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RESEARCH ARTICLE

Effectiveness Evaluation of Emergency Rescuing Plans Oriented to Urban Waterlogging Based on a Neural Network Model

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ABSTRACT In response to the significant impact of urban waterlogging on residents, the economy, and urban infrastructure in recent years, this study introduces an innovative wargame-based evaluation approach for emergency rescue plans. The primary goal of this research is to improve emergency rescue capabilities while minimizing costs and identifying gaps in existing emergency rescue plans. To effectively evaluate these capabilities, we extract specific content related to OODA (Observe, Orient, Decide, Act) dynamics in rescue actions. Furthermore, a comprehensive index system is developed to evaluate emergency rescue capabilities in the context of urban waterlogging scenarios. To address the challenges associated with intelligent optimization and evaluation of such systems, we employ a radial basis function neural network and conduct wargame experiments to obtain data and measure capability indices. The evaluation model is trained using data samples to ensure robust performance. In addition to the proposed model evaluation and analysis framework, we also present an evaluation and analysis method for RBF (Radical Basis Function) neural networks and compare the prediction results with those obtained from GRNN (Generalized Regression Neural Network), PNN (Product-based Neural Network), and BP (Back Propagation) neural network algorithms. This model efficiently processes and fits data by simulating expert experience for evaluation purposes. Such an approach takes advantage of machine learning's sensitivity to data characteristics, effectively avoiding the influence of human factors while stably reflecting the mapping relationship between indicators and performance outcomes. This research presents a novel solution with significant implications for the development of urban emergency rescue systems that address the challenges posed by urban waterlogging incidents.

INDEX TERMS Emergency services, performance evaluation, command and control, neural networks.

I. INTRODUCTION

The city, acting as a crucial regional center in the realms of politics, economics, and culture, continues to be susceptible to diverse calamities. Human activities often undermine the city's capacity to prevent and withstand disasters, thereby diminishing its safety resilience and exacerbating the impact of natural calamities. Revealing the persisting challenge, despite remarkable advancements in science and technology, lies in accurately predicting certain abrupt natural disasters such as waterlogging. This inherent challenge significantly complicates disaster management efforts. The acceleration of urbanization has led to an increased frequency of urban waterlogging disasters and subsequent losses, posing a substantial threat to the socio-economic fabric of cities [1]. Given the intricate nature [2], unpredictable characteristics [3], and extensive damage potential [4] associated with urban waterlogging disasters, urban emergency management faces multifaceted challenges encompassing establishing a harmonious and stable urban environment, judicious utilization of

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limited resources, and enhancing the emergency management department's ability to promptly respond to crises while mitigating risks. Adopting a scientific approach is imperative for disaster mitigation.

Currently, both domestic and international researchers have conducted extensive research on disaster management, focusing on various technical aspects such as communications, computers and networks, geographic information systems (GIS), global positioning systems (GPS), among others [5], [6], [7]. Notably, significant contributions have been made in the development of advanced machine learning and optimization algorithms in this field. For instance, a novel approach for real-time monitoring of Automated Guided Vehicles (AGVs) against cyber attacks has been proposed using an integrated Internet of Things (IoT) architecture and a developed Deep Neural Network (DNN) with rectified linear units [8]. This innovative method enables effective detection of potential cyber-attacks on AGVs. Furthermore, in [9], a fault detection and correction approach based on IoT and deep learning was proposed to detect bearing faults during motor operation by analyzing vibration signals. A novel system based on IoT and deep learning, as presented in [10], demonstrates real-time detection of cyberattacks and accurate classification of various cutting conditions, enabling online monitoring for CNC machines. In this study, we propose a novel approach that utilizes convolutional neural networks and an innovative image mixing method for data augmentation to achieve precise and reliable measurement of Vickers hardness value directly from high-resolution images of SCM 440 steel specimens, as described in [11]. The authors in [12] introduce a deep learning strategy utilizing a convolutional neural network (CNN) with two convolutional layers and two pooling layers for disease detection and classification of tomato plants. Furthermore, [13] introduces Bash Bunny, a novel tool designed to assist military personnel, law enforcement agencies, and penetration testing teams in successfully extracting data from air-gapped networks using specific techniques that yield exceptionally high success rates.

As previously indicated in the literature [14], [15], [16], the implementation of a situational emergency response program can significantly enhance the reliability and efficiency of emergency operations. Numerous research studies have focused on urban flood emergency response [17], [18], [19]. In a recent investigation [20], the utilization of urban flood soldier chess projection combined with dynamic Bayesian networks was explored for contingency analysis in disaster systems. Power system contingency strategies were examined in another study [21] to assess the effectiveness of artificial neural network-based analysis for rapid decision-making. Additionally, an architectural strategy for a disaster management simulation exercise platform was proposed by [22] to enhance support for verifying decision-making activities related to command and control as well as resource allocation. Considering that flood disasters are characterized by urgent situations and limited access to information, incorporating neural network technology into the design and development of an emergency decision support system enables quantitative decision support for on-site emergency command and dispatch. In the literature [23], a multi-criteria decision model was used to evaluate critical factors for cost reduction in solar power plants. This study used the Criteria Importance Through Inter-criteria Correlation (CRITIC) methodology to determine the weights of the criteria, and also incorporated C.I.C. Set Theory to handle uncertain information during the evaluation process, thereby facilitating decision making.

In practice, establishing a comprehensive urban emergency management system is a time-consuming process; therefore, it is crucial to further improve the urban emergency management mechanism and strengthen the government's ability to respond effectively. However, the intricate nature of urban waterlogging emergencies poses challenges in conducting practical exercises due to the necessity for repetitive and extensive reasoning and analysis. Therefore, this study adopts a modeling, simulation, and deductive evaluation approach based on the concept of urban waterlogging emergency command processes, with the aim of reducing the burden on decision makers and promoting innovation in modern urban flood emergency management.

