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Robust optimization method of emergency resource allocation for risk management in inland waterways

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ABSTRACT

This study proposes a robust optimization method for waterborne emergency resource allocation in inland waterways that addresses the uncertainties and mismatches between supply and demand. To accomplish this, we integrate the risk evaluation of maritime with a robust optimization model and employ the Entropy Weighted Method (EWM)-Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)-Analytic Hierarchy Process (AHP) method to evaluate the risk of various areas. The approach enables exploration of the relationship between maritime risk and emergency resource allocation strategy. The robust optimization method is used to deal with uncertainty and derive the robust counterpart of the proposed model. We establish an emergency resource allocation model that considers both the economy and timeliness of emergency resource allocation. We construct an optimization model and transform it into an easily solvable robust counterpart model. The results demonstrate that the proposed method can adapt to real-world scenarios, and effectively optimize the configuration effect while improving rescue efficiency under reasonable resource allocation. Specifically, the proportion of rescue time saved ranges from 28.52% to 92.60%, and the proportion of total cost saved is 95.82%. Our approach has significant potential to provide a valuable reference for decision-making related to emergency resource allocation in maritime management.

1. Introduction

With the growth of economic activities in inland waterway transport, inland waterway freight volume ranks first globally [1]. The traffic density of inland waterways is increasing yearly, maritime accidents frequently occur, and the demand for emergency resources increases [2].

As one of the major inland waterways in China, the Yangtze River plays an important supporting role in inland waterway transport. However, the continuous increase in waterway transport activities has led to an increase in the risk of maritime risk [3]. Similarly, the Mississippi River plays a crucial role in logistics transportation in the United States, accounting for approximately 60% of inland waterway shipping in the United States. However, due to the special climate in the past few years, the water level of the Mississippi

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River was significantly lower than the same period in previous years, and the risk of maritime accidents gradually increased [4].

In such situations, emergency management becomes extremely vital to the safety and health of human beings [5]. A reasonable and practical allocation of emergency resources has become an important issue to be resolved in the inland waterway transportation industry.

Waterborne emergency resource allocation is developed based on traditional emergency resource allocation. The existing research on waterborne emergency resource allocation optimization can be broadly classified into two categories, which are reactive and proactive emergency resource allocation strategies [6]. The former mainly focuses on how to enhance the performance of operations in terms of efficiency and precision after the occurrence of a maritime accident. The dynamic allocation approach is a major method of reactive emergency resource allocation at this stage:

The aims of dynamic allocation approach establish a dynamic allocation model to reduce the losses and the economic cost of the emergency relief operations. For example, Friedrich et al. [7] introduced dynamic planning theory to establish an optimal allocation model for emergency resources, to minimize accident casualties to calculate the performance and efficiency of resources under different emergency demands. Mahdi et al. [8] constructed a dynamic emergency resource allocation model to optimize the number and location of ambulance allocations under different accident times and to minimize the number of uncovered points and the total cost. Zhang et al. [9] determined the optimal allocation level of emergency resources for each reserve base by considering the dynamic demand characteristics of emergency resources and the particular characteristics of the reserve base reserve environment. Liu et al. [10] considered the dynamic characteristics of disasters and accidents and the demand continuity for emergency relief materials, in order to reduce the losses and the economic cost of the emergency relief operations. The reactive emergency resource allocation strategies can accurately dispatch emergency resources according to the demands. However, delay or a shortage of emergency resources will be inevitable if sufficient emergency resources cannot be deployed in the appropriate rescue base timely.

In view of this, proactive emergency resource allocation strategies are proposed, focusing on how to allocate different types of emergency resources before the occurrence of maritime accidents. Four main factors affecting the allocation of emergency resources: the distance between rescue bases and accidents, the type of emergency resources, the number of emergency resources, and the allocation cost. Balancing these factors is the core of emergency resource allocation to cope with uncertainty. The two-stage allocation approach is a major method of proactive emergency resource allocation at this stage:

The aims of the two-stage allocation approach construct a two-stage stochastic programming model to reduce the shortage of emergency resources [11]. For example, Salmerón et al. [12] established a model based on the uncertainty of the accident point and the severity of the accident. Zhang and Zeng [13] established a model considering the total input, dispatching the cost of emergency resources at the supply point, and solving it using a robust optimization method. Zhang et al. [14] considered the allocation problem of limited medical reserves during a public health emergency and the priorities of healthcare centres and regarded the donated supplies as an efficient recourse action, aiming to minimize the total losses. Liu et al. [15] proposed a two-phase framework to optimize location and capacity design strategies during pandemics, and creatively developed an OCO approach with Lagrangian multipliers and proved its asymptotic consistency. The standard two-stage stochastic programming model incorporate different aspects of uncertainty in demand and supplies. However, the study usually focuses on emergency resource deployment and emergency resource allocation networks, few explore the relationship between the risk of various areas and emergency resources allocation strategy.

Based on existing researches and the demand of a reasonable and practical allocation of emergency resources, a novel risk evaluation of maritime method is proposed in this study to guide decision-makings, composing of EWM, TOPSIS and AHP. The EWM-TOPSIS-AHP is used to determine the maritime accident risk in various areas according to accident types, level and numbers of each area, which can optimize the configuration effect and improve the rescue efficiency [16-20]. The main advantage lies in that it can provide a basis for optimizing emergency resource allocation and making the allocation scheme more reliable. For the emergency resource allocation in inland waterways, the emergency resource demand of each disaster area is uncertain, varying in a set [21-22]. The robust optimization method is the most applicable in the study of emergency resource allocation under dynamic demand. It is good at solving the optimization problem with some data expressed as a set [21]. Furthermore, the optimal solution could satisfy all the constraints absolutely. Therefore, the robust optimization method is used to deal with uncertainty of demand, this paper establishes an emergency resource allocation robust optimization model that considers both the economy and timeliness of emergency resource allocation.

The rest of the paper is organized as follows: The proposed approach is introduced in Section 2: The risk evaluation of waters method is proposed and robust optimization of emergency resources allocation model is demonstrated. A case study of the Jiangsu section of the Yangtze River is presented in Section 3 to evaluate the performance of the proposed model. Finally, Section 4 summarizes the key findings of this study.

2. Methods

The paper introduces a robust optimization method of emergency resource allocation in inland waterways. The flowchart is presented as shown in Figure 1. The steps of the proposed method can be summarized as follows:

•Step 1: This step proposes the EWM-TOPSIS-AHP method to evaluate the maritime accident risk in various areas.

•Step 2: Under the process of step 1, this step proposes a waterborne emergency resource allocation model based on the risk evaluation results. The proposed model considers the economics and timeliness of rescue [23], which can be used to obtain the emergency resource allocation strategy.

•Step 3: This step adapts the robust optimization method proposed by Bertsimas and Sim in order to obtain the robust counterpart of the proposed model, which can effectively avoid uncertainty according to the decision-maker's most preferred allocation policy [24-25]. The effectiveness of the proposed method is tested by comparing the results with the results of the emergency resource allocation model, through a real case study on the allocation of rescue ships for different types of water rescue bases in the Jiangsu section of the Yangtze River.

2.1 Step 1: The risk evaluation of maritime method

In order to make the watershed risk evaluation more scientific and reasonable, this step innovatively uses the EWM-TOPSIS-AHP method to calculate the watershed risk degree of each accident area.

Risk evaluation of waters can provide a basis for optimizing emergency resource allocation and make the configuration plan more reliable. In the past, the importance of watershed risk evaluation was neglected when emergency resources in inland waterway were allocated. Some scholars have considered a watershed risk in their studies. However, the evaluation taken the number of accidents as the only criterion to measure watershed risk, ignored the influence of accident type and accident level on watershed risk [26].

The risk evaluation of maritime method includes the following three methods:

(1) EWM

EWM (Entropy Weight Method) is an important application of entropy theory in management science [27-28]. EWM objectively evaluates the validity of the information based on the given raw data of each index by virtue of the disorderly algorithm, and finally finds the weight corresponding to each index.

