types of emergency relief supplies: bulge splints, rails, and sleepers, as shown in Table 3.

**Table 3.** The number of rescue materials needed after the accident in different scenarios (items).

| Scenario | $j_1$ | $j_2$ | $j_3$ |
|---|---|---|---|
| $q_1$ | 85 | 40 | 65 |
| $q_2$ | 50 | 25 | 35 |

The initial fund $k$ of the emergency rescue base is 50,000 yuan, and the other relevant economic parameters are shown in Table 4.

**Table 4.** Unit rescue cost and unit penalty cost of relief supplies (Yuan/100 km).

| | $j_1$ | $j_2$ | $j_3$ |
|---|---|---|---|
| Unit rescue cost | [45,55] | [80,90] | [50,65] |
| Unit penalty cost | [20,24] | [30,35] | [24,28] |

Considering the actual situation, besides the emergency rescue base, other relevant departments also provide part of the emergency rescue resources when a major accident happens. The amount of rescue materials in this model is divided into two parts: the rescue base and the other related rescue departments. Based on the actual situation, the material reserves of the emergency rescue base are divided into three types of reserve status: low, medium, and high, which the probability of occurrence is 0.3, 0.6 and 0.1; then, we used triangular fuzzy numbers to characterize the reserves at different levels. The three types of emergency relief supply reserves of the relevant departments are [6,8,10], [4,5,6], and [6,7,8]. The material reserves of each emergency rescue base are shown in Table 5.

**Table 5.** Quantity and probability distribution of $R_i$ materials in each emergency rescue base (items).

| Rescue Base | Reserve Level | $j_1$ | $j_2$ | $j_3$ | Probability |
|---|---|---|---|---|---|
| $R_1$ | $h_1$ | [24,27,29] | [12,14,15] | [19,23,24] | 0.3 |
| | $h_2$ | [30,32,33] | [16,17,18] | [25,27,29] | 0.6 |
| | $h_3$ | [34,35,36] | [19,20,21] | [30,31,32] | 0.1 |
| $R_2$ | $h_1$ | [23,28,29] | [12,13,15] | [18,22,23] | 0.3 |
| | $h_2$ | [30,31,32] | [16,18,20] | [24,26,28] | 0.6 |
| | $h_3$ | [33,34,35] | [21,22,23] | [29,30,31] | 0.1 |
| $R_3$ | $h_1$ | [24,27,28] | [12,13,15] | [18,22,23] | 0.3 |
| | $h_2$ | [29,30,32] | [16,18,20] | [24,25,28] | 0.6 |
| | $h_3$ | [33,34,35] | [21,22,23] | [29,30,31] | 0.1 |
| $R_4$ | $h_1$ | [23,27,29] | [12,14,15] | [17,22,24] | 0.3 |
| | $h_2$ | [30,31,33] | [16,17,18] | [25,27,29] | 0.6 |
| | $h_3$ | [34,35,36] | [19,20,21] | [30,31,32] | 0.1 |
| $R_5$ | $h_1$ | [24,28,29] | [12,13,15] | [18,22,23] | 0.3 |
| | $h_2$ | [30,31,33] | [16,18,20] | [24,25,28] | 0.6 |
| | $h_3$ | [34,35,36] | [21,22,23] | [29,30,31] | 0.1 |
| $R_6$ | $h_1$ | [23,27,28] | [12,13,15] | [17,21,23] | 0.3 |
| | $h_2$ | [29,30,32] | [16,18,20] | [24,25,28] | 0.6 |
| | $h_3$ | [33,34,35] | [21,22,23] | [29,30,31] | 0.1 |

### *4.2. Formatting of Mathematical Components*

Use Lingo software to find the major accident $q_2$ or the extraordinarily serious accident $q_1$ under different credibility confidence levels $\lambda_i$. Each emergency rescue base provides different types of rescue materials for the two accident sites.

The two emergencies both come under the major accident $q_2$, and the relevant calculation results are shown in Tables 6 and 7.