A. MAIN CONTRIBUTIONS

The objective of this article is to enhance commanders' command proficiency and the coordination ability of flood control and disaster relief among emergency departments. To accomplish this objective, we propose a pragmatic and efficacious evaluation methodology for urban waterlogging emergency response plans that integrates a radial basis function neural network with a wargame experiment to acquire data and measure capability indices. The contributions of this paper can be summarized as follows:

- A comprehensive wargame evaluation methodology that provides valuable insight into the development of urban emergency response systems and has significant practical implications. By employing a wargame approach, we simulate the process of urban emergency waterlogging. Furthermore, intelligent techniques are employed to assess and analyze the emergency procedure, providing feedback for optimizing the planning scheme of emergency construction.
- A novel approach is proposed that integrates urban waterlogging wargame inference with simulated data collection for comprehensive analysis. This technique allows for efficient processing and fitting of large data sets, while simulating expert experience to improve evaluation accuracy. By employing these advanced methodologies, we have developed a cost-effective and efficient framework that significantly enhances emergency rescue capabilities and identifies gaps in existing plans. Overall, our findings demonstrate the immense potential of this approach for improving urban waterlogging emergency services.

- Furthermore, this study effectively demonstrates the efficacy of employing the OODA loop as a decision-making framework in urban waterlogging incidents. This approach offers commanders an invaluable opportunity to test and refine their response strategies, thereby enhancing the efficiency and effectiveness of emergency services. By presenting a practical and cost-effective methodology for improving emergency response capabilities, our work contributes to real-world scenarios aimed at bolstering public safety and mitigating flooding impacts.

B. CHALLENGES IN URBAN WATERLOGGING EMERGENCY

There are numerous challenges associated with the process of emergency decision-making for urban waterlogging. The subsequent enumeration highlights some typical difficulties encountered during the development of emergency plans.

i The effectiveness evaluation method of flood emergency response is influenced by subjective experience, despite its ability to process information and quantify the effectiveness of the emergency response program.

ii Although traditional neural network-based methods for performance assessment can predict and quantify performance values through data mining, the interpretation of assessment principles is impeded by the sole extraction of data features. Additionally, these methods are prone to programming results. To address this limitation, military chess projection simulation technology needs to be incorporated for improvement.

iii The proposed evaluation method, which combines simulation data and neural networks, facilitates comprehensive learning from index processing to the mapping of final effectiveness values. This approach is suitable for evaluating large samples and multi-tasks, offering improved evaluation effects and robustness.

In summary, the proposed research scheme employs a Radial Basis Function (RBF) neural network due to its advantageous features of simplicity, rapid convergence speed, and suitability for pattern classification. The effectiveness assessment of flood emergency response is based on mapping capacity indicator parameters to action plan categories and military chess projections in a multi-level decision space. Simulation data plays a fundamental role in various analyses, while this research methodology effectively addresses the realistic need for increasing capacity index parameters over time and better tackles the challenges associated with prompt decision-making during urban flood emergency rescue.

II. EMERGENCY RESCUE OPERATION BASED ON A WATERLOGGING OODA LOOP

Emergency management is crucial for a city, enabling proactive prevention and an effective response to emergencies. Urban Flood Emergency Management Command Centers provide vital support for analysis and decision-making, facilitating intelligent decision support throughout flood rescue operations.

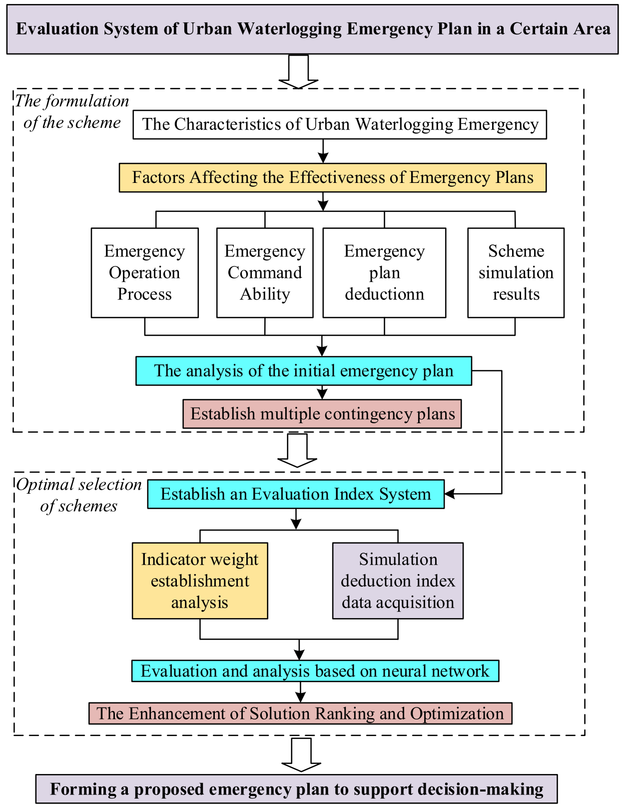


FIGURE 1. Framework of processes for the rescue efficacy evaluation. The framework of the effectiveness of the rescue operation reflects the synergy of plans, equipment, and systems.

Urban waterlogging emergency management involves a decision-making process in which governments at all levels promptly mobilize and allocate the necessary resources (teams and materials) for disaster relief, with the aim of minimizing losses caused by the disaster and maintaining social order. However, the role of emergency relief in waterlogging disasters is increasingly challenging due to their unique characteristics, such as the complexity and uncertainty of secondary disasters. As a result, it is increasingly difficult to rapidly evaluate and analyze immediate rescue action plans. Waterlogging rescue command decisions serve as guidance for emergency responders to effectively utilize limited resources in the field with the goal of mitigating risks within a minimal timeframe while minimizing post-disaster losses and adverse impacts. To facilitate this process, a framework (Figure 1) has been developed to help assess the feasibility of rescue plans, efficiently evaluate the quality of actions and command effectiveness, and provide feedback mechanisms to adjust emergency rescue plans to maximize overall rescue capacity.

