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## REVIEW AND COMPARISON OF THE DEMAND ANALYSIS METHODS OF MARITIME EMERGENCY RESOURCES

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### Summary

The demand analysis method of maritime emergency resources is the key technology to promote a reasonable emergency resource allocation during maritime emergency management. It is widely used to improve the efficiency of maritime emergency rescue and reduce the loss of maritime accidents. However, it requires a scientific and effective method of the demand analysis of maritime emergency resources. This paper aims to analyze the underlying modeling paradigms and to assess the extent to which the demand analysis methods of maritime emergency resources can meet the requirements. Focusing on the demand analysis methods, this paper provides a broad overview of the current literature on maritime emergency resources of the last decades, by considering the models' purposes, theoretical frameworks, factors, and outputs. The results indicate that the existing methods can be classified into three concepts: the linear regression theory, Back Propagation (BP) Neural Network, and Case-based Reasoning (CBR) technology. Combined with the characteristics of China's maritime emergency management field, the interaction between theoretical framework and applications is not sufficiently understood and thus needs to be further studied. Being familiar with knowledge gaps acts as a catalyst for further research on scientific and efficient demand analysis methods of maritime emergency resources in various navigation conditions.

*Key words:* Maritime traffic accident; Maritime emergency resource; Demand prediction; The demand analysis method

### 1. Introduction

The environment of maritime traffic is complex and changeable, and natural conditions such as wind and flow are often very terrible when accidents occur, which brings greater difficulties to emergency rescue work [1]. Due to the uncertainty of information about maritime emergencies, it often occurs that the resource supply at the time of the incident is larger than the demand of emergency points or can not meet the needs of rescue. According to the statistics of maritime accidents published by CHINA SAR from August 2019 to August 2020, the security situation of waterborne traffic in China is serious. Taking the maritime distress in August 2020 as an example, 171 maritime accidents occurred in China. 141 ships in distress were searched, of which 108 were rescued, and the number of capsized vessels

increased by 22.2% year on year and 83.3% month on month. 1,212 people in distress were searched, of whom 1,162 were saved. The success rate of search and rescue was 95.9%, a year-on-year decreased of 1.5% and a month-on-month decreased of 0.5%. Compared with August 2019, the number of capsized ships and the number of dead and missing has increased, and the success rate of maritime emergency rescue has decreased significantly. Life safety and property suffered huge losses. Therefore, the research on the prediction method of maritime emergency resources demand not only improves the basic theory of maritime emergency management but also promotes the emergency management ability of maritime emergency system, which has important practical significance.

Hu et al. [2] divided the process of emergency management into four phases, including mitigation, preparedness, response, and recovery. The process of maritime emergency management is the allocation, scheduling, and use of maritime resources. Some research about this topic has been done. Zhang et al. [3] presented a novel dynamic multi-objective location-routing model with split delivery considering the dynamic motion of oil films at sea. Zhang et al. [4] proposed a maritime emergency resource allocation model and a robust approach to make sure that the emergency resource scheduling performs well with uncertain data. Ai et al. [5] proposed the SAR resource scheduling model based on a genetic simulated annealing algorithm (GSAA) and the regional task allocation algorithm based on space-time characteristics to solving the problem of resource scheduling and task allocation. Ai et al. [6] studied a discrete nonlinear integer-programming model, which integrated the location, allocation, and configuration. Wang et al. [7] build a multi-objective optimization model for maritime emergency resources allocation, with “minimum amount of goods in short” and “minimum transportation costs” as its goals.

The demand prediction on emergency resources is the premise and basis of optimal allocation of emergency resources [8]. However, it can be found that most of these studies on maritime emergency management have some deficiencies. The majority of approaches ignored the impact caused by real hydro-meteorological conditions or maritime traffic uncertainty [9]. When a maritime traffic accident occurs, the emergency rescue department is often unable to know the actual situation of the accident area in time. If the supply of resources exceeds the demand at the emergency point, it will cause unnecessary waste. Insufficient emergency resources can more seriously affect the efficiency of emergency rescue. As is known to all, the accurate and scientific prediction of the demand for emergency resources can carry out emergency rescue quickly and efficiently to achieve the best results [10].

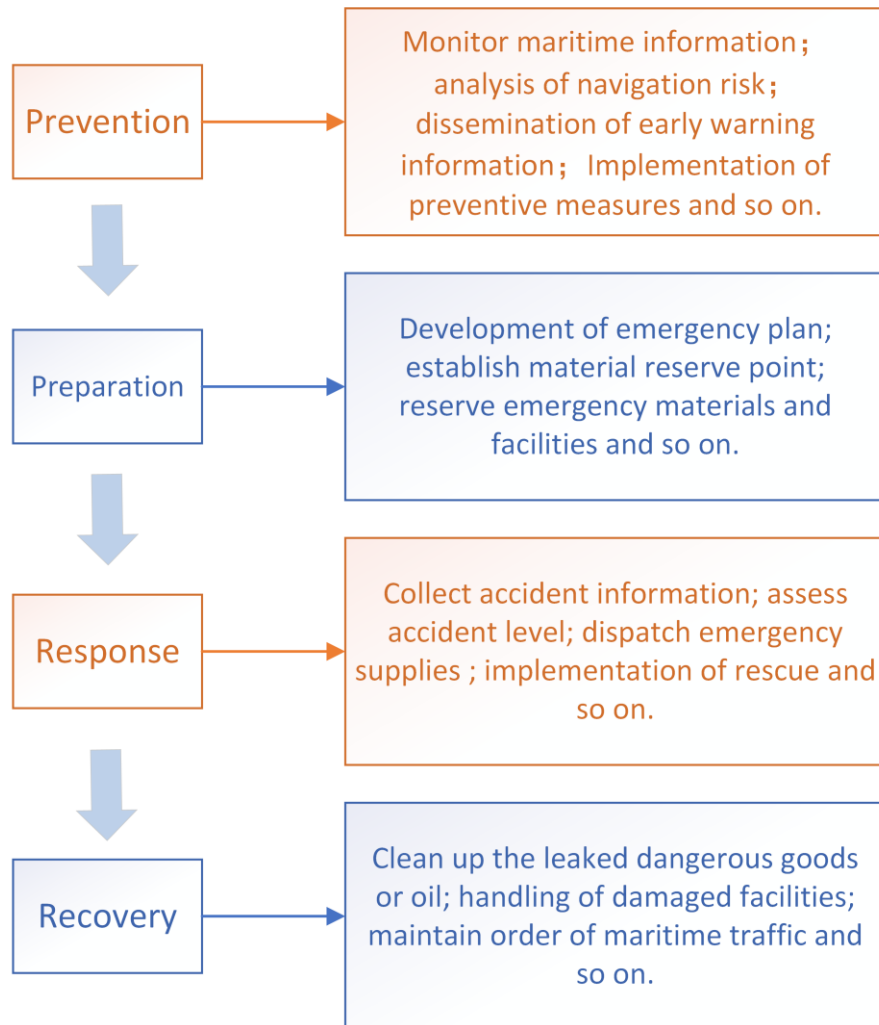
At present, there are many studies on emergency demand prediction methods for land traffic accidents and natural disasters such as earthquakes, floods. Relatively speaking, the research on the forecasting of maritime emergency resources remains at an early stage. Deng et al. [11] put forward a CBR method to forecast the demand for maritime emergency resources. Zhang [12] proposed a linear regression model for forecasting the dynamic demand of marine emergency resources. The above two research results provide valuable insights and research directions for the research of maritime emergency resource demand prediction methods. However, they are coarse-grained in dealing with the ambiguous and uncertain characteristics of maritime emergencies, and the scene of water emergency rescue in previous work lack of pertinence. Therefore, it is significant to apply these methods in emergency resources demand analysis.