**Table 6.** Optimal decision-making quantities under different confidence levels in major accidents $q_2$.

| | | λ=0.8 | | λ=0.9 | | λ=1 | |
|---|---|---|---|---|---|---|---|
| $A_1$ | $R_i$ | $R_3$ | $R_6$ | $R_3$ | $R_6$ | $R_3$ | $R_6$ |
| | $j_1$ | 18 | 32 | 19 | 31 | 19 | 31 |
| | $j_2$ | 8 | 17 | 8 | 17 | 8 | 17 |
| | $j_3$ | 10 | 25 | 11 | 24 | 11 | 24 |
| $A_2$ | $R_i$ | $R_1$ | $R_2$ | $R_1$ | $R_2$ | $R_1$ | $R_2$ |
| | $j_1$ | 20 | 30 | 20 | 30 | 20 | 30 |
| | $j_2$ | 9 | 16 | 9 | 16 | 9 | 16 |
| | $j_3$ | 11 | 24 | 11 | 24 | 11 | 24 |

**Table 7.** The upper and lower bounds of the total cost under different confidence levels (CNY).

| Rescue Cost | λ=1 | λ=0.9 | λ=0.8 |
|---|---|---|---|
| $f_{opt}^-$ | 1,144,838 | 1,144,538 | 1,129,771 |
| $f_{opt}^+$ | 1,345,082 | 1,344,722 | 1,326,026 |

The two emergencies are both under extraordinarily serious accident $q_1$, and the relevant calculation results are shown in Tables 8 and 9.

**Table 8.** Optimal decision-making quantities under different confidence levels in an extraordinarily serious accident $q_1$.

| | | λ=0.8 | | | λ=0.9 | | | λ=1 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| $A_1$ | $R_i$ | $R_2$ | $R_3$ | $R_6$ | $R_2$ | $R_3$ | $R_6$ | $R_2$ | $R_3$ | $R_6$ |
| | $j_1$ | 33 | 20 | 32 | 31 | 23 | 31 | 31 | 23 | 31 |
| | $j_2$ | 17 | 6 | 17 | 17 | 6 | 17 | 17 | 6 | 17 |
| | $j_3$ | 26 | 14 | 25 | 25 | 16 | 24 | 25 | 16 | 24 |
| $A_2$ | $R_i$ | $R_1$ | $R_4$ | $R_5$ | $R_1$ | $R_4$ | $R_5$ | $R_1$ | $R_4$ | $R_5$ |
| | $j_1$ | 33 | 31 | 21 | 32 | 31 | 22 | 32 | 31 | 22 |
| | $j_2$ | 17 | 17 | 6 | 17 | 17 | 6 | 17 | 17 | 6 |
| | $j_3$ | 27 | 26 | 12 | 26 | 25 | 14 | 26 | 24 | 15 |

**Table 9.** The upper and lower bounds of the total cost under different confidence levels (CNY).

| Rescue Cost | λ=1 | λ=0.9 | λ=0.8 |
|---|---|---|---|
| $f_{opt}^-$ | 3,316,654 | 3,304,784 | 3,250,665 |
| $f_{opt}^+$ | 3,975,919 | 3,960,736 | 3,891,343 |