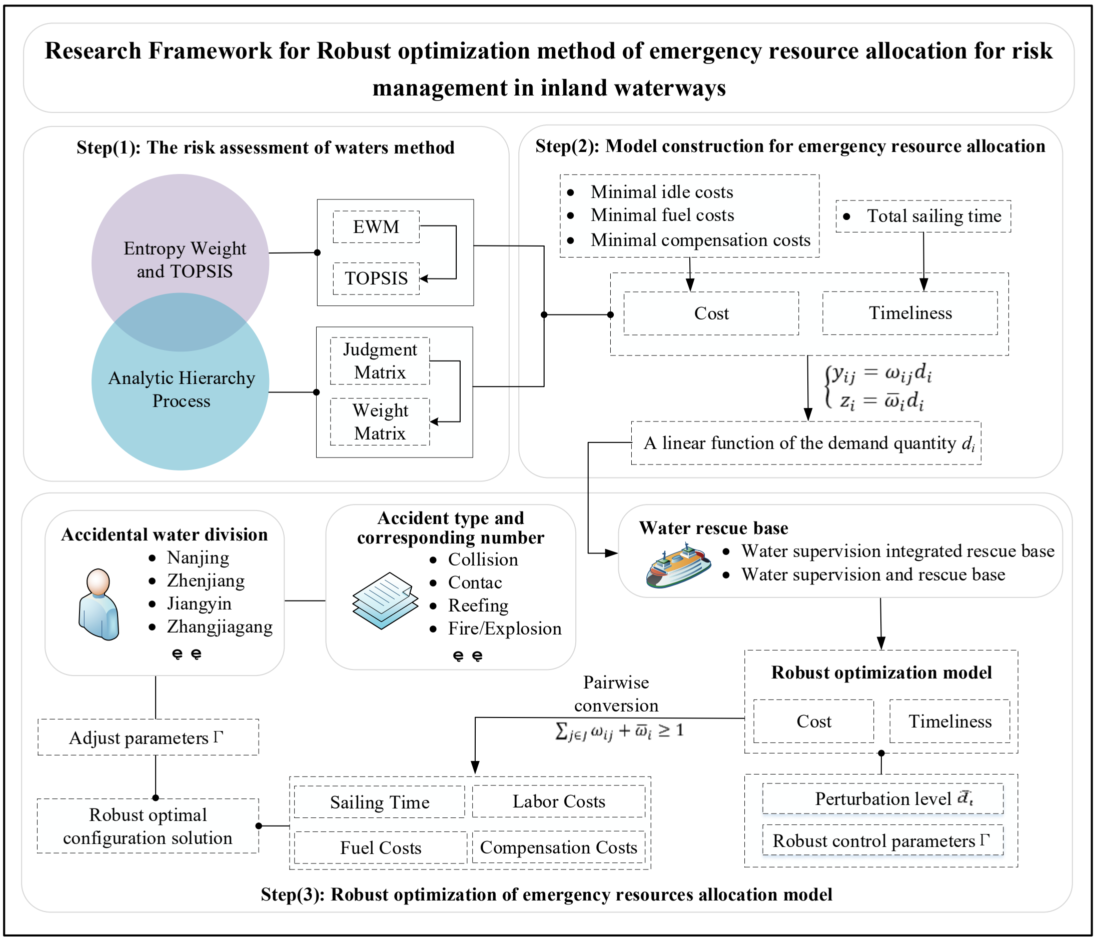

Fig. 1 Research framework

Using EWM, the amounts of accident areas and accident types in inland waterways are denoted as m and n. In most cases, the dimensions of each accident are different [28]. Therefore, accident data should be normalized before calculating entropies.

$$y_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{1}$$

where x_{ij} and y_{ij} are the observation and normalized data of the ith object for the jth indicator [26-29].

In EWM, the entropy H_j of the jth accident types is defined as

$$H_j = -\frac{1}{\ln m} \sum_{i=1}^{m} y_{ij} \ln y_{ij} \tag{2}$$

H_j lies in [0,1]. The higher the accident type's dipartite condition, the smaller H_j is. EWM assigns weights on the basis of the dipartite degree [27-30]. A large weight is assigned for accident types with high dipartite degree, and vice versa. Therefore, the weight parameter ω_j of the jth accident type is generated by

$$W = \frac{1-H_j}{n-\sum_{j=1}^{n} H_j} \tag{3}$$

The detailed calculation process of the EWM is described in Appendix 1.

(2) TOPSIS

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a comprehensive evaluation method, which uses a pair of a positive ideal solution and a negative ideal solution as two reference points to rank a set of decision alternatives [31].

Using TOPSIS, the complexity characteristics of accident types obtained from different accident areas can be merged to rank the risk of various areas in inland waterways [32].

If there are m sets of accident area in inland waterways, for each set, there is an accident type n. The eigenvalues of the accident areas are the attributes of m sets of sequence [33-34]. For each m_i, the eigen attribution is y_{ij}. Hence, the multi-decision matrix $Y = [y_{ij}]_{m\times n}$ becomes:

$$Y = \begin{pmatrix} y_{11} & \cdots & y_{1n} \\ \vdots & \ddots & \vdots \\ y_{m1} & \cdots & y_{mn} \end{pmatrix} \tag{4}$$

Finally, the closeness of each evaluation target's vector of evaluation values to the maximum risk set is obtained, and the ranking of each closeness is used to determine the risk value of the target [35]. As the closeness increases, the distance between the evaluation on the accident areas in inland waterways, and the defined most complex accident area decrease.

The detailed calculation process of the TOPSIS is described in Appendix 2.

(3) Analytic Hierarchy Process

AHP (Analytic Hierarchy Process) (Appendix 3) is a decision-making method combining qualitative and quantitative analysis, which American scholar Saaty in the 1970s proposed [36]. It classifies various factors in a complex problem into three levels association, order and organization, uses subjective judgments of two comparisons or objective data to analyze the importance of different objectives [37].

Using AHP and combining above methods to calculate the risk ranking of each accident areas, the weight values of each accident areas and the eigenvector values is obtained.

AHP based on the judgement matrix constructing (shown as Eq. (5)), a_i and a_j denoted the fraud factors, n denoted number of fraud factors. a_{ij} denoted the relative importance of a_i to a_j [38]. Scores 1 through 9 indicate ascending degrees of importance, with 1 indicating equivalence and higher scores successively greater importance [39]. Define $a_{ji}=1/a_{ij}$.

$$A = \begin{pmatrix} 1 & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & 1 \end{pmatrix} \tag{5}$$

The AHP operation flow as shown in Fig. 2, and the detailed calculation process of the AHP is described in Appendix 3.

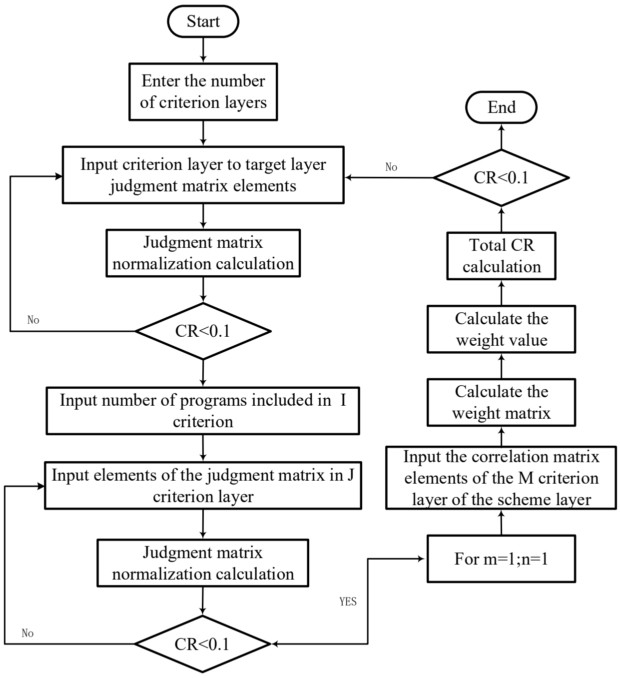

Fig. 2 Analytic Hierarchy Process operation flow

(4) EWM-TOPSIS-AHP

The EWM-TOPSIS-AHP method combines EWM, TOPSIS and AHP. The AHP is based on subjective information, and EWM is based on the degree of information disorder in the assessment system, TOPSIS is based on the gap between the evaluation schemes.