The main objective of this paper is to explore the challenges and future research directions of forecasting maritime emergency demand. Given that there is not a complete theoretical foundation in maritime emergency resources demand forecasting, we hope to develop the methodologies through the consideration of emergency resource demand

forecasting methods application in other scenes. Furthermore, based on the investigation and analysis of the existing emergency resource demand prediction methods, this paper takes three typical methods, linear regression, BP Neural Network, and CBR technology, as examples, to analyze the development direction and research focus of maritime emergency resource demand prediction methods in the future. The content is organized as follows: Section 1 introduces the research background and the relevant literature; Section 2 introduces several common methods of forecasting emergency resource demand; Section 3 mainly describes the research results about three typical methods and compares and analyzes the advantages and disadvantages of the three methods; Section 4 discusses the existing problems in the field of forecasting maritime emergency resource demand, and puts forward some suggestions for future research work; finally, Section 5 summarizes and prospects the content of this paper.

## **2. Overview of maritime emergency**

Maritime emergency work includes preventing maritime traffic emergencies, controlling, mitigating, and eliminating serious social hazards caused by maritime traffic emergencies, restoring the normal order of maritime traffic in time, and ensuring the smooth flow of maritime roads, as show in 0. The chronological process of maritime emergency work can be divided into four stages: prevention, preparation, response and recovery. In the phase of prevention and preparation, before maritime emergencies occur, the main work is to eliminate hidden dangers that may lead to maritime emergencies and store important emergency resources for emergencies. The response and recovery phase are after maritime emergencies, the main work is to reduce the impact of maritime emergencies, prevent further deterioration of the danger, and restore the order of maritime transportation as quickly as possible.



**Fig. 1** The stages of maritime emergency

It can be seen that maritime emergency resources, which contain all kinds of required resources needed in each process of maritime emergency work, run through the entire process of maritime emergency work. Therefore, the generalized maritime emergency resources are the sum of human resources, material resources, financial resources, facilities resources and other hardware resources, as well as soft resources such as information technology, emergency preplan, emergency system, laws and regulations, which are required by the maritime transportation emergency system for carrying out emergency activities. Considering the characteristics of various resources, the main objects of forecasting maritime emergency resource demand are the types and quantities of emergency materials and facilities needed in the event of maritime emergency. For example, the demand for oil boom and oil dispersant in oil spill accident, or the demand for tugboat from out of control ship, etc.

### 3. Overview of emergency demand prediction methods

There is a long history of research on forecasting emergency resource demand. 0 lists some of the main emergency resource demand prediction methods, which can be roughly divided into two categories. The first is to use historical datum to build mathematical models that are directly or indirectly adopted to predict the demand for emergency resources. The second one is the prediction method based on CBR through referencing the solution of similar historical cases to analyze and deal with target cases.

**Table 1** Research status of emergency demand prediction methods at home and abroad

Prediction methods	Applied theory	References
Mathematical models	Liner regression analysis	(Nie et al., 2001[13]; Zhang,Yang, 2015[12]; Sun, 2016[14]; Wu et al., 2020[15])
	Neural network model	(Qian,Cui, 2013[16]; Liu et al., 2015[17]; Wang, 2016[18]; Wang et al. 2018[19]; Wen, Yuan, 2020[20]; Ma et al, 2020[21])
	Grey system theory	(Tang, 2012[22]; Chen, Liu, 2015[23])
	Time series analysis	(Wang et al.,2018[24]; Liu,2018[25]; Fang et al.,2020[26])
CBR technology	Case-based reasoning	(Li,2010[27]; Liu, 2011[8]; Zhang,2012[28]; Deng et al.,2014[11];Duan et al.,2014[29]; Wang et al.,2016[30]; Guo,2017[31])

Linear regression analysis is a typical quantitative analysis method. It analyzes the influence of various factors on demand based on statistical data and reflects the relationship through mathematical models. For example, the conceptual model of earthquake emergency demand proposed by Nie et al. [13] applies linear regression theory to the prediction of earthquake emergency resource demand. The method can quantify the demand for earthquake emergency resources, prompt the disaster relief personnel to schedule scientifically, and shorten the concentration-time of disaster relief personnel and materials. The research lays a foundation for the linear regression theory in the emergency resource demand prediction. At present, this method has been successfully applied in earthquake disasters, flood disasters, snow disasters in pastoral areas, and waterborne traffic accidents.

As more and more mathematical methods are implemented on the computer, a variety of neural network models greatly enrich the technical means of emergency resource demand prediction. One of the most widely models is the BP network, which has good multi-dimensional function mapping ability and can objectively reflect the relationship between the impact factors and the demand for emergency resources. It can also be combined with intelligent algorithms such as Genetic algorithm (GA) and Particle Swarm Optimization (PSO) [32] to optimize the model and to improve the prediction effect of the model. The prediction based on BP network model prediction gives full play to the intelligence of the network and has been widely used in medical, transportation, agriculture, mining, meteorology, and other fields.

Gray system theory can sort out the incomplete original data into a series with strong regularity and then find the potential knowledge from it, and thus it can also be used to construct prediction methods. For example, Chen and Liu [23] used the gray system theory to analyze the factors affecting the number of casualties and extracted the factors with a high degree of correlation to build a GM (0,3) model to predict the number of casualties. The model makes use of the characteristics of the gray theory and does not require large historical data, reflecting the excellent performance of the gray system theory to solve the prediction value in the absence of historical information. The disadvantage is that it is difficult to improve the prediction accuracy when processing data with a non-exponential variation.