Following Boyd's proposal of the OODA ring theory, it has emerged as a seminal framework for elucidating the combat process. Based on the fundamental logical

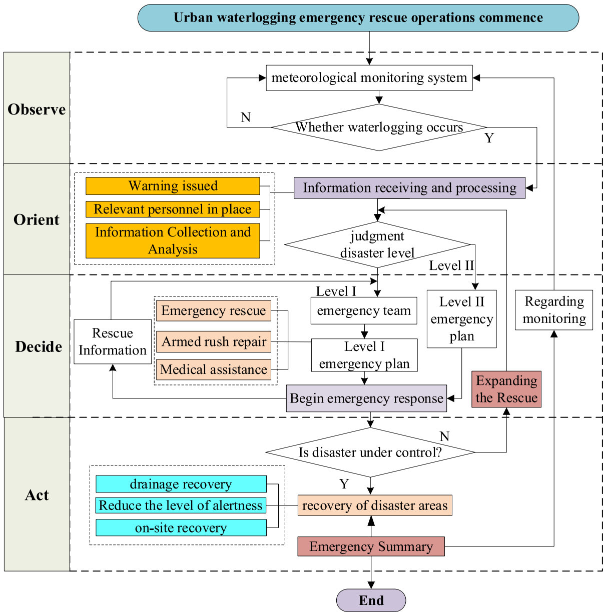


FIGURE 2. Emergency linkage system for the OODA Loop. The OODA assesses the effectiveness of urban waterlogging emergency rescue plans during urban waterlogging disasters.

connection of OODA [24], an emergency response force can be abstracted into four essential system components: (1) observation, which includes reconnaissance and early warning systems; (2) orientation, which includes situation assessment mechanisms; (3) decision, which includes command and decision systems; and (4) action, which includes rescue implementation procedures. Figure 2 illustrates the waterlogging emergency response process.

The effective performance of the same type of rescue activity program varies under different emergency task requirements, and the development of rescue programs is based on certain assumptions or prerequisites. However, due to varying degrees of human subjective evaluation factors, the evaluation results are subject to certain limitations. Furthermore, the absence of dynamic process simulation and scenario prediction hinders the evaluation results from adequately supporting flood prevention emergency management.

Thus, the research process begins by conducting a thorough analysis of the rescue operation procedure, including simulation of rescue protocols and prediction of program implementation effects based on predetermined parameters and assumptions. The main goal is to strengthen the process's strengths while reducing its weaknesses, aiming to improve the effectiveness of internal flood rescue operations in real-world scenarios. The proposed methodology is based on the OODA loop, which includes the stages of Observe, Orient, Decide, and Act. This approach demonstrates adaptability by effectively accommodating evolving circumstances and unforeseen events. By utilizing this methodological framework, emergency responders and decision-makers can make more informed judgments while avoiding unnecessary actions or deliberations.

III. ANALYSIS OF EFFICIENCY IN URBAN WATERLOGGING EMERGENCY RESCUE

The concept of effectiveness, which originated in military systems engineering, refers to the actual combat capability of equipment systems [25]. In the context of emergency rescue, effectiveness assessment is defined as the ability of a system to meet specific task requirements.

In urban flood rescue, the goal is to effectively control the spatial scale and environmental impact of disasters. As such, the full utilization of limited rescue resources becomes a competition. Urban waterlogging emergency rescue aims to combat rapidly developing flood situations and minimize disaster losses through comprehensive disaster monitoring, rapid police dispatch, scientific emergency response forces, efficient traffic control measures, and effective command and recovery operations [26]. The smooth implementation of each link affects the task efficiency of urban flood emergency rescue. Emergency plans for urban flooding fully consider comprehensive and accurate disaster monitoring, fast police dispatching, scientific deployment of emergency response forces, and maximum benefits achieved during rescue operations. Thus, an ultimate evaluation index system for emergency rescue has been developed.

Considering the characteristics of emergency rescue and the sequential stages involved in the process [27], we developed an evaluation system capable of integrating heterogeneous evaluation indices to assess the effectiveness of urban waterlogging rescue plans. Figure 3 illustrates our evaluation system, which adopts a hierarchical structure based on factors influencing emergency rescue capability. The proposed approach integrates various evaluation measures, including flood depth, response time, and number of rescued people, unlike other systems that focus on specific indices. This integration allows for a more comprehensive and accurate assessment of rescue plan effectiveness.

The evaluation index of the effectiveness of the contingency plan serves as the foundation for assessing the capability of waterlogging contingency plans. Once a set of evaluation indicators for the contingency plan is established, it becomes imperative to calculate the weight values of these indicators using the analytical hierarchy method [28]. To ensure a more rational and comprehensive evaluation result, experts provide their conclusions on the assigned weights for each evaluation indicator (Table 1).