AHP is vulnerable to the perceptions of interviewees, EWM and TOPSIS is vulnerable to extreme values. To reduce the potential bias caused by AHP, EWM-TOPSIS was employed for objectively weighting [40]. The process of evaluating the martime risk in inland waterways using the EWM-TOPSIS-AHP method is shown in Fig. 3.

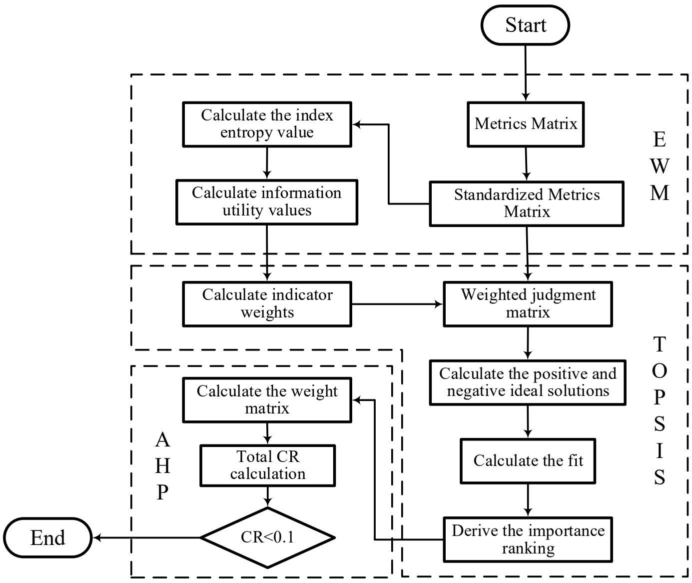

Fig. 3 Entropy power TOPSIS-AHP operation process

The process concluded on three main parts.

Part1: The amounts of accident areas and accident types in inland waterways are inputted, obtains the weight coefficients of each accident type through the EWM processing.

Part2: The weight coefficients of accident types from different accident areas obtained from Part 1 can be merged to rank the risk of various areas in inland waterways, obtains the importance ranking of each accident area through the TOPSIS processing.

Part 3: The importance ranking of each accident area obtained from Part 2 are used to construct judgement matrix, obtains the weight values of each accident interval through the AHP processing.

2.2 Step 2: Model construction for emergency resource allocation

Under step 1, this step has been reviewed the emergency resource allocation mechanism of different types of water rescue bases. Based on the weight values of each accident areas and emergency resource allocation mechanism, this step proposes a waterborne emergency resource allocation model.

2.2.1 Emergency resource allocation mechanism

In this section, we discuss the emergency resource allocation mechanism for inland waterway, which considers the possible existence of continuous accident rescue and major accident rescue in inland waterway, the differences in the scale and responsibility of different types of water rescue bases [41].

As shown in Fig. 4, the configuration mechanism of the rescue ship is optimized:

(1) S1, S5 for the regulatory rescue integrated bases, S2, S3, S4 for the regulatory rescue bases, Di for the accident areas.

(2) The jurisdiction of the regulatory rescue integrated base is larger than the regulatory rescue base; Any accident areas shall be jointly supervised and rescued by the regulatory rescue integrated base and the regulatory rescue base.

(3) The water rescue bases give priority to sending rescue boats to the accident areas near the jurisdiction and with low rescue costs.

(4) It is considered to dispatch rescue ships to the accident areas outside the jurisdiction for rescue when there are enough rescue ships in the rescue base, and the principle of proximity shall be followed when dispatching.

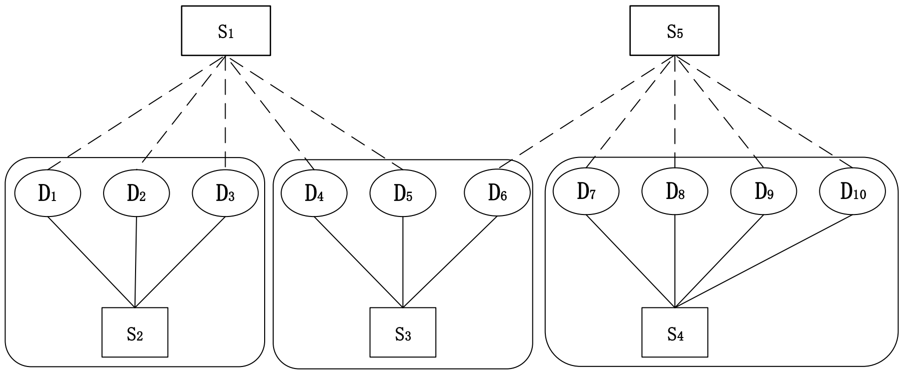

Fig. 4 Emergency resource allocation network topology

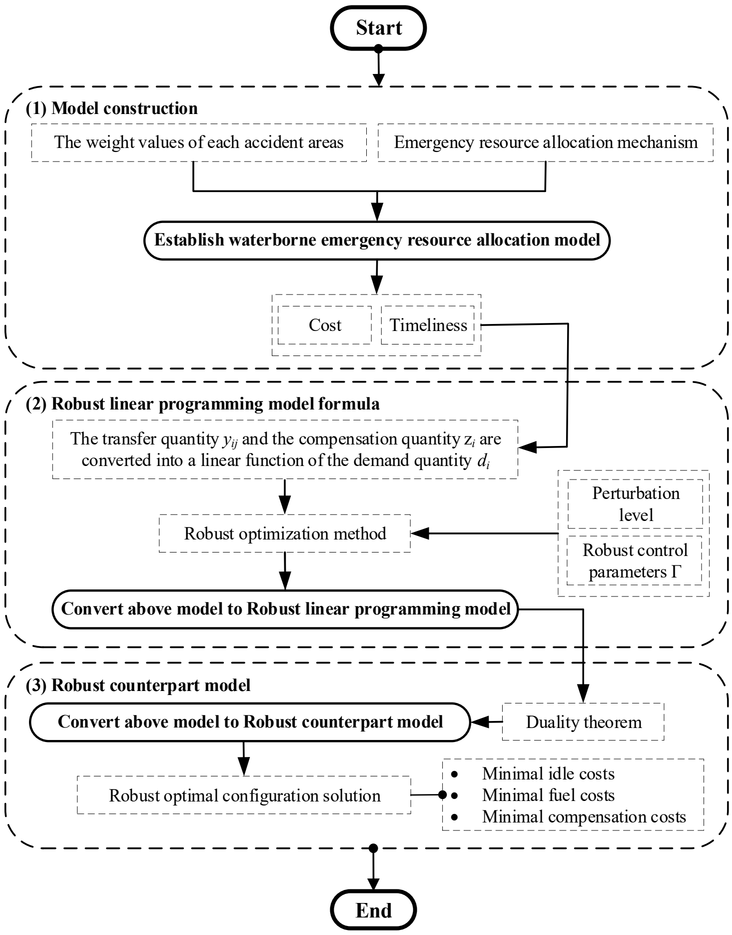

Fig. 5 The flowchart of robust optimization method of emergency resource allocation

The flowchart of robust optimization method of emergency resource allocation as shown in Fig. 5.

The steps of the robust optimization method of emergency resource allocation model construction are summarized as follows:

(1) Model construction. Proposing a waterborne emergency resource allocation model, which considers the economics and timeliness of rescue.