Time series analysis is to arrange the historical statistics according to the time sequence of occurrence and to predict the data characteristics of the future time by analyzing the dynamic changes of the data. At present, there are many kinds of time series prediction models, such as auto-regressive (AR) model, moving average (MA) model, and the variation

of basic models such as auto-regressive moving average (ARMA) model, auto-regressive integrated moving average (ARIMA) model [33] and seasonal auto-regressive moving average (SARIMA) model [34]. Compared with other prediction methods, time series analysis is easier to operate and understand. But it has a poor prediction effect for data with large fluctuation and serious environmental impact. Therefore, it is generally used to predict short-term time series.

The prediction method based on CBR is to solve the current problems by reusing or modifying the solutions of historical similar problems. Therefore, it can predict the demand for emergency resources without any mathematical model. CBR theory has been developed since 1982, thus its basic theory and application are very mature. It has been widely used in emergency management, legal cases, medical treatment, computer and other fields. However, the first step of carrying out prediction is the establishment of the case base which is difficult to carry out the case reasoning and analysis. There were many problems in current research such as incomplete data, and no systematic filing. In addition, this prediction method was greatly affected by personal experience

#### 4. Research on the typical demand-analysis method of emergency resources demand

##### 4.1 Linear regression analysis

###### (1) Fundamental theory

Linear Regression is a mathematical calculation method to calculate the quantitative relationship among several variables through the regression analysis method in statistics [35]. Linear regression is defined as the expected target value is a linear combination of input variables. In short, a linear function is used to fit the historical statistics, and then the unknown data can be calculated according to the function.

The general form of a linear regression model is:

$$Z = w_0 + w_1x_1 + w_2x_2 + \dots + w_nx_n = [w_0w_1w_2 \dots w_n] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad (1)$$

In which:

$Z$  is the dependent variable, which is the prediction function;

$w_i$  is the parameter of linear regression equation;

$x_i$  stands for a unique independent variable and represents several related factors that have a greater influence on  $Z$ .

###### (2) Application of linear regression

Based on the principle of correlation, the natural conditions, navigation environment, types of ships, and other factors of maritime emergencies will have a certain impact on the types and demands of maritime emergency resources. Some researchers defined the demand coefficient according to the attribute characteristics of the main factors by analyzing the impact of the main factors on the demand for emergency resources. The impact of various factors on the demand for emergency resources are quantified in order to carry out the prediction of the emergency resources demand. This method was initially applied to the research of earthquake disaster emergency demand prediction. Nie et al. [13] proposed a conceptual model for earthquake emergency demand prediction based on the influence of regional coefficient and climate coefficient on earthquake emergency demand. This conceptual model provides a new idea for the research of the emergency resource demand method. And the advanced model has been successfully applied in flood, snow disaster in

pastoral areas, and waterborne traffic accidents.

Zhang [12] proposed the conceptual model of dynamic demand for marine emergency resources. It is the first time to apply the linear regression analysis to the maritime emergency resource demand prediction. The form of this model is:

$$D_M = Q_M * F * S * L \quad (2)$$

In which:

M represents the type of maritime emergency resources;

$D_M$  is the total demand for this resource during the forecast period;

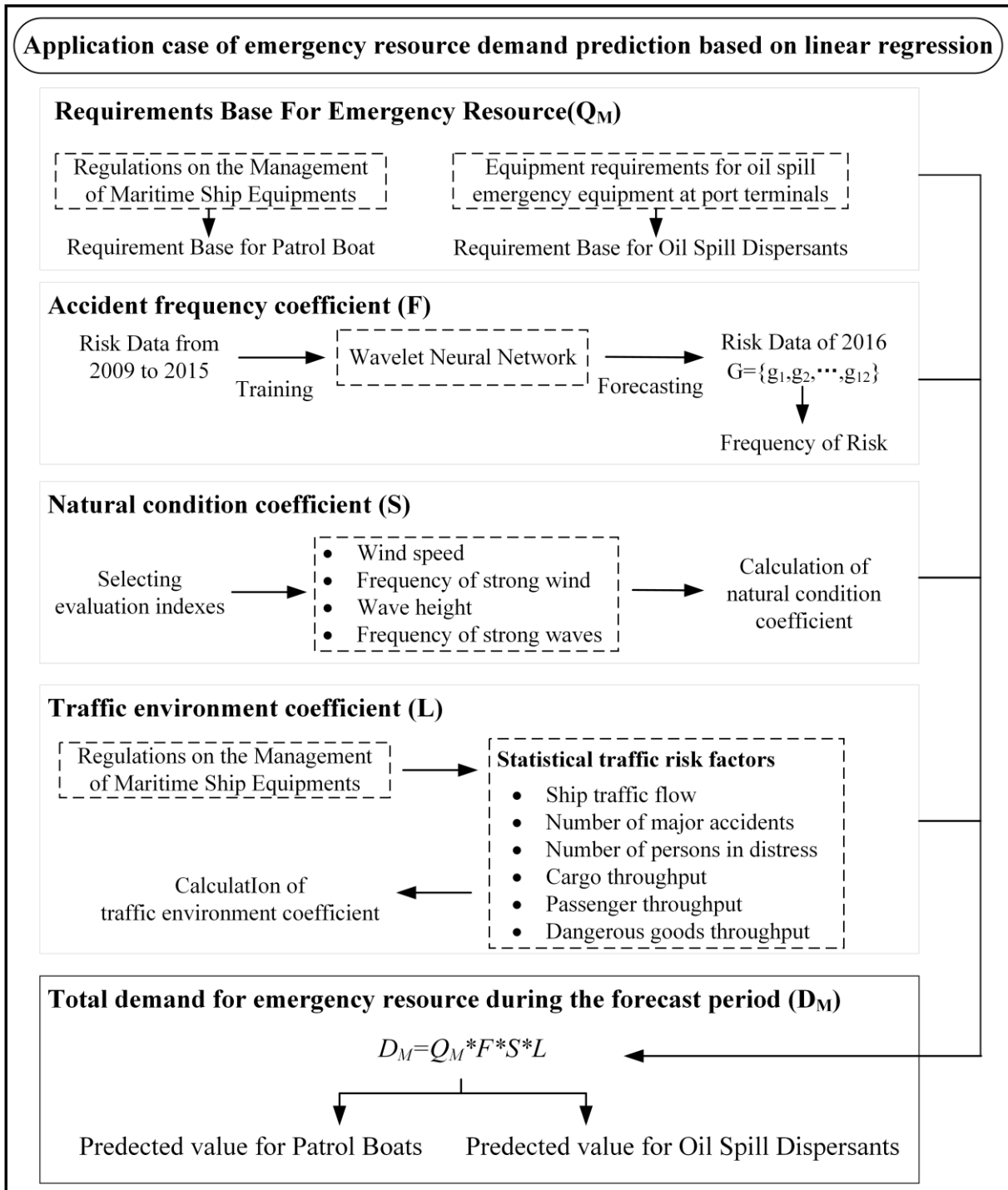
$Q_M$  is the theoretical demand for this resource under general conditions, which is calculated according to the requirements of relevant maritime regulations;

F is the accident frequency coefficient, which is the ratio of the average of the annual accident prediction times in the prediction period to the average of the accident statistics times over the years, reflecting the impact of the accident frequency in the prediction period on the resource demand;

S is the natural condition coefficient, reflecting the impact of natural conditions of the port or route on the quantity of the resource demand;

L is a comprehensive risk factor, reflecting the impact of the traffic environment of the port or route on the quantity of the resource demand.