The Emergency Rescue Plan is utilized for simulation purposes, wherein the operator conducts simulations in a specified sequence and adheres to resource allocation requirements. The evaluation of each skill's simulation process is based on predetermined indicator evaluation rules. When designing our emergency rescue evaluation system, we considered the specific characteristics and phases of such operations. Consequently, our system is specifically tailored to assess emergency rescue plans with a more focused approach compared to existing evaluation systems that have a broader scope. Our system incorporates a unique

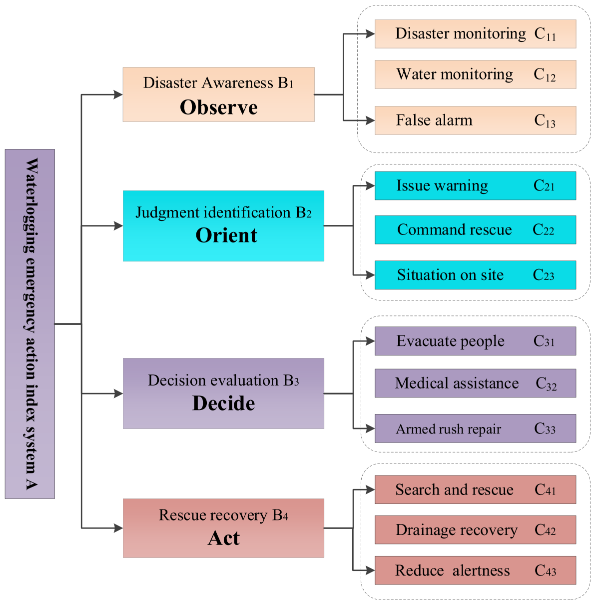


FIGURE 3. **Evaluation system of the effectiveness of waterlogging emergencies. The same level of indicators is comparable, such as positioning identification and action objectives.**

TABLE 1. **Weight of each index.**

Symbol	Ability indicator	Factor Indicator	
Weight of index	Disaster Awareness (0.2115)	Disaster monitoring	(0.1351)
		Water monitoring	(0.0516)
		False alarm	(0.0247)
	Judgment identification (0.1551)	Issue warning	(0.0388)
		Command rescue	(0.0663)
		Situation on site	(0.0500)
	Decision evaluation (0.2997)	Evacuate people	(0.1312)
		Medical assistance	(0.0587)
		Armed rush repair	(0.1099)
	Rescue recovery (0.3336)	Search and rescue	(0.1095)
		Drainage recovery	(0.1790)
		Reduce alertness	(0.0451)

feature that employs the OODA (Observe, Orient, Decide, Act) rescue action dynamics framework to extract specific content pertaining to emergency rescue capabilities. This approach ensures a structured assessment of rescue plans by systematically considering all critical information, thereby distinguishing our system from other existing works.

IV. EVALUATION OF RESCUE EFFECTIVENESS BASED ON NEURAL NETWORKS

The ease of training and rapid convergence render it an optimal choice for evaluating processing performance in neural network-based systems. Given the inevitable increase in data collected for deriving rescue scenarios in urban flood emergency response capability assessment over time, wargame simulations can provide a substantial amount of information as training samples. Hence, RBF neural networks are highly suitable for assessing the effectiveness of flood rescue operations. Furthermore, through analyzing the capabilities of various rescue schemes, we can propose optimization trends to enhance the decision-making process based on valuable insights.

By utilizing the aforementioned indicator system, pertinent data can be gathered to assess the emergency response capability during the wargame simulation process. In order to substantiate the efficacy of contingency plans, it is imperative for experts to evaluate these plans based on the assessment results of contingency capabilities and decision outcomes derived from wargaming.

A. EMERGENCY DEDUCTION MODEL FOR WATERLOGGING

The wargame serves as a scientific approach for evaluating and implementing operational plans [29]. By simulating a scenario of urban waterlogging emergency rescue through rounds of gameplay, the wargame enables prediction and simulation of the emergency response process to waterlogging disasters. In this study, we utilize a hexagonal grid for mapping purposes, as depicted below. Compared to a square grid, the hexagonal grid offers advantages such as uniformly adjacent grid cells that facilitate direction selection for inference operators. It also allows for compact unit arrangement and high spatial sampling efficiency, thereby reducing quantization errors [30]. The linkage process of urban waterlogging emergency rescue necessitates analyzing the underlying mechanism behind waterlogging formation [31], [32]. Building upon existing research in this field, we establish fundamental rules for urban waterlogging wargames to create an enabling environment [33], [34], [35].

According to the geographical location of Nanjing City and the characteristics of the rainfall data, the wargame assumes a 5-year rainfall intensity. The simulation consists of eight rounds, each lasting 10 minutes, as determined by the decision table employed in this study. The rainfall loss calculation includes initial loss, interception and depression storage, infiltration loss, runoff generation round, and drainage pipe volume.

The infiltration equation is determined based on typical urban conditions and the Houghton formula, in accordance with established academic standards.

$$J = a + bP^n \tag{1}$$

The intercepted rainfall (J) in millimeters is determined by the stable infiltration rate (a) in millimeters per minute, the coefficient of variation of the infiltration rate with time (b) in millimeters, the rainfall amount (P), and a parameter denoted by n. The infiltration loss can be calculated accordingly. Considering that concrete and asphalt have an infiltration coefficient represented by c, the resulting infiltration loss is obtained.

$$R = c \times P \tag{2}$$

The rainfall intensity P_d is determined in the current round by considering the occurrence of runoff, and the specific procedure is as follows:

The variable P_1 represents the rainfall intensity from the initial turn to the current turn, while P_2 denotes the rainfall intensity from the initial turn to the preceding turn of the current one.

If $P_1 < J$, all rainfall suffers the initial loss, and no runoff occurs;

If $P_2 < J < P_1$, there is no runoff in the first part of the round, but runoff occurs in the middle part, with rainfall intensity of

$$P_d = (P - J) \times 0.9 \tag{3}$$

If $P_2 > J$ and $P_1 > J$, the rainfall intensity of this round is

$$P_d = P \times 0.9 \tag{4}$$

The calculation method of hydraulic gradient i is

$$i = \frac{|h_1 - h_2|}{d} \tag{5}$$

The variables h_1 and h_2 represent the height differences between adjacent hexagonal meshes, while d is the distance between these meshes.