(2) Robust linear programming model. Employing the robust optimization method to obtain robust linear programming model.

(3) Robust counterpart model. Employing the duality theorem to transformed robust linear programming model into a robust counterpart model

Details about the robust optimization method shown in Fig.5 is given in the following sections.

2.2.2 Model construction

Based on the above configuration mechanism, in order to address the allocation optimization of emergency resources in inland waterways, the water rescue base emergency resource allocation model is established as Eq. (6)-(11).

Objective functions:

$$f_1 = min \sum_{j\in J} \overline{S} \left(x_j - \sum_{i\in I} y_{ij}\right) + \sum_{i\in I}\sum_{j\in J} \overline{F}\, y_{ij} t_{ij} + \sum_{i\in I} \overline{U}\, z_i \quad (6)$$

$$f_2 = min \sum_{i\in I}\sum_{j\in J} y_{ij} t_{ij} \quad (7)$$

Constraints:

$$x_j \le V_j, \forall j \quad (8)$$

$$\sum_{i\in I} y_{ij} \le x_j, \forall j \quad (9)$$

$$\sum_{i\in I} y_{ij} + z_i \ge 0\,, \forall i \quad (10)$$

$$x_j, y_{ij}, z_i \ge 0, \forall i \quad (11)$$

In the above optimization model, Eq. (6) represents cost control, which is used to control the cost of emergency resource deployment; Eq. (7) represents time control, which is used to ensure the timeliness of emergency rescue; Eq. (8) indicates that the number of emergency resource allocation cannot exceed the capacity limit of the rescue base; Eq. (9) indicates that the number of emergency resources transported from the rescue base *Sj* to the accident areas cannot exceed the allocation number of the rescue base; Eq. (10) indicates that the demand for emergency resources transferred to the accident areas *Di* can be satisfied when the water accident occurs; Eq. (11) indicates that the allocation amount of emergency resources of the rescue base, the number of emergency resources transported to each accident area, and the compensation amount of emergency resources are all non-negative.

The parameters involved in the model are as follows:

- V_j is the upper limit of emergency resources that the relief base can accommodate.
- t_{ij} is the time for emergency resources to be dispatched from relief base S_j to the accident areas D_i.
- d_i is the demand for emergency resources in the accident areas D_i.
- x_j is the number of emergency resources configured in relief base A_j.
- y_{ij} is the number of emergency resources dispatched from relief base S_j to the accident areas D_i.
- z_i is the compensation amount when the demand for emergency resources in the accident areas D_j is not met.

$\bar{S}$, $\overline{F}$ and $\overline{U}$ are constant coefficients, which denote rescue personnel wages, domestic fuel prices, and compensation prices when emergency resources are insufficient and will be analysed later.

2.3 Step 3: Robust optimization of emergency resources allocation model

Under step 2, based on the above constructed model, this step employs the robust optimization method to obtain robust linear programming model. In order to transform into a robust counterpart that is easier to solve, this step adapts the duality theorem, the robust waterborne emergency resource allocation optimization model is transformed into a robust counterpart model.

2.3.1 Robust linear programming model

Usually, the mobilization and compensation of emergency resources vary with demand [26], which can be expressed as a linear function of demand, as in Eq. (12).

$$\begin{cases} y_{ij} = \omega_{ij} d_i \\ z_i = \varpi_i d_i \end{cases} \forall i, j \tag{12}$$

In the above equation, ω_{ij}, $\overline{\omega}_i$ denote the correlation coefficients of the emergency resource transfer and compensation volume, which used to map the demand respectively. They are positive and non-adjustable variables. After the above linear transformation, the water rescue base emergency resource allocation model can be transformed into an Eq. (13)-(18). The emergency resource demand d_i becomes the only uncertain variable in the model.

Objective functions:

$$f_1 = min \sum_{j \in J} \overline{S}\, x_j - \sum_{i \in I} \sum_{j \in J} \overline{S} \omega_{ij} d_i + \sum_{i \in I} \overline{F}\, d_i \big(\sum_{j \in J} \omega_{ij} t_{ij}\big) + \sum_{i \in I} \overline{U}\, \varpi_i d_i \tag{13}$$

$$f_2 = min \sum_{i \in I} d_i \big(\sum_{j \in J} \omega_{ij} t_{ij}\big) \tag{14}$$

Constraints:

$$x_j \leq V_j, \forall j \tag{15}$$

$$\sum_{i \in I} \omega_{ij} d_i \leq x_j, \forall j \tag{16}$$

$$\sum_{j \in J} \omega_{ij} + \varpi_i \geq 1, \forall i \tag{17}$$

$$x_{ij}, y_{ij}, z_i \geq 0, \forall i, j \tag{18}$$

In the above optimization model, the emergency resource requirements for each accident area d_i can be denoted by the set $d_i \in (d_i^0 - \widehat{d_\iota},\ \ d_i^0 + \widehat{d_\iota})$, $\forall i$. d_i^0 denotes the value of emergency resource demand for the ith accident area. $\widehat{d_\iota}$ denotes the level of perturbation that deviates from the statistical demand. The robust control parameter Γ represents the number of perturbed demands, $\Gamma \in [0, J_0]$, $J_0 = |I|$. There are $|\Gamma|$ perturbed demand $\widehat{d_\iota}$, and the other is $(\Gamma - |\Gamma|)\ \widehat{d_\iota}$ [24, 42-43].

To protect against all cases in which Γ_i coefficients of set J_i are permitted to change [44], and one coefficient ($\widehat{d_\iota}$) changes by $(\Gamma - |\Gamma|)\ \widehat{d_\iota}$, a protective function denoted $\beta\ (x, \Gamma_i)$ for each row i is defined as follows:

$$\beta\ \ (x, \Gamma_i) = \left. \max_{\left\{ \left(\substack{\langle U_0 \cup r_0 | U_0 \subseteq J_0 \rangle \\ |U_0| = |\Gamma_0| \\ r_0 \in J_0 \setminus U_0} \right) \right\}} \left[\sum_{i \in U_0} \widehat{d_\iota} (x_i) + (\Gamma - |\Gamma|) \widehat{d_{r_0}} |x_{r_0}| \right] \right\} \tag{19}$$

Objective functions (13)-(14) can be rewritten as follows:

$$f_1 = min\left\{\sum_{j\in J}\bar{S}x_j - \sum_{i\in I}\sum_{j\in J}\bar{S}d_i^0\omega_{ij} + \sum_{i\in I}\bar{F}d_i^0\left(\sum_{j\in J}\omega_{ij}t_{ij}\right) + \sum_{i\in I}\bar{U}d_i^0\varpi_i \right.$$
$$+ \max_{\left\{\left(\langle U_0 \cup r_0 | U_0 \subseteq J_0\rangle \atop {|U_0|=|\Gamma_0| \atop r_0\in J_0\backslash U_0}\right)\right\}}\left[\sum_{i\in U_0}\bar{F}\hat{d}_\imath\left(\sum_{j\in J}\omega_{ij}t_{ij}\right)\right.$$
$$\left.\left. + \sum_{i\in U_0}\bar{U}\hat{d}_\imath\varpi_i - \sum_{i\in U_0}\sum_{j\in J}\bar{S}\hat{d}_\imath\omega_{ij} + (\Gamma - |\Gamma|)\widehat{d_{r_0}}\left(\sum_{j\in J}\bar{F}\omega_{r_0 j}t_{r_0 j}\right) + \bar{U}\varpi_{r_0} - \sum_{j\in J}\bar{S}\omega_{r_0 j}\right]\right\} \tag{20}$$

$$f_2 = min\left\{\sum\nolimits_{i\in I} d_i^0\left(\sum\nolimits_{j\in J}\omega_{ij}t_{ij}\right) + \max_{\left\{\left(\langle U_0 \cup r_0 | U_0 \subseteq J_0\rangle \atop {|U_0|=|\Gamma_0| \atop r_0\in J_0\backslash U_0}\right)\right\}}\left[\sum\nolimits_{i\in U_0}\hat{d}_\imath\left(\sum\nolimits_{j\in J}\omega_{ij}t_{ij}\right) + (\Gamma - |\Gamma|)\widehat{d_{r_0}}\left(\sum\nolimits_{j\in J}\omega_{r_0 j}t_{r_0 j}\right)\right]\right\} \tag{21}$$

Constraint (16) can be rewritten as follows:

$$\sum\nolimits_{i\in I}\omega_{ij}d_i^0 + \max_{\left\{\left(\langle U_0 \cup r_0 | U_0 \subseteq J_0\rangle \atop {|U_0|=|\Gamma_0| \atop r_0\in J_0\backslash U_0}\right)\right\}}\left[\sum\nolimits_{i\in U_0}\hat{d}_\imath\varpi_{ij} + (\Gamma - |\Gamma|)\varpi_{r_0 j}\widehat{d_{r_0}}\right] \le x_j, \forall j \tag{22}$$

Based on above analysis, Eq. (13)-(18) can be translated into a robust optimization model for waterborne emergency resource allocation, as in Eq. (15), (17)-(18), (20)-(22).