The model defines the corresponding demand coefficient according to the impact of risk frequency, natural environment of sea area, and traffic environment on emergency resource demand in the forecast period, and then calculates the total demand of certain maritime emergency resources in the forecast period. This paper takes Shandong maritime jurisdiction as an example to verify the validity and applicability of the model, and the specific application process is shown in Fig 2. It can be seen that the input data of this model contains the basic requirements of official emergency resources, future accident data predicted from historical accident data, natural conditions such as wind and waves, traffic flow, port throughput and so on, because the influencing factors considered are relatively comprehensive. Based on the calculation results of this model, the demand for maritime emergency resources can be obtained. In this case, the demand for patrol vessels is 132, and the demand for oil spill dispersants is 488 tons. Assuming that the variation of emergency resources is 5%, the dynamic demand of patrol vessels in Shandong maritime jurisdiction in 2016 is 128 to 139, and that of oil spill dispersants is 464 to 512 tons.



**Fig. 2** Application case of emergency resource demand prediction based on linear regression

The main advantage of linear regression prediction method is that the model is simple in structure, and can prevent over-fitting. Because the demand coefficient can concisely reflect the correlation between various factors and the demand for maritime emergency resources, the mathematical model constructed by the linear regression analysis method has a good explainability. It can effectively prompt emergency managers to make scientific dispatch and shorten the centralized time of disaster relief personnel and materials when applied in the field of maritime emergency resource demand forecasting.

(3) Development trend

Actually, the demand for maritime emergency resources in actual maritime emergencies



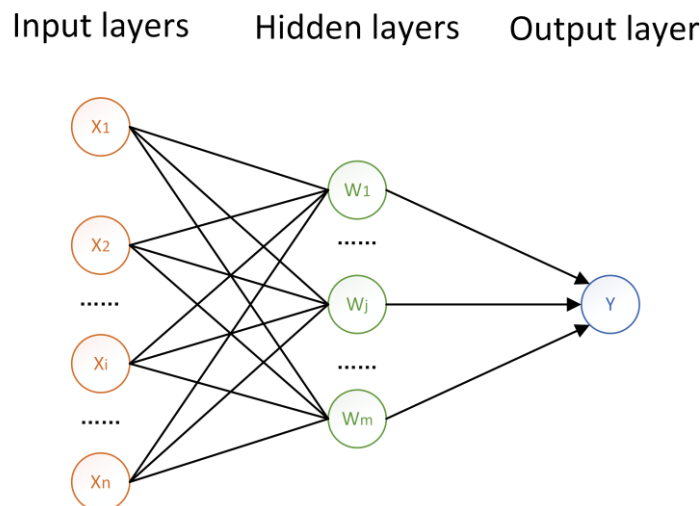
is affected by many factors, including the type of accidents, the number of casualties, the status of ships, visibility, traffic environment, and the scope of accidents [36, 37]. As a typical quantitative analysis method, it is impossible that linear regression analysis covers all the factors for the complex maritime transportation systems. Zhang's [12] model only involves the impact of accident frequency, natural environment, and maritime traffic environment on the demand of emergency resources. When it is applied to the complex maritime traffic system, there will be a certain error between the predicted value and the actual value. Therefore, the main direction of further research in the field of forecasting maritime emergency resource demand is to construct and solve the forecasting model considering the influence of multiple factors.

In addition, in the application of the linear regression prediction method, the independent variables are usually obtained by expert experience or case statistical analysis, resulting that the calculation of emergency resource demand base is seriously affected by subjective factors. Calculating the emergency resource demand base scientifically and objectively is the primary problem of applying the linear regression model.

## 4.2 BP network

### (1) Fundamental

In 1986, Rumelhart and McClelland et al. [21] proposed a multi-layer feed-forward neural network, called BP network, which is trained by the error back propagation algorithm. BP network optimizes the weights and thresholds of the network by using the forward transmission of information and the reverse transmission of errors and reduces the errors to the minimum error range after several training sessions. Its network structure is shown in 03, consisting of the input layer, hidden layers, and output layer. Any layer (one or more layers) of neurons can be set between the input and output layers, which are called hidden neurons. The neurons in the latent layer are not directly related to the outside world. But when their state changes, they can affect the relationship between input and output. Therefore, the complexity and prediction accuracy of the network is usually altered by adjusting the number of neurons in the hidden layers.



**Fig. 3** The structure of the BP network

BP network has excellent ability of pattern classification and multidimensional function mapping, so it can find potential rules in historical data. Therefore, the BP network has outstanding performance in solving the problem of complex logical relationships. In recent years, with the in-depth study of the BP network, many research results have been obtained in the field of emergency resource demand prediction for large disasters such as earthquakes and floods. They have made a great contribution to the development of emergency management

science, reflecting the research potential of the BP network in the field of maritime emergency resource demand prediction.

## (2) Application

BP network is very mature in basic theory and applied research. Its advantages include good fault tolerance, self-adaptive, self-learning, and non-linear conversion ability. However, the drawbacks of BP network are also obvious, such as slow learning speed, high probability to fall into a local minimum, weak generalization ability. Therefore, how to solve the defects of BP network is also a research hotspot about the BP network in recent years.

As shown in 0, many scholars combined the BP network with an intelligent optimization algorithm to optimize the BP network model from the aspects of data processing, parameter selection and model structure, so as to improve the prediction accuracy and convergence speed of BP networks. For example, Qian and Cui [16] combined the BP network with Principal Component Analysis (PCA) to the prediction of earthquake casualties, and the specific study process is shown in Fig 4. First, they extracted six factors that had a significant impact on the number of casualties from China's earthquake casualties data between 1990 and 2010, including time of earthquake, magnitude, epicenter intensity, population density, seismic fortification intensity and forecast level. Then the principal component factors are extracted by using PCA to reduce the dimension of the data. Finally, the BP network model is built using the MATLAB toolbox. The data in the input layer is the new data reorganized by PCA, and the data in the output layer is the number of casualties. The number of hidden layer neurons was determined to be 9 by experiential formula trial. The validity of the method is also validated by using earthquake information indicators. The actual number of casualties is 875, and the predicted number of casualties is 1033 by the model calculation. The error rate for predicting casualties is 18.06%, this result satisfies China National Commission for Disaster Reduction's emergency security requirements error (no more than 30%).