B. CALCULATION OF RAINFALL DISCHARGED INTO THE PIPE NETWORK

According to the rainfall characteristics of Nanjing City and the actual design of the pipe network, a 5-year return period is assigned for the rainfall discharged into the underground pipe network. The specific design flow of the drainage pipe network is expressed as follows:

$$q_{max} = i \times s \times \lambda \tag{6}$$

where q_{max} is the flow, s is the hexagonal grid area, and is the discharge coefficient. Rainwater flow per round, as in

$$V = P_d - J - R - q_{max} \tag{7}$$

Ponding depth of hexagonal grid, as in

$$h = \frac{V}{s} \tag{8}$$

C. COLLECTION OF DATA FOR EVALUATION SCHEME

The urban waterlogging emergency rescue simulation is based on wargame techniques and uses evaluation simulation experiments to evaluate the effectiveness of the urban waterlogging emergency rescue system. Experimental conditions are established, the simulation system is executed, and experimental results are obtained and analyzed, all of which support the design of this system (Figure 5). In order to improve the accuracy and effectiveness of evaluating urban waterlogging emergency rescue plans, approaches such as data cleaning, feature selection, regularization, and comprehensive evaluation can be used to deal with data noise during model development.

According to the action results of each contingency plan and using the triangular fuzzy number method, the scores of

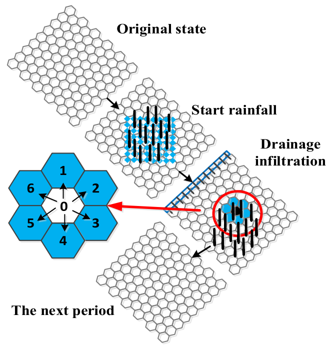


FIGURE 4. Precipitation and drainage simulation process. When rain begins, the water flow around the hexagon flows in, and the simulated water volume increases. As drainage seepage or flow to other areas increases, the amount of water in the hexagon decreases.

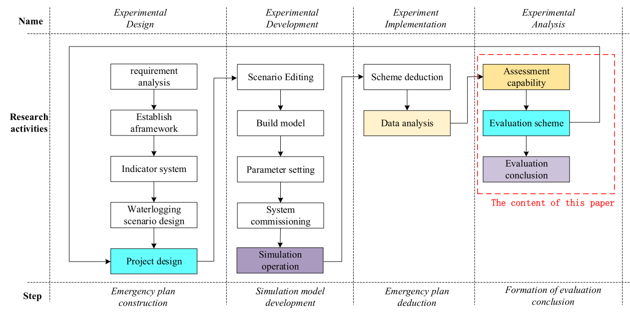


FIGURE 5. Urban waterlogging evaluation simulation process. The simulation experiment is divided into four stages: experiment design, experiment development, experiment implementation, and experiment analysis.

the corresponding index parameters are calculated according to the system shown in Table 1. Then, the quantitative results of the corresponding emergency linkage capacity indicators are obtained. The rescue operation stage uses the linear weighting method to form the effective parameters of each stage. It is calculated by combining the index score data to obtain the quantitative capability results for each stage.

$$E_i = f_i(x_{i1}, x_{i2}, \ldots, x_{im_i}) = K \times \sum_{j=1}^{m_i} w_{ij} f_i(x_{ij}) \tag{9}$$

For Scheme I, the weights of indicators at all levels can be obtained (Table 2).

According to the action results of each contingency plan and using the triangular fuzzy number method, the scores of the corresponding index parameters are calculated based on the system shown in Table 1. Then, the quantitative results are derived for the respective indicators of the emergency linkage capacity. In the stage of rescue operation, the linear weighting method is employed to determine the effective parameters for each stage by integrating the index score data, thereby obtaining quantitative capability results for each stage.

In the context of the wargame, the Rescue Score serves as an evaluation of the outcomes achieved in emergency water rescues. It encompasses various facets of rescue operations, including flood and hazard management, as well as personal

TABLE 2. Score of the indicator parameters of scheme I.

Scheme name	Ability indicator	Factor Indicator	Factor Indicator score	Ability indicator quantification
		C_{11}	0.480	
	B_1	C_{12}	0.544	0.444
		C_{13}	0.035	
		C_{21}	0.129	
	B_2	C_{22}	0.752	0.523
I		C_{23}	0.527	
		C_{31}	0.735	
	B_3	C_{32}	0.897	0.604
		C_{33}	0.290	
		C_{41}	0.960	
	B_4	C_{42}	0.698	0.712
		C_{43}	0.164	

and property retrieval, while also considering associated factors such as casualties, fuel consumption, and time expended. The rescue score is computed using the formula provided below.

$$G = \begin{cases} 1 - e^{(P-M)\times(Q'-Q)/MQ'}, \; 0 < P < M, Q' > Q \\ 0, \; M < P, Q' < Q \end{cases} \tag{10}$$

G represents the program deduction score, while M represents the reward for successful rescues. If the rescue goal is not achieved, there is no task reward, and M becomes 0. P represents the consumption of rescue actions, while Q represents the number of action steps taken. The scoring procedure assigns a step value based on each action performed. Furthermore, Q' denotes the upper limit of permissible action steps, which is determined by the intricacy of the rescue tasks.

The selection of four representative data sets is based on a combination of various capability indices, deductions from contingency plans, and the results of expert assessments, as shown in Table 3.

The contingency planning process involves numerous contingency plans and requires a significant allocation of human resources. At the same time, the evaluation process is time-consuming to meet the actual requirements. Therefore, this study proposes the use of neural networks to develop a model for rapid evaluation of emergency scenarios based on simulation data from rescue operations. This model enables rapid identification and ranking of the strengths and weaknesses of various solutions, providing commanders with selection and evaluation services.