In general, the control parameter Γ varies between 0 and J_0, part of the demand is perturbed and the other is stabilized at the demand average. When $\Gamma = J_0$, all accident areas exhibit uncertainty and all emergency resource demands take the maximum value, which is the most conservative case; when $\Gamma = 0$, The impact of perturbed demand is completely ignored.

However, the specifically accident areas corresponding to the perturbed demands are uncertain, the problem of emergency resource allocation shows uncertainty at this time. The core of robust optimization is to find the optimal solution under various uncertainties to satisfy the worst case [45-47].

2.3.2 Robust counterpart model

The model introduces robust adjustable optimization to cope with uncertain emergency resource demands and changes in decision-makers' attitudes toward resource allocation, which can significantly improve the robustness of the emergency resource allocation. The robust optimization model belongs to the NP-hard problem, which is extremely difficult to solve directly [48]. Using the duality theorem, the above model is transformed into a robust counterpart model which is easier to solve., as in Eq. (23)-(31) [49].

Objective functions:

$$f_1 = min\left[\sum\nolimits_{i\in I} d_i^0\left(\sum\nolimits_{j\in J}\omega_{ij}t_{ij}\right) + \Gamma\gamma + \sum\nolimits_{i\in J_0}\lambda_i\right] \tag{23}$$

$$f_2 = min\left[\sum_{j\in J_0} \overline{S}x_j - \sum_{i\in I}\sum_{j\in J} \overline{S} d_i^0 \omega_{ij} + \sum_{i\in I} \overline{F} d_i^0 \left(\sum_{j\in J} \omega_{ij} t_{ij}\right) + \sum_{i\in I} \overline{U} d_i^0 \varpi_i + \Gamma\gamma' + \sum_{i\in J_0} \lambda_i'\right] \quad (24)$$

Constraints:

$$x_j \le V_j, \forall j \quad (25)$$

$$\sum_{i\in I} \omega_{ij} d_i^0 + \Gamma\xi_j + \sum_{i\in J_0} \tau_{ij} \le x_j, \forall j \quad (26)$$

$$\sum_{j\in J} \omega_{ij} + \varpi_i \ge 1, \forall i \quad (27)$$

$$\xi_j + \tau_{ij} \ge \widehat{d}_\iota \omega_{ij}, \forall i \in J_0 \quad (28)$$

$$\gamma + \lambda_i \ge \widehat{d}_\iota \left(\sum_{j\in J} \omega_{ij} t_{ij}\right), \forall i \in J_0 \quad (29)$$

$$\gamma' + \lambda_i' \ge \widehat{d}_\iota \left(\sum_{j\in J} \omega_{ij} t_{ij} - \sum_{j\in J} \omega_{ij} + \varpi_i\right), \forall i \in J_0 \quad (30)$$

$$x_j, \omega_{ij}, \varpi_i, \tau_{ij}, \xi_j, \gamma, \lambda_i, \gamma', \lambda_i' \ge 0, \forall i, j \quad (31)$$

In the above robust counterpart model, x_j denotes the number of emergency resources allocated for rescue base S_j. d_i^0 denotes the emergency resource demand of accident area D_i. $\omega_{ij}, \overline{\omega}_i$ denote the demand correlation coefficient of emergency resource dispatching volume and compensation volume respectively. $\widehat{d}_\iota$ and Γ denote the demand for disturbance and the corresponding quantity respectively. t_{ij} denotes the time of rescue ships from the rescue base S_j to the accident areas D_i. γ, γ', λ_i, λ_i' are the new decision variables introduced by the pairwise transformation.

3. Case Study

To test the performance of our proposed model, the section takes the Jiangsu section of the Yangtze River as an example, allocates emergency resources (rescue ships) to several water rescue bases in inland waterways based on the accident data of the Jiangsu section of the Yangtze River for many years. The model is implemented by Matlab to run NSGA-II (The Non-dominated Sorting Genetic Algorithm) to solve.

3.1 Data sources

The case study presented in this paper makes use of accident data from Jiangsu Maritime Office for the Jiangsu section of the Yangtze River between 2019 and 2021.

In order to facilitate the subsequent study on the optimization of emergency resource allocation, this case divides the Jiangsu section of Yangtze River into ten accident areas through the maritime department.

For example, the Nanjing section of Yangtze River refer to the accident areas under the jurisdiction of the Nanjing maritime department. Each maritime department corresponds to one accident area. The extent of various areas in inland waterways and the number of cross-river bridges are shown in Table 1.

Table 1 Division of waters of Jiangsu section of Yangtze River

Water serial number	Name of accident area	Accident area/km	Waterway mileage/km	Number of cross-river bridges /seat
1	Nanjing	332.5-390	56.5	6
2	Qixia	292.5-332.5	40	1
3	Zhenjiang	240-292.5	54.5	2
4	Taixing	200-240	40	1
5	Yangzhong	190-240	43	4
6	Jiangyin	157.5-200	43.5	1
7	Jingjiang (Zhangjiagang)	105-157.5	52.5	5
8	Nantong	67.5-117.5	52	1
9	Haimen	0-67.5	67.5	1
10	Changshu (Taicang)	27.5-57.5	30	0

3.2 Results and analysis

3.2.1 Evaluation of maritime risk in inland waterway

The accidents were classified into ten types of accidents: contacting, collision, reefing, fire/explosion, grounding, sinking, wind damage, wave loss, pollution, and others. As shown in Fig. 6, the accident data of Jiangsu Maritime Office from 2019-2021 were counted and visualized. The accident types and corresponding accident numbers of each accident area in the waters of Jiangsu section of Yangtze River are shown in Table 2.