**Table 2** Applications and analysis of BP network optimization algorithm

References	Optimization method	Value of application	Deficiency	Application scenarios
Wang, et al. 2018[19]	Using GA algorithm to optimize the weight and threshold of BP network	The prediction accuracy of the model is improved. The convergence speed of the network is accelerated.	Long training time, irregular code, and inaccurate representation	Prediction of wave height
Wen, Yuan, 2020[20]	The best weight of the BP network is found by the iteration of the BP neural network and PSO algorithm	The accuracy of prediction and the convergence speed of the network is improved	Higher requirements for historical data. It does not adapt to the uncertainty of the system	Forecasting CO2 emissions
Wang R., Wang N., 2104 [38]	ACO-BP algorithm adopts the ant colony algorithm for global optimization of the network weights	The algorithm reduces the number of iterations and improves the accuracy and stability of prediction.	The convergence and global optimality are poor; Search time is too long, easy to stagnate	Study on the shortest path of intelligent transportation
Qian, Cui, 2013[16]	PCA is used to select the key influencing factors of earthquake emergency demand as the input layers of the BP network	It can make more accurate prediction under the condition of incomplete information	Learning speed is slow. Easy to fall into a local minimum.	Prediction of earthquake casualties
Ma et al, 2020[21]	The GA-PSO-BP algorithm was proposed to improve the parameter randomness and local minimization of BP network	The model achieves fast convergence speed, avoiding local minima, stronger stability and more accurate prediction.	Higher requirements for historical data.	Prediction of ship trajectory
Wang, 2016[18]	The world carbon emission index is selected by the method of system cluster analysis, which is used as the transport layer neuron of the BP neural network.	The input layer structure of BP network is simplified and the training speed is improved	Easy to fall into a local minimum.	Forecasting CO <sub>2</sub> emissions
Liu et al., 2015[17]	GA is adopted to initialize the network connection weights and thresholds of BP and PSO is used to update them in the iteration process.	The Hybrid Intelligent Algorithm can avoid falling into a local optimal solution and improve its convergence rate and obtain more accurate results.	The network structure is complex, the calculation cost is high. Higher requirements for historical data.	Geological hazard risk assessment

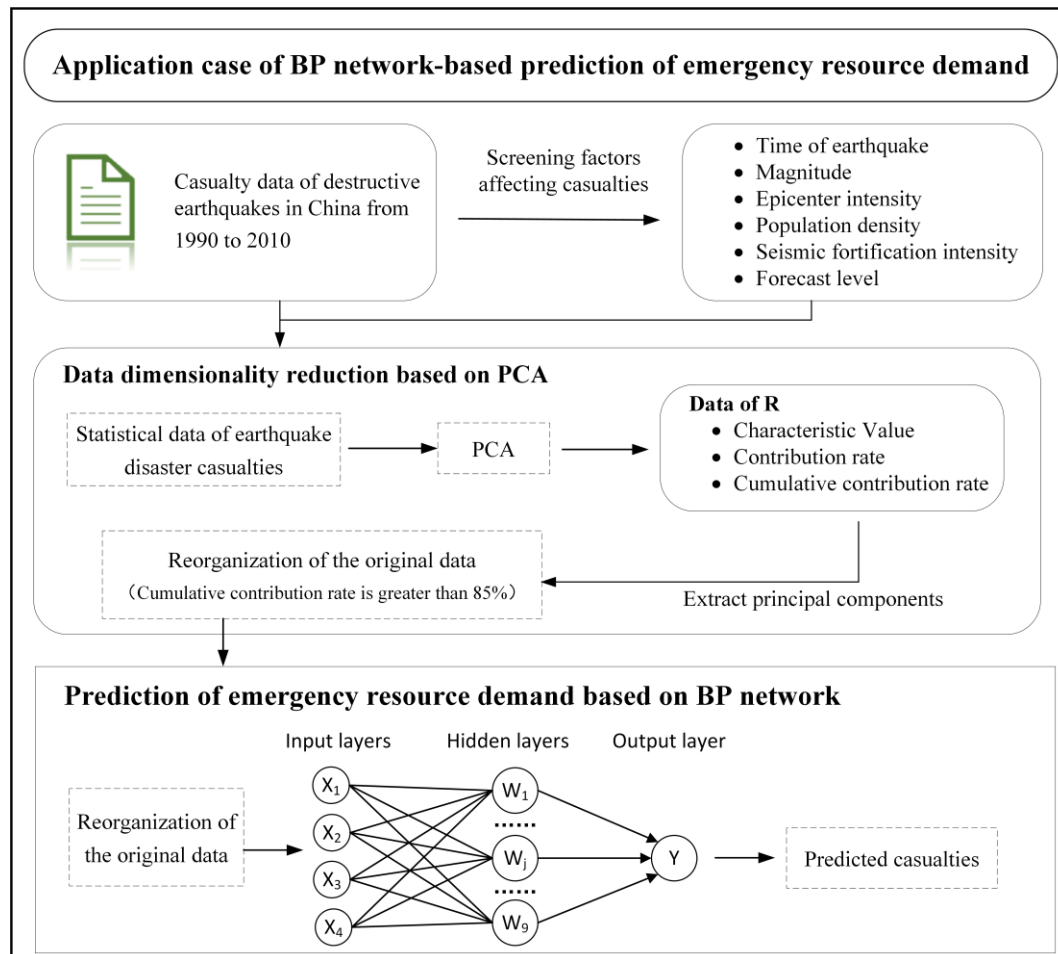


Fig. 4 Application case of BP network-based prediction of emergency resource requirements

PCA and Systematic Clustering Analysis (SCA) simplify the input layer structure of BP network by processing statistical data, which can also improve the training speed of the network. Similar data processing methods include singular spectral analysis, empirical mode decomposition and wavelet denoising, which can remove noise from sample data and ensure data stability.

Genetic algorithm, PSO algorithm (Particle Swarm Optimization) and Ant Colony Optimization algorithm (ACO) are three common intelligent optimization algorithms. They optimize network weights, topology and transfer function by simulating some natural characteristics to make up for some deficiencies of BP network. Similar intelligent optimization algorithms include the firefly algorithm, the simulated annealing algorithm, and the artificial fish swarm algorithm.