D. RBF NEURAL NETWORK

The use of neural networks is ideal for modeling complex and non-linear relationships between input and output variables. In the context of emergency response plans, there can be intricate and nonlinear connections among various factors that contribute to plan success. RBF neural networks excel in their ability to map and generalize nonlinear functions.

TABLE 3. Evaluation data of typical emergency plan.

Evaluation Category	Ability indicator quantification (B_1 B_2 B_3 B_4)	Deduction score	Scheme evaluation	Index content
I	0.4440 0.5230 0.6040 0.7120	0.8170	Excellent	The rescue action is timely, the phase action cohesion is smooth, and it is operable
II	0.1803 0.1829 0.5527 0.3048	0.5685	Good	The scheme needs optimization to cover rescue tasks.
III	0.1567 0.3230 0.0056 0.2712	0.2933	Medium	The scheme is generally inefficient due to resource waste or poor capacity in certain stages.
IV	0.0926 0.3300 0.3118 0.2625	0	Poor	The rescue action is timely, the phase action cohesion is smooth, and it is operable.

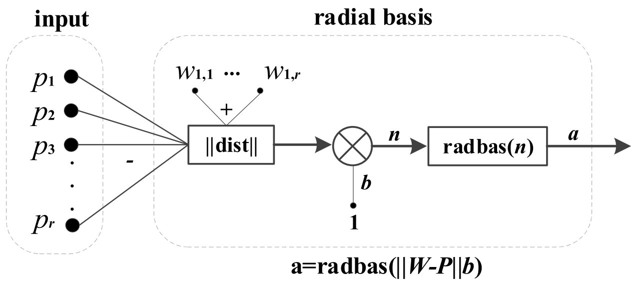


FIGURE 6. Network neuron structure of the RBF neural network, which shows how neurons interact with each other to form a network.

Compared to other algorithmic networks, such as convolutional neural networks, RBF neural networks are better suited to lightweight intelligent model applications, making them easier to construct and train. In addition, unlike back-propagation artificial neural networks, the parameters of the RBF model can be obtained directly through matrix operations and random sampling, resulting in fast training speeds [36].

The learning model is constructed based on the inference data from action plans, facilitating the evaluation and rapid optimization of emergency plan effectiveness. Neural networks are capable of modeling various types of data, including numerical, categorical, and ordinal variables. The number of personnel, available equipment and resources, severity of flood events, and time of occurrence should be considered in emergency response plans. The hidden layer in radial basis function (RBF) neural networks represents a nonlinear structure, wherein an input vector space is transformed into a hidden layer space through the utilization of radial basis functions as basis functions (Figure 6).

The output expression of the radial basis function (RBF) neural network is formulated as follows:

$$a = f(||w-p||b) = radbas(||w-p||) \quad (11)$$

The radial basis function, radbas, is used in this study due to its desirable smoothness and simple shape, making it an optimal choice for the network.

$$a(n) = radbas(n) = e^{-n^2} \quad (12)$$

$$||w-p|| = \sqrt{\sum_{i=1}^{R}(w_{1,i}-p_i)^2} = \left[(w-p^T)(w-p^T)^T\right]^{\frac{1}{2}} \quad (13)$$

The activation function of a neural network is mathematically formulated as follows:

$$R\left(x_p - c_i\right) = exp\left(-\frac{1}{2\sigma^2}\left\|x_p - c_i\right\|^2\right) \quad (14)$$

Here, the Euclidean norm $\|x_p - c_i\|$ is the center of the Gauss function, and c_i is the variance of the Gauss function.

The output of the radial basis neural network is formulated as follows:

$$y_i = \sum_{i=1}^{h} w_{ij}\, exp\left(-\frac{1}{2\sigma^2}\left\|x_p - c_i\right\|^2\right), \quad i = 1, 2 \ldots, n, \quad j = 1, 2 \ldots, n \quad (15)$$

The sample matrix x_p, the center c_i of the hidden layer node center, the weight w_{ij} from the hidden layer to the output layer, and h, which represents the number of hidden layer nodes, are all essential components in constructing a model for an emergency linkage system based on an RBF (Radical Basis Function) neural network. In addition, y_i denotes the actual output of the output node j of the network corresponding to a given input sample. Figure 7 illustrates the sequential steps involved in this modeling process.

In the research process, an urban waterlogging scenario is established, and the contingency plan is derived based on the military chess deduction system adopted in this study. During the experimental process, a total of 360 sets of contingency plan deduction data were obtained using the simulation data acquisition model based on the OODA (Observe, Orient, Decide, Act). After preliminary processing, a total of 357 data sets can be used for model training.

As shown in Figure 3, a total of 12 evaluation indices are considered, resulting in the configuration of an output layer with 12 nodes. Based on empirical knowledge, the training and test datasets are divided in an 8:2 ratio for neural network training purposes. Consequently, the training dataset consists of 285 instances while the test dataset consists of 72 instances. Since it is essential to predict simulation deduction schemes, four evaluation criteria are incorporated in this study, resulting in an output layer with four nodes as shown in Figure 8.