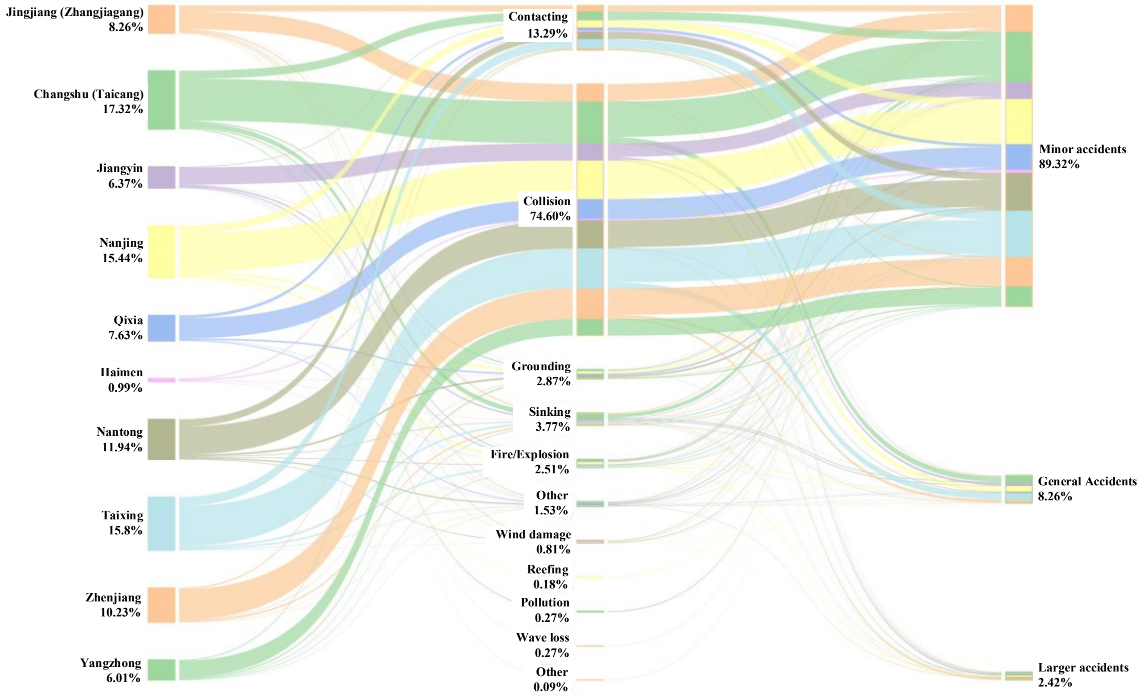

Fig. 6 Accident statistics in study area

Table 2 Types and number of accidents in study area between 2019 and 2021

Accident area	Contacting	Collision	Reefing	Fire/Explosion	Grounding	Sinking	Wind damage	Wave loss	Pollution	Other
Nanjing	24	110	2	9	8	1	2	0	0	3
Qixia	10	83	0	1	5	0	0	0	0	0
Zhenjiang	4	101	0	1	2	6	0	0	0	1
Taixing (Taizhou)	30	132	0	1	0	6	1	0	0	2
Yangzhong	3	55	0	2	4	2	0	0	0	1
Jiangyin	2	57	0	7	1	5	1	0	0	1
Jingjiang (Zhangjiagang)	20	58	0	1	1	4	3	1	0	4
Nantong	24	93	0	2	6	2	2	0	0	4
Haimen	4	4	0	0	1	1	0	0	0	1
Changshu (Taicang)	27	138	0	4	4	16	0	0	3	1

For each accident area, the above data were used to the EWM-TOPSIS-AHP method to evaluate maritime risks as explained in Section 2.1 (Fig. 3). The process concluded on three main parts, namely: Part 1 obtains the weight coefficients of each accident type through the EWM processing, as shown in Table 3. Part 2 obtains the importance ranking of each accident area through the TOPSIS processing, as shown in Table

4. Part 3 obtains the weight values of each accident interval through the AHP processing, as shown in Table 5.

Table 3 EWM processing results and weighting coefficients

Accident Type	Information entropy value e	Information utility value d	Weighting factor w
Contacting	0.8724	0.1276	3.25%
Collision	0.94	0.06	1.53%
Reefing	0.1177	0.8823	22.45%
Fire/Explosion	0.8022	0.1978	5.03%
Grounding	0.8565	0.1435	3.65%
Sinking	0.8044	0.1956	4.98%
Wind damage	0.6768	0.3232	8.22%
Wave loss	0.2011	0.7989	20.33%
Pollution	0.0848	0.9152	23.29%
Other	0.8771	0.1229	3.13%
Number of cross-river bridges	0.8368	0.1632	4.15%

Table 4 TOPSIS processing results and importance ranking of each watershed

Accident areas	Positive ideal solution distance D+	Negative ideal solution distance D-	Relative proximity C	Importance Ranking
Nanjing	1.147	1.929	0.627	3
Qixia	1.669	1.249	0.428	6
Zhenjiang	1.522	1.517	0.499	5
Taixing (Taizhou)	1.144	2.179	0.656	2
Yangzhong	1.953	0.823	0.297	9
Jiangyin	1.882	0.923	0.329	8
Jingjiang (Zhangjiagang)	1.695	1.107	0.395	7
Nantong	1.38	1.571	0.532	4
Haimen	2.563	0.104	0.039	10
Changshu (Taicang)	0.685	2.455	0.782	1

Table 5 AHP processing results and maritime risk

Accident areas	Maritime risk	Weighting value	Maximum Eigenvalue	CI value
Nanjing	1.138	11.381%	10	0
Qixia	0.569	5.690%		
Zhenjiang	0.683	6.828%		
Taixing (Taizhou)	1.707	17.071%		
Yangzhong	0.379	3.794%		
Jiangyin	0.427	4.268%		
Jingjiang (Zhangjiagang)	0.488	4.877%		
Nantong	0.854	8.535%		
Haimen	0.341	3.414%		
Changshu (Taicang)	3.414	34.142%		

In the Table 4, D+ and D- denote the distance between the evaluation object and the positive and negative ideal solutions, respectively; C denotes the proximity of the evaluation object to the optimal solution. The eigenvector values were used as the maritime risk (see Table 5).

Table 5 shows that Changshu (Taicang) maritime department has the highest accident risk, and the maritime risk is 3.414. The types of accidents in Changshu (Taicang) maritime department mainly include collision and contacting. It is because Changshu (Taicang) maritime department is located at the estuary of the Yangtze River, which leads to complex traffic flow and difficult ship operation. Therefore, the number of emergency resources in the nearby rescue base should be increased correspondingly.

Haimen maritime department has the lowest accident risk, and the maritime risk is 0.341. This is mainly because Haimen maritime department has a smaller jurisdiction and fewer ships than other maritime departments. Haimen maritime department can relatively reduce the allocation of emergency resources and improve resource utilization.

Other rescue bases should also make corresponding adjustments to the allocation of emergency resources according to the maritime risk of various areas, in order to improve the rescue efficiency under the premise of ensuring reasonable resource allocation.

3.2.2 Relevant calculation of emergency resource allocation

Rescue ships, as an important rescue equipment in maritime, has the advantages of speed, convenience, flexibility, can quickly reach the accident areas to participate in the rescue. It has a pivotal position in the supervision of inland waterways and waterborne emergency rescue [50]. The case uses rescue ships to study the emergency resource allocation method for inland waters.

Rescue ship is mainly divided into 40 m class, 30 m class, and 20 m class, the following mainly explores the $30m$ rescue ship emergency resource configuration program.

According to the provisions on the administration of maritime ship allocation, the number of 30 m class rescue ship configuration d_{30m} is provided as in Eq. (32).

$$d_{30m} = \frac{L}{60} \times \alpha + n \times \beta \tag{32}$$

L is the water channel mileage; α is maritime risk; n is the number of cross-river bridges; β is the demand adjustment factor (It is up to the safety and technical performance of the cross-river bridge and the traffic environment in inland waterways, which generally takes a value between 1 to 2).

According to Eq. (32), the demand adjustment factor β is uncertain, so the demand for emergency resources in the Jiangsu section of the Yangtze River within a specific range. The demand of 30 m class rescue ships for each accident area were summarized in Table 6. The results were based on the maritime risk (Table 5) and the upper and lower limits of β.

Table 6 Demand for $30m$ rescue ships in study area

Accident areas	Lower limit of demand	Demand ceiling	Average value of demand
Nanjing	7.1	13.1	10.1
Qixia	1.4	2.4	1.9
Zhenjiang	2.6	4.6	3.6
Taixing (Taizhou)	2.1	3.1	2.6
Yangzhong	4.3	8.3	6.3
Jiangyin	1.3	2.3	1.8
Jingjiang (Zhangjiagang)	5.4	10.4	7.9
Nantong	1.7	2.7	2.2
Haimen	1.4	2.4	1.9
Changshu (Taicang)	1.7	1.7	1.7

In the Jiangsu section of the Yangtze River, there are two regulatory rescue integrated base in Nanjing and Taicang, three regulatory rescue bases in Zhenjiang, Taizhou, and Zhangjiagang.