### (3) Development trend

Due to the complexity of the waterway transportation system, it is difficult to describe the relationship between the factors affecting the demand for emergency resources with an accurate mathematical formula. The neural network prediction model can accurately reflect the mapping relationship between the factors without a priori formula, which solves the problem of the lack of theoretical calculation method of emergency resource demand prediction in the field of maritime transportation security. Therefore, the neural network has great application potential in maritime emergency resource demand prediction.

However, the structure of BP network is relatively simple, and there are some shortcomings, resulting in its limited development. The hybrid prediction model with various optimization algorithms can make up for the deficiency of BP network and significantly improve the prediction. Therefore, in the future, the research focus of using neural networks

to forecast the demand of maritime emergency resources is to build a hybrid prediction model optimized by intelligent algorithms combined with the characteristics of maritime emergency resources demand.

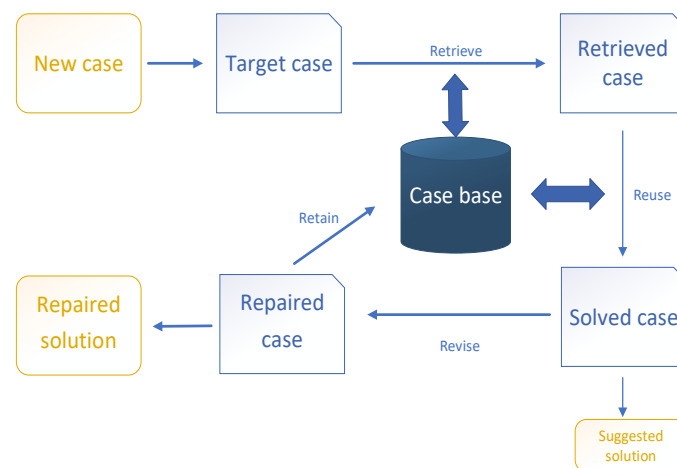
In recent years, the research in the field of artificial intelligence has developed rapidly, such as Big Data, Cloud Computing, and Virtual Reality, and other cutting-edge technologies have been widely applied. Obviously, the lack of available statistical data information is a major difficulty in forecasting maritime emergency demand. Combining machine learning-based data mining technology to obtain dynamic demand information with the neural network to build demand prediction model, a dynamic demand forecasting method for maritime emergencies is a promising research point.

### 4.3 Case-based Reasoning

#### (1) Fundamental

The theory of CBR was first recorded in the book *Dynamic Memory* by Roger C. Schank, an American scholar [39]. It is a method to solve the problem of target cases by referencing similar historical cases. The idea of analogy with the previous events is applied to solve the practical problems in real life, that is, using the experience and methods of solving the problems to make reasoning analysis on the current similar situation, to get the solutions to deal with the current similar situation, which produces CBR technology.

In the theory of CBR, the emerging emergencies are generally called target cases, while the similar cases that have happened before are called source cases [40]. The case base is the collection of source cases. As shown in 0, the process of forecasting maritime emergency resource demand based on CBR mainly includes following steps: a) when a new maritime emergency occurs, it is retrieved as a target case to extract the case attributes; b) when retrieving source cases that are similar to the target case, the solutions of similar cases are reused to obtain some solutions for new maritime emergencies; c) if these solutions fail to solve the target case, the solution of similar cases will be modified to get the appropriate new solution; d) the target case is saved into the case base, which is used as the source case for the next retrieval.



**Fig.5** The process of forecasting maritime emergency resource demand based on CBR

#### (2) Application

At present, due to the lack of a unified standard for the representation of maritime emergency cases, there is a few complete case base of maritime emergencies. Case representation is the core and basic content of CBR technology. The case describes the characteristics of emergencies and their solutions. Its representation not only directly affects the efficiency of retrieval but also indirectly affects the quality of solutions. Various case

knowledge representations emerge endlessly, such as predicate logic representation, frame representation, object-oriented representation, semantics web representation, feature vector representation, ontology-based case representation.

**Table 3** Applications and analysis of common case knowledge representation based on CBR

Authors and documents	Optimization method	Value of application	Deficiency	Application scenarios
Deng et al., 2014[11]	The main attribute features of 25 maritime traffic accident cases are extracted, and the structural case representation framework is used to represent the emergency cases	The reasoning is convenient, has good adaptability and knowledge generalization ability	It lacks strict formal semantics and clear semantics	Demand forecast of maritime emergency resources
Zhang, 2012[28]	Rough similarity relation is introduced into ontology language, and rough ontology description language is proposed to construct an emergency case ontology model.	It realizes the knowledge representation of imprecise information	The construction of large-scale ontology is difficult, high cost, and complex in practical application	Knowledge representation of Fukushima nuclear crisis in Japan
Guo, 2017[31]	The feature vector representation is combined with ontology knowledge to describe emergency cases in the form of ontology	It can express the numerical information and semantic information of the case at the same time, and express the semantic connection clearly.	The construction of ontology is greatly influenced by subjective factors and lacks scientific management and evaluation mechanism	Prediction of earthquake emergency resource demand
Wang et al., 2016[30]	The object-oriented representation is used to express the emergency resource demand forecasting cases and the current emergency state.	It supports the expression of different types of cases and has a wide range of adaptability	The prediction accuracy is low and is easily affected by subjective factors	Demand forecast of disinfectant water in Yushu earthquake
Qu, 2016[41]	Based on fuzzy rough set theory, a fuzzy similarity matrix is established to reduce the feature attributes of emergency cases	It can effectively deal with the uncertain information of emergencies and eliminate the influence of case attributes	It can not express the semantic information in the case, and its practicability needs to be improved	Representation of earthquake disaster case information
Li, 2010[27]	The principle of fuzzy control and object-oriented representation are combined to describe the material demand cases	The expression is simple and easy to implement, which is suitable for processing numerical information	Cannot represent complex case information	Demand forecast of emergency resources for water pollution in Three Gorges Reservoir Area
Duan et al., 2014[42]	The emergency cases are described in the form of matrix by feature vector representation.	The case structure is concise and suitable for dealing with simple cases with strong data significance	The semantic information in the case cannot be expressed	Prediction of emergency demand of chemical enterprises

As shown in 0, many scholars have done a lot of research on the representation methods of cases according to the characteristics of their respective professional fields. For example, Deng et al. [11] applies CBR technology to predict maritime emergency resource demand of traffic accidents in the Yangtze River, and the detailed study process is shown in Fig 6. First, they extracted 25 case feature attributes from maritime traffic accidents happened on the trunk line of the Yangtze River in recent years. Then, according to the attribute characteristics, the case features are divided into crisp symbolic, crisp numeric, interval numeric and fuzzy linguistic. The local similarity between the target case and the source cases can be calculated according to the similarity calculation method of different attributes. The relative importance of attributes is evaluated, and the weight of each attribute is determined by combining the expert's understanding of the knowledge in the field of maritime rescue and the analysis of historical cases. Finally, the K-nearest neighbor is used to calculate the global similarity of cases, and returns cases where the similarity value exceeds the threshold. Using the above methods, similar maritime traffic accident cases can be obtained, so that the maritime emergency resource demand of the target cases can be predicted based on the experience of emergency resource allocation of historical cases.