The wargaming methodology employed in this study can enhance commanders' command capabilities by providing

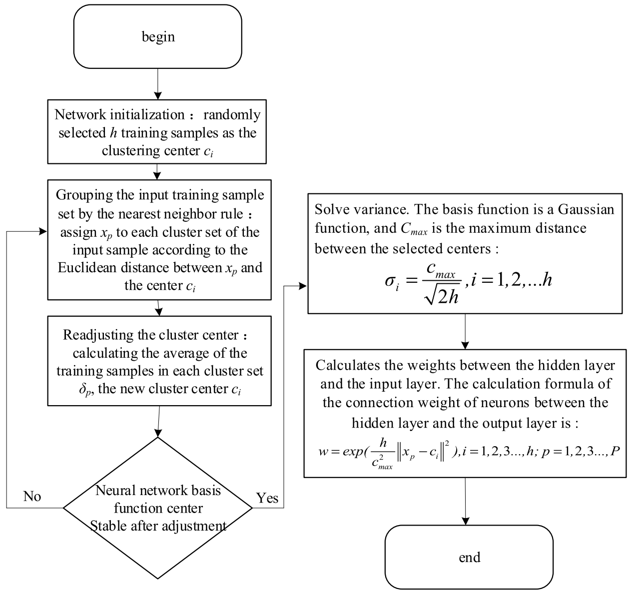


FIGURE 7. Process steps of the learning training principles. The steps in the process of constructing the evaluation model of the emergency linkage system are based on the RBF neural network.

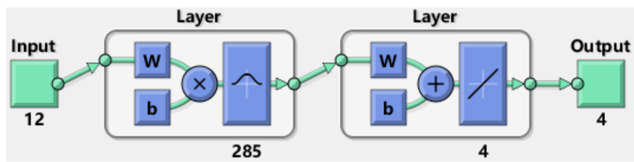


FIGURE 8. Neural network framework. According to the evaluation system, the data samples were used to build a training network. The dimension of the input signal refers to the number of secondary indexes.

them with a simulated environment in which to test their decision-making skills and evaluate the effectiveness of their response strategies. This approach facilitates the identification of areas for improvement and the optimization of contingency plans. The intelligent techniques used in this study, such as the neural network method, allow for rapid data processing and fitting, simulating expert experience for response evaluation. This approach saves time and resources, allowing emergency responders to quickly evaluate and improve their response strategies.

V. CASE ANALYSIS AND TESTING

A. EMERGENCY DEDUCTION MODEL FOR WATERLOGGING

Nanjing City covers a total area of 80.97 km2 and experiences a subtropical monsoon climate with distinct winter and summer seasons. Figure 9 shows a segment of a wargame map based on the contour spectrum within a specific region of the urban area. The demarcated red zone indicates the location of the waterlogging disaster caused by annual rainfall exceeding 1000 mm and the plum rain season in June and July.

Utilizing the military chess deduction approach, this study simulates the process of urban emergency waterlogging and

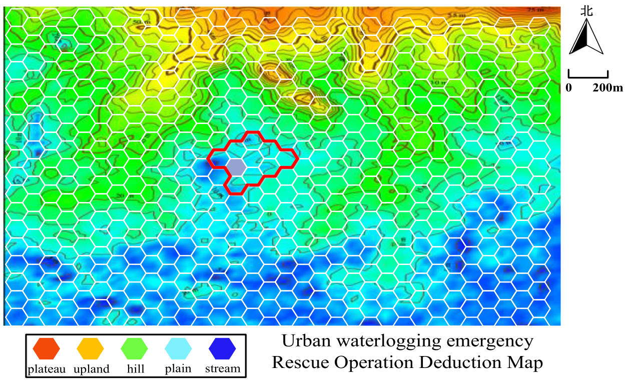


FIGURE 9. Map of the waterlogging wargame of the city. Each hexagon represents an area of 0.1 square kilometers, and the hexagonal side length represented in the graph is 200 m.

establishes an emergency action model framework for urban waterlogging based on the OODA (Observe, Orient, Decide, Act) ring theory. By leveraging data from military chess deduction, the effectiveness of emergency schemes is analyzed to evaluate decision makers' command ability and the coordination capability of emergency departments in addressing waterlogging.

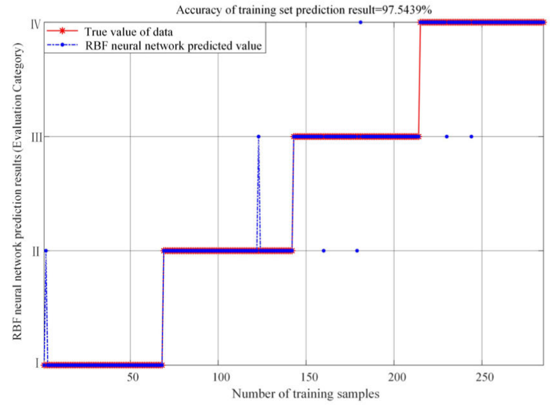
B. CONSTRUCTION AND TRAINING OF THE NETWORK MODEL

The simulation prediction results of the RBF (Radical Basis Function) neural network for the training data are presented below. We conducted a comprehensive quantitative analysis by considering the accuracy rate of the prediction results and utilizing a heat map to assess the impact of various deduction schemes across four levels.

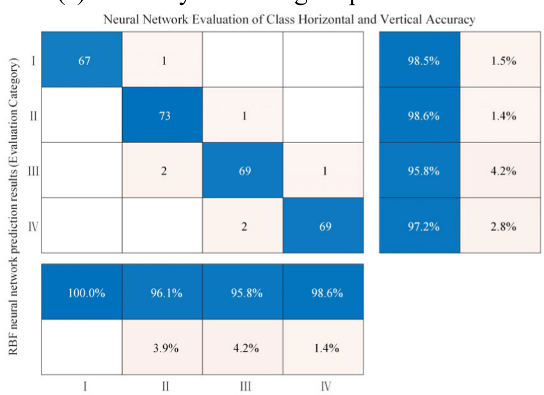
The neural network demonstrates its capability for effectively evaluating waterlogging emergency plans and providing relatively accurate conclusions. Additionally, the heat map presents the evaluation results of real data using blue markers, wherein the analysis of horizontal and vertical prediction accuracy can better reflect the classification model's performance. However, based on the prediction set analysis, it is observed that the model lacks sensitivity in identifying instances belonging to the third category, resulting in errors. Nevertheless, our research primarily focuses on selecting optimal emergency plans; thus, our main emphasis lies within the first category.