As the waterway of study area is extremely complex and the traffic flow is dense. In order to simplify the study, the distance from the centre of each accident area to the rescue base is regarded as the navigation distance of the rescue ship. Assuming that the speed of the rescue ship is 20 km/h, the sailing time of the rescue ship from the rescue base to each accident area is shown in Table 7.

Table 7 Sailing time from rescue base to each water center

Name of water area	Time t_{ij} /h				
	Nanjing	Zhenjiang	Taizhou	Zhangjiagang	Taicang
Nanjing	0.35	3.90	7.40	11.08	16.08
Qixia	2.05	1.50	5.00	8.68	13.68
Zhenjiang	4.35	0.70	2.70	6.38	11.38
Taixing (Taizhou)	6.63	2.98	0.45	4.10	9.10
Yangzhong	6.85	3.20	2.40	3.48	8.53
Jiangyin	8.78	5.13	1.75	1.90	6.95
Jingjiang (Zhangjiagang)	11.23	7.58	4.20	0.55	4.50
Nantong	13.23	9.58	6.20	2.55	2.50
Haimen	17.05	13.40	10.03	6.38	3.20
Changshu (Taicang)	15.63	11.98	8.60	4.95	0.18

By analysing the accident data of ships sailing on the mainline of the Yangtze River from 2010 to 2019, the economic losses caused by accidents of different ship types in the study area are obtained [51]. The Weighted accident loss $\bar{U}$ is 162,500 yuan (see Table 8).

Table 8 Economic losses of inland waterway accidents

Ship type	Single-ship economic loss (million yuan)	Accident rate	Weighted accident loss (million yuan)
Passenger Ship	19.09	0.28	16.25
Dangerous Goods Ships	23.12	0.51	
Bulk Carrier	17.81	1.78	
Dry Cargo Ship	22.64	1.97	
Barges	13.19	0.96	
Multi-purpose ships	12.00	1.70	
Tugship	8.81	1.24	
Container ship	16.14	1.69	

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Tugship	8.81	1.24	
Container ship	16.14	1.69	

The 30 m class rescue ship can accommodate up to 10 people. In the actual patrol and rescue work, each rescue ship usually takes 2 to 4 crew members. The rescue ship is diesel driven, and the host continuous service power is 323 KW×2100 r/min.

To simplify the study, it is assumed that the crew of all the 30 m class rescue ships is 3 members, and the hourly fuel consumption is 6% of the total power of the host. The rescue personnel wages $\bar{S}$ and domestic fuel prices $\bar{F}$ can be obtained through the civil service salary level of Jiangsu Maritime Office and diesel fuel price [52].

3.2.3 Analysis of robust optimization allocation strategy

According to the above analysis (Tables 6-8), assuming the demand perturbation level $\widehat{d_i}$ is 20%, the robust control parameter Γ is between 0 and 10. By using the model proposed in Section 2, the robust allocation strategy of rescue ships is presented in Table 9.

Table 9 Robust optimal alloctaion of rescue ships in each water rescue base

Number of perturbations (Γ)	Rescue Base					Configuration Goals		
	Nanjing	Zhenjiang	Taizhou	Zhangjiagang	Taicang	Total	Total time	Total Cost
0	9.09	12.81	13.12	10.42	5.61	51.05	7523	839.70
1	8.98	12.89	15.71	12.89	5.54	56.00	7750	878.37
2	8.09	16.55	15.79	16.55	5.00	61.98	13101	2104.77
3	9.37	11.09	16.31	11.09	5.78	53.63	32075	2292.60
4	8.46	19.36	11.72	19.36	5.22	64.11	28688	3894.66
5	8.82	9.27	8.40	9.27	5.45	41.20	29853	2839.51
6	10.42	7.59	10.31	7.59	6.43	42.34	34820	8032.39
7	10.44	11.68	13.41	11.68	6.45	53.66	44917	11048.68
8	9.47	12.22	15.23	12.22	5.84	54.98	72632	7015.91
9	11.00	9.56	12.61	9.56	6.79	49.53	102225	6905.43
10	10.87	16.12	6.70	16.12	6.71	56.52	101612	20108.61

According to Table 9, with the number of rescue ships in the regulatory rescue integrated base configuration increase, the number of rescue ships in the regulatory rescue base configuration will decrease correspondingly. It will affect the total number of rescue ship configuration. This is due to the difference in positioning and scale between the regulatory rescue integrated base and regulatory rescue base (see Section 2.2.1).

By using the robust adjustable optimization introduced in Section 2, the number of perturbations (robust control parameters Γ) can reflect the decision-maker's attitude towards accident risk. The higher the value of Γ, the decision-maker is more cautious when facing the risk, otherwise the more optimistic.

Γ=0 and Γ=10 is extreme case of robust optimization: When $\Gamma = 0$, the decision-maker believes that all areas in the Jiangsu section of the Yangtze River are safe, which is the optimal solution for the allocation of rescue ships; When $\Gamma = 10$, the decision maker believes that the demand for emergency resources in all areas is uncertain, which is the most conservative solution for the allocation of rescue ships. It is generally believed that decision makers will consider both security and efficiency in the face of risk, and will not choose two extreme allocation strategy.

When $\Gamma = 1\sim9$, the total number of rescue ships varies with the increase of robust control parameters (see Fig. 7). Fig. 8 shows that the total time and total cost can be saved by using the robust optimal allocation strategy.

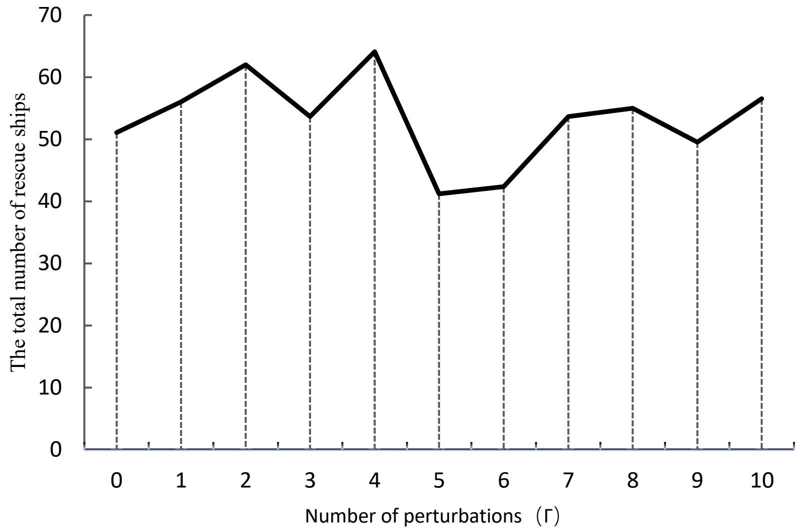

Fig. 7 Total robust optimal configuration of rescue ships

Fig. 7 shows that the total number of rescue ships increased first and then decreased, and then increased after reaching the minimum value. The maximum number of rescue ships is 66, the average is 55. When Γ= 5, regulatory rescue base in Nanjing, Zhenjiang, Taizhou, Zhangjiagang and Taicang were respectively equipped with 10, 9, 9, 9 and 6 rescue ships, which could achieve a minimum of 43 rescue ships.