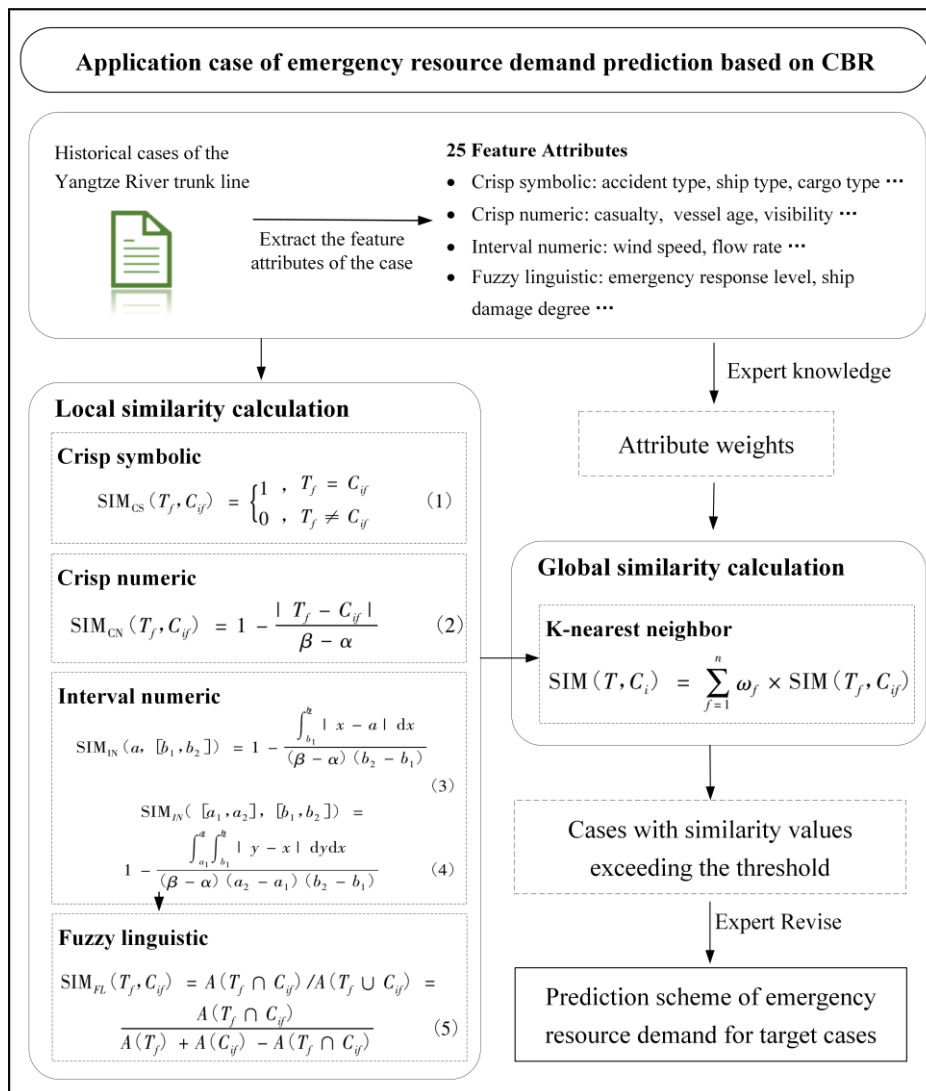


Fig.6 Application case of emergency resource demand prediction based on CBR

In addition to the traditional case knowledge representations such as frame representation, object-oriented representation, and feature vector representation, the case

representation combining multiple technologies is increasingly applied to CBR technology by scholars in dealing with the uncertain information of emergencies. It has good performance in expressing semantic connection and case storage.

### (3) Development trend

Due to the complexity of the maritime traffic environment, there are many factors that affect the demand for emergency resources in the process of maritime emergency rescue. There are many types of characteristic attributes of these factors, and their representations are complex. For example, deterministic symbol attributes are used to represent information such as types of emergencies and ships. The deterministic number attribute is used to represent information such as the number of casualties, wind speed, flow rate [43]. The interval number attributes used to represent uncertain information and the fuzzy conceptual attributes used to represent the damage to the ship. Moreover, many factors will interact with each other. Traditional case representations are often difficult to fully represent the relationship between the various factors, unavoidably missing the case characteristics of maritime traffic accidents. This situation seriously restricts the application of CBR technology in the field of maritime transportation security.

A single case representation cannot fully describe the characteristics of maritime emergencies due to the complexity of maritime transportation systems. Each case representation has its own advantages and disadvantages. For example, fuzzy rough set theory has a good performance in dealing with the uncertain information of maritime traffic emergencies [44]. Ontology-based representation can process both numerical information and semantic information. It can also express the knowledge of the complex system. Therefore, the case representation of multi-technology integration is an effective method to solve the problem of maritime emergency case representation, which is worth in-depth study. It is the focus of the application of CBR in the field of maritime traffic safety in the future to construct an appropriate case representation method and establish a unified and standardized case representation standard for water traffic accidents.

## 4.4 Comparison and analysis of three typical demand analysis methods

Due to the different principles of the methods, the three typical emergency resource demand prediction methods have great differences in input indicators, application process and output results. For example, a prediction model based on linear regression can calculate the total demand for an emergency resource over a year. However, the demand prediction method based on BP network work or CBR technology is suitable for forecasting the demand for emergency resources in a short time after maritime traffic accidents. Overall, the applicability and accuracy of the three methods in predicting maritime emergency resource demand are verified based on the results of historical cases. The following is a comparative analysis of the three typical methods from four aspects: the principles, advantages, limitations and applicability of the methods.