As for the scheduling scheme under the major emergency $q_2$, with the credibility changes, the second scheduling scheme appears when $\lambda = 0.8$. In the scheme of accident spot $A_1$, due to the Shaowu emergency rescue base $R_6$ being closer to the accident spot, with a reduction in the credibility and relaxation of the constraints, then the amount of dispatched resources at the Shangrao emergency rescue base $R_3$ were reduced and thus increased the amount of dispatched resources at Shaowu emergency rescue base $R_6$. When $\lambda = 1$ and $\lambda = 0.9$, the first decision quantity in the scheduling scheme has not changed, thus with the relaxation of constraints, the reduction of system risks, and the penalties for insufficient supplies, the interval of the overall rescue costs becomes smaller. As for the scheduling scheme under the extraordinarily serious accident $q_1$, due to the high level of the accident, each accident spot requires three emergency rescue bases to rescue together. In the previous three scenarios, the Yingtan emergency rescue base $R_2$ provided rescue for accident point $A_1$, while in this scenario, it provided rescue for accident point $A_2$. It can be seen from the distance that this is in line with the actual needs. With the change in credibility, three different scheduling schemes are obtained under three different credibility conditions. When it is reduced from $\lambda = 1$ to $\lambda = 0.9$, for accident spot $A_1$, the amount of dispatching resources at Shangrao emergency rescue base $R_3$ is reduced, and the amount of dispatching resources at Yingtan emergency rescue base $R_2$ is increased. For accident point $A_2$, the amount of dispatching resources at the Laizhou emergency rescue base $R_5$ was reduced, and the amount of dispatching resources at the Jingdezhen emergency rescue base $R_4$ was increased. When it reduces from $\lambda = 0.9$ to $\lambda = 0.8$, with the relaxation of the restrictions in addition to the changes mentioned above, for accident point $A_1$, the amount of dispatched resources at the Shaowu emergency rescue base $R_6$ is also increased. For accident spot $A_2$, the amount of dispatched resources at the Xiangtang emergency rescue base is increased. These indicate that with the relaxation of the resource reserves, the corresponding amount of transportable resources increases, the decision-making space expands, and the total rescue cost decreases. Therefore, the trade-off between the total cost of rescue and the degree of constraint satisfaction can provide managers with different decision-making schemes.

The research results of this paper can provide a scientific theoretical basis and effective decision-making methods for resource scheduling in large-scale emergency rescues within the railway sector, which can help realize fast, accurate, and efficient emergency resource dispatching, thus further improving the response capability of railway emergency management, reduce the impact of emergency events on the railway transportation system, and ensure the safety and smooth flow of railway transportation.

## 5. Conclusions

This paper aims to optimize emergency resource scheduling for large-scale railway emergencies under uncertain conditions. Considering that the demand for emergency rescue materials has fuzzy properties, the upper limit, the maximum value, and the lower limit of the uncertainty factors are expressed intuitively using triangular fuzzy numbers. Additionally, the calculation results, in the form of intervals, are constructed in such a way as to ensure the inclusion of the real results of the data, using the number of intervals to characterize the transport cost parameters.

Due to the existence of fuzzy and probability distribution features in the constraints, the two-stage stochastic programming model and fuzzy credibility constraint programming are used to deal with the system's risk violation problem, and an interval two-stage fuzzy credibility constraint programming model is constructed with the objective of minimizing the total cost of an emergency rescue, which is solved using the interval interactive algorithm. Under different scenarios and confidence levels, the resource scheduling scheme with the lowest total cost of emergency resource dispatch is obtained, which supports the decision makers in formulating scientific dispatch plans under multiple incident points and variable incident classification scenarios. The main innovations of this paper are summarized in the following two aspects:

Starting from the analysis of multiple sources of uncertainty, considering the uncertainty of emergency resource reserves, demand, and emergency scenarios, combined with the related methods in uncertainty optimization theory, using triangular fuzzy numbers and probability distributions to characterize rescue bases and the daily reserves of relevant departments, we used the interval form to express the relevant cost parameters in emergency rescue. By analyzing the actual situation, a two-stage scheduling model was constructed and applied to the emergency scheduling research of railway emergencies.

When considering the multiple uncertainties in emergency rescue missions, an interval two-stage fuzzy credibility constraint model was constructed under multiple uncertain conditions, which extended the scenario of interval two-stage stochastic programming and constraint violation and considered fuzzy credibility constraint programming to solve fuzzy risk problems with violation probabilities.

In future studies, other uncertainties can be introduced, and the intrinsic correlation and coupling effects between various uncertain parameters can be explored in depth to further improve and refine the model. In addition, the multiparty collaborative rescue of local governments and other rescue departments with railway departments should be considered with a view to constructing models and methods that align more with the actual situation.

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