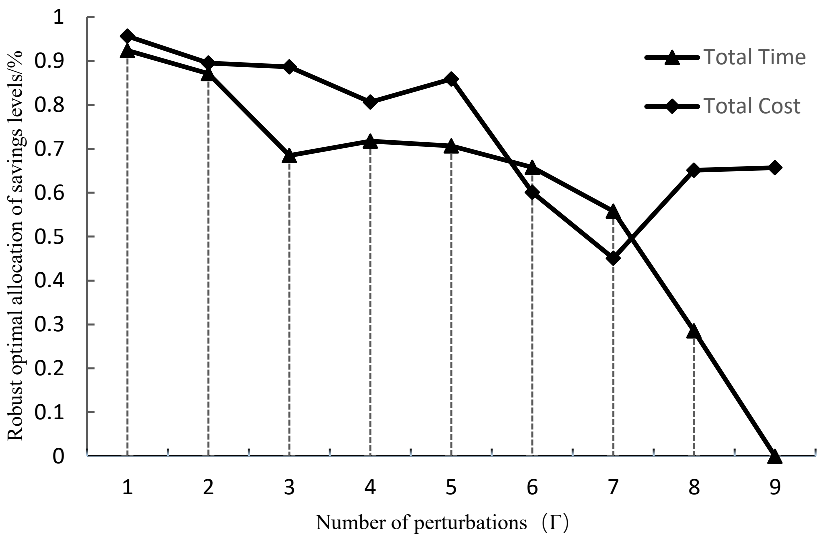

Fig. 8 Robust optimal configuration effect

Fig. 8 shows that compared with the traditional emergency resource allocation strategy (see Section 2.2.2, Γ= 0). Using the robust optimization method, the proportion of the total rescue time saved is between 28.52% and 92.60%, the proportion of the maximum total cost saved is 95.82%. When the number of perturbations Γ takes values from 1 to 5, the savings in total rescue time and total cost are pronounced.

4. Conclusions

This study proposes an EWM-TOPSIS-AHP method to evaluate the risk differences of different waters and develops an emergency robust optimization model to address the uncertainties of emergency resource allocation in inland waterways. The objective function of the model is to minimize the cost and time of emergency rescue. The model considers the evaluation results on the maritime accident risk and the attitude of decision-makers towards risk, and outputs the emergency resource allocation strategy. Numerical examples based on accident data from the Jiangsu section of the Yangtze River over many years demonstrate that the model can be used to make decisions on emergency resource allocation and rescue ship dispatching plans for different water rescue bases.

The numerical results lead to the following conclusions: Firstly, as the number of perturbations increases, decision-makers become more cautious in the face of risks, and the proportion of total configuration loss gradually decreases, while the proportion of total time saved initially decreases and then increases. Secondly, decision-makers need to allocate more rescue ships to cope with uncertain demand when they are more cautious in the face of risk. Thirdly, when the robust control parameter is in the median value, the rescue ship configuration system exhibits better stability, and the mobility of rescue ships among water rescue bases is more significant. Fourthly, an excessive input of rescue ships, when the robust control parameter is larger than the median value, will cause partial idle loss, leading to an increase in the total configuration loss and affecting the configuration effect. Lastly, an increase in the number of rescue ships in the regulatory rescue integrated base configuration results in a decrease in the number of rescue ships in the regulatory rescue base configuration, which, in turn, affects the total number of rescue ship configuration.

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Appendix 1. EWM (Entropy Weight Method)

Entropy Weight Method can be divided into the following steps [27-30]:

1) Construction of risk judgment matrix

With m targets to be evaluated, n evaluation indicators, x_{ij} represents the value of the j-th evaluation indicator of the i-th target to be evaluated, introducing the concept of risk judgment matrix A.

$$A=(X_{ij})_{m\times n}, i=1,2,3...m, j=1,2,3...n \tag{2}$$

The calculation formula is as follows:

Isotropic risk indicator:

$$b_{ij}=\frac{x_{ij}-\min_i x_{ij}}{\max_i x_{ij}-\min_j x_{ij}} \tag{3}$$

Reverse risk indicator:

$$b_{ij}=\frac{max_i\, x_{ij}-x_{ij}}{\max_i x_{ij}-\min_j x_{ij}} \tag{4}$$

This yields the standard risk judgment matrix B:

$$B=(b_{ij})_{m\times n}, i=1,2,3...m; j=1,2,3...n \tag{5}$$

2) Calculate the entropy value of each index f_{ij}

$$f_{ij}=\frac{(b_{ij}+1)}{\sum_{i=1}^{m}(b_{ij}+1)}, i=1,2,3...m, j=1,2,3...n \tag{6}$$

The entropy of each evaluation index H_j is obtained.

$$H_j = -\frac{1}{\ln m}\sum_{i=1}^{m} f_{ij} \ln f_{ij} \tag{7}$$

3) Calculate the entropy weight of each indicator ω_j

$$\omega_j = \frac{1-H_j}{n-\sum_{j=1}^{n} H_j} \tag{8}$$

And satisfies $\sum_{j=1}^{n}\omega_j = 1$, which yields the weight vector W

$$W = \frac{1-H_j}{n-\sum_{j=1}^{n} H_j} \tag{9}$$

The weighted standard risk judgment matrix R can be obtained

$$R = (\omega_j b_{ij})_{m\times n} \tag{10}$$

4) Let $r = \omega_j b_{ij}$, R can be expressed as:

$$R = (r_{ij})_{m\times n}, i = 1,2,3...m; j = 1,2,3...n \tag{11}$$

Appendix 2. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a comprehensive evaluation method, also called the distance method of superior and inferior solutions, which can fully use the original data's information and accurately reflect the gap between the evaluation schemes [31-35]. TOPSIS can be divided into the following steps:

Use S^* to denote the maximum risk set and S^0 to denote the minimum risk set.

$$s^* = \left\{ r_j^* \,|\, j = 1,2,...,n \right\} = \left\{ \max_i r_{ij} \,|\, j = 1,2,...,n \right\} \tag{12}$$

$$s^0 = \left\{ r_j^0 \,|\, j = 1,2,...,n \right\} = \left\{ \min_i r_{ij} \,|\, j = 1,2,...,n \right\} \tag{13}$$

The distance between the vector of assessed values of indicators for each evaluated target and the maximum risk set is D_i^* , and the distance between the minimum risk set D_i^0 can be expressed as

$$D_i^* = \left[\sum_{j=1}^{n} \left| r_{ij} - r_j^* \right|^q \right]^{\frac{1}{q}} \tag{14}$$

$$D_i^0 = \left[\sum_{j=1}^{n} \left| r_{ij} - r_j^0 \right|^q \right]^{\frac{1}{q}} \tag{15}$$

where $i = 1,2,...,m; j = 1,2,...,n$.

$$F_i = \frac{D_i^0}{D_i^* + D_i^0}, i = 1,2,...,m \tag{16}$$

Finally, the closeness of each evaluation target's vector of evaluation values to the maximum risk set is obtained F_i, and the ranking of each closeness is used to determine the risk value of the target.

Appendix 3. AHP (Analytic Hierarchy Process)

This paper uses the square root method to calculate the weights.

Step1: Calculating the product M_i of each row of the judgment matrix$_{i,}$

$$M_i = \prod_{j=1}^{n} a_{ij} \tag{17}$$

Step2: Calculating the nth root of M_i,

$$\overline{W_i} = \sqrt[n]{M_i} \tag{18}$$

Step3: The vector $\overline{W} = [\overline{W}_1, \overline{W}_{2....}\overline{W}_n]^T$ by regularizing it,

$$W_i = \frac{\overline{W}_i}{\sum_{j=1}^{n} \overline{W}_i} \tag{19}$$

$\overline{W} = [\overline{W}_1, \overline{W}_{2....}\overline{W}_n]^T$ is the feature vector, where W_i is the weight of the hierarchical single ranking.

Step4: the maximum eigenvalue of the judgment matrix is calculated λ_{max}, and where $(AW)_i$ denotes the i-th element of AW.

$$\lambda_{max} = \sum_{i=1}^{n} \frac{(AW)_i}{nW} \tag{20}$$

The consistency for pair-wise comparisons in AHP is calculated by consistency ratio (CR), which measures the probability that the pairwise comparison matrix was filled in, purely at random [36, 37]. The CI is the consistency index that can be obtained from Eq. (2), where RI is the random index for the matrix A [38]:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{21}$$

$$CR = \frac{CI}{RI} \tag{22}$$

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