**Table 4** Comparison and analysis of three typical demand the demand analysis methods

Method	Principle	Advantage	Limitation	Researches emphasis
Linear regression model	The relationship between the influencing factors and the demand for emergency resources is quantitatively expressed based on the principle of correlation.	Simple structure, easy modeling, avoiding over-fitting, and good interpretation	Influencing factors are not fully considered and are strongly influenced by subjective factors.	As a baseline model, it combines hierarchical structure or high-dimensional mapping modeling
BP network model	The information processing is realized based on changing the contact information between the nodes in the network.	Good fault tolerance and adaptability; The ability of self-learning and nonlinear transformation is strong	It is difficult to build a network model; Large amount of calculation; Less application	Using intelligent optimization algorithm to improve model performance
CBR technology	Use the experience and methods of solving similar historical problems to deal with new problems.	Combining quantitative analysis with qualitative analysis, it has the characteristics of a dynamic knowledge base and incremental learning	Lack of unified and standardized representation standard of maritime emergency cases	Combining with artificial intelligence to construct a CBR system suitable for maritime emergency demand prediction

Linear regression analysis is one of the common methods for emergency resource demand prediction. Through a simple and clear mathematical model, it can clearly reflect the impact of various factors on emergency resource demand. This method is simpler and easier to understand than the other two methods. However, due to a large number of uncertainties in water emergencies, it is difficult to handle lots of variables, resulting in large errors in the results obtained by the linear regression prediction method. For complex systems, the linear regression function is more suitable as the baseline model. Based on the linear model, a hierarchical structure or high-dimensional mapping model is introduced to build a maritime emergency resource demand forecasting model considering the influence of multiple factors.

BP network also solves the problem of forecasting demand by establishing a mathematical model. Its advantage is that it can process sample information through an algorithm model without a prior formula. And BP network can describe the mapping relationship between various factors accurately, to predict emergency resource demand. It also has good self-learning, fault tolerance, and adaptability, and it can improve the accuracy and efficiency of prediction by changing the structure and parameters of the network. Compared with the linear regression model, the neural network prediction method is more adaptable and widely used. However, due to the difficulty of neural network modeling and the lack of a

fixed model structure, the application of neural networks in the field of maritime emergency resource demand prediction is not yet mature.

CBR technology differs from the first two methods in that it resolves current problems by reusing or modifying previous solutions to similar events. The emergency resource demand prediction method based on CBR combines quantitative analysis with qualitative analysis to solve the problem of the lack of theoretical calculation formula in the field of water emergency resource demand forecasting. With the increase of the number of cases, the retrieval effect of the CBR system can be continuously improved, and the accuracy of forecasting emergency resource demand can be improved. However, this method has a high requirement for the case library. The statistical standards of maritime accidents in different areas are uneven, and the records of maritime accidents are mostly lack information about emergency rescue cases, resulting in fewer cases of water emergency rescue can be used. This situation has greatly limited the development of CBR technology in the field of maritime emergency resource demand prediction.

## 5. Future research prospects

The accuracy of the maritime emergency resource demand prediction method is of great importance to improve the efficiency of maritime emergency rescue. At present, although there are a few research results in this field, they have not reached the stage of practical application. And with the trend of large-scale and intelligent ships [45], there will be more new problems to be solved. Based on the research of emergency resource demand the demand analysis methods, the following possible research directions are summarized.

(1) The basic problem of forecasting maritime emergency resource demand is the lack of objective data collected from maritime emergencies. In recent years, the development of artificial intelligence technology is very rapid, and emerging information technology can collect a large number of data from all aspects of life to extract potential knowledge [46], including data mining, geographic information system and remote sensing. Therefore, the combination of traditional emergency resource demand analysis methods with big data and intelligent devices can effectively solve the problem of forecasting maritime emergency resource demand. On this basis, through scientific and reasonable case representation methods, it is significant to develop a unified and standardized representation standard of water transportation emergency rescue cases, so as to realize the sharing of maritime emergency information.

(2) The instability factors of the maritime transportation system are complicated [47]. It is difficult to consider all factors comprehensively only by using the quantitative demand analysis method, which results in a large error between the prediction value and the demand under real conditions. Qualitative analysis based on pure experience is greatly influenced by subjective factors. Decision-makers need to bear great pressure in the process of emergency rescue, which easily affects the efficiency of emergency rescue. Aiming at the complex situation of maritime transportation system, the multi-technology fusion of the demand analysis method combining quantitative analysis with qualitative analysis can make up the shortcomings and achieve comprehensive analysis, which can improve the accuracy of forecasting maritime emergency resource demand and provide a more consistent forecasting scheme with the actual situation.

(3) Traditional demand analysis methods that use statistical analysis to get empirical formulas have some limitations because of the complexity of the maritime emergency rescue system. As a dynamic intelligent demand analysis method, the neural network can better respond to the changing navigation environment factors in the process of maritime emergency rescue. It has a great application prospect. In addition to the BP network, the theories of wavelet neural network, generalized regression neural network (GRNN), and support vector

machine (SVM) neural network have mature applications in demand prediction [48,49]. Therefore, according to the characteristics of water emergency resource demand, choosing an appropriate neural network and constructing a hybrid prediction model with intelligent algorithm optimization will be the focus of future research on water emergency resource demand prediction.

(4) After decades of development and improvement, CBR technology has a relatively mature basic theory and application prospect. Many mature CBR systems and development tools have emerged. CBR technology combines quantitative analysis with qualitative analysis, and it improves the prediction effect with the update of cases. It has irreplaceable advantages over other prediction methods. At the same time, the application results in the field of forecasting maritime emergency resource demand also prove the feasibility of CBR technology. It is a valuable research direction to establish a perfect case base for maritime emergencies and develop a CBR system for forecasting maritime emergency resource demand.

(5) Reviewing the existing prediction methods of maritime emergency resource demand, we can find that the existing methods are less specific to maritime emergency rescue scenarios. The types of maritime traffic accidents are roughly divided into collision, damage, touch rocks, damage by waves, stranding, fire, explosion, sinking, etc [50-52]. There are some differences in emergency rescue measures for different types of accidents. Therefore, taking the accident scenarios as one of the prediction indexes has important practical significance for improving the accuracy of emergency demand prediction

## 6. Conclusion

When maritime emergencies occur, it is of great significance to accurately and timely predict the demand of emergency resources for maritime emergencies to improve the efficiency of emergency rescue. This paper summarizes the research status of emergency resource demand the demand analysis methods. Through analyzing three typical methods of forecasting emergency resource demand, the development direction and research focus of the maritime emergency resource demand prediction are analyzed. Finally, according to the characteristics of maritime emergency management, some suggestions are put forward for future research work, which provides theoretical support for researchers in the field of maritime emergency resource demand prediction to grasp the potential research direction.

The future research can conduct in-depth studies to quantitatively express the demand for maritime emergency resources according to actual ship distress, meteorological and hydrological conditions, maritime risk level, and ship density, and to find a demand prediction method suitable for the characteristics of maritime emergency management. It lays a foundation for the construction of a modern water safety assistance system with rapid emergency response capability.

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