Based on the analysis of the test set, the RBF (Radical Basis Function) neural network demonstrates a high evaluation accuracy in effectively assessing emergency plans. Given that our focus lies primarily on optimizing the first type of emergency plans, which aims to provide decision makers with optimal solutions for plan design and decision support, this model adequately fulfills the task requirements.

In order to enhance the model's evaluation performance regarding the effectiveness of emergency plans, a random test was conducted using 5% (18 samples) of the data. The resulting test outcomes are presented below.



(a) Accuracy of training set prediction results



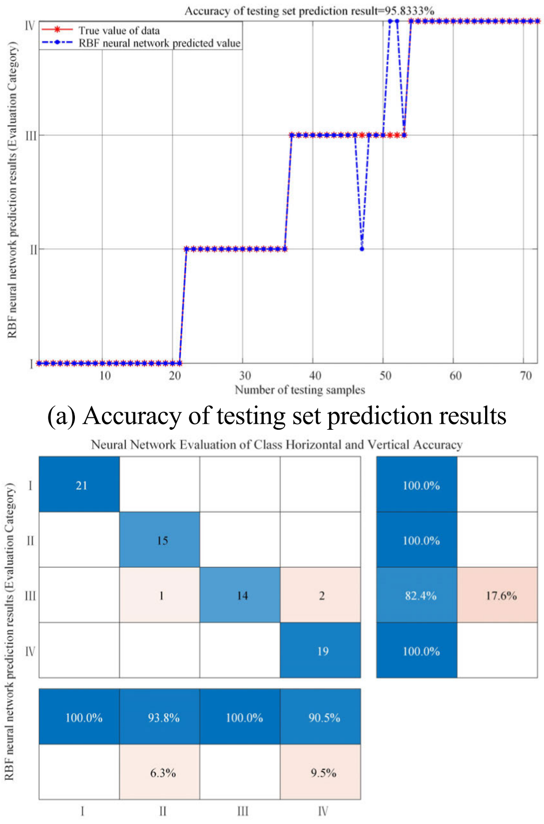
(b) Class Horizontal and Vertical Accuracy

FIGURE 10. The prediction results of the neural network on the training set. The model achieved a prediction success rate of 97.5439% for the training set, comprising a total of 285 groups.

The proposed model in this paper also demonstrates favorable outcomes in the experimental assessment of random data samples. Based on the analysis presented in Figure 12, the model exhibits a 100% accuracy rate for evaluating and predicting results pertaining to the first type of emergency plan, with an overall accuracy of 94%. These findings substantiate that the model satisfies the requisite precision criteria for practical applications.

Based on the aforementioned research experiments, it is evident that the RBF (Radical Basis Function) neural network prediction model exhibits superior accuracy. However, one experiment was deemed accidental. In this study, distinct prediction models were constructed using PNN (Product-based Neural Network), GRNN (Generalized Regression Neural Network), and BP (Back Propagation) neural network respectively. The urban waterlogging emergency scheme dataset was employed for training and testing purposes as well. These experiments were repeated 10 times to generate 10 models, with their respective accuracy and running time recorded accordingly. Figure 12 illustrates the evaluation of accuracy and running time for all four algorithms.

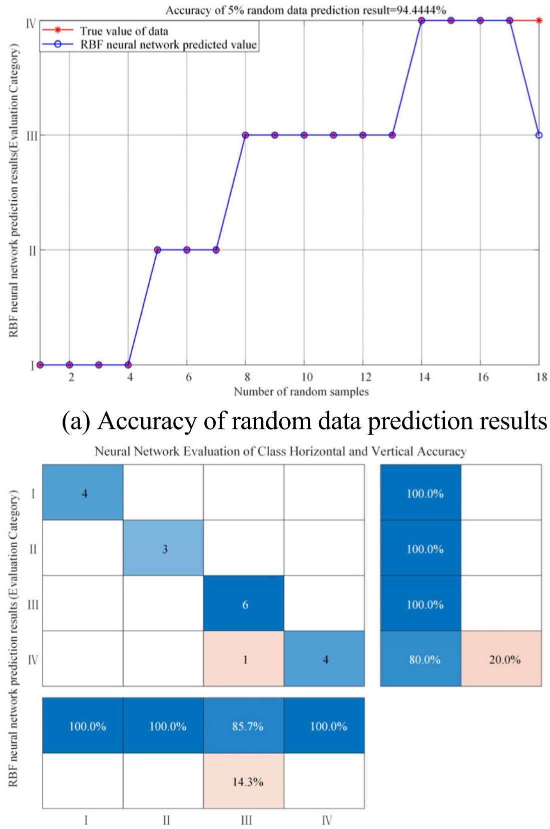
The average values of the ten models were respectively calculated from Figure 13(a) and Figure 13(b), and the



(a) Accuracy of testing set prediction results

(b) Class Horizontal and Vertical Accuracy

FIGURE 11. Test results of the RBF neural network on the testing set. The model achieved a prediction success rate of 95.8333% for the testing set, comprising a total of 72 groups.



(a) Accuracy of random data prediction results

(b) Class Horizontal and Vertical Accuracy

FIGURE 12. Test results of the RBF neural network on the 5% random data. The model achieved a prediction success rate of 94.4444% for the random data, comprising a total of 18 groups.

TABLE 4. Comparison of prediction results of four algorithms for emergency plan evaluation.

Name	RBFNN	GRNN	PNN	BP
Accuracy（%）	95.6084	93.1440	91.2672	89.9682
Running time（s）	4.5647	4.6890	4.8325	5.5098

comparative evaluation results of the four algorithms are presented in Table 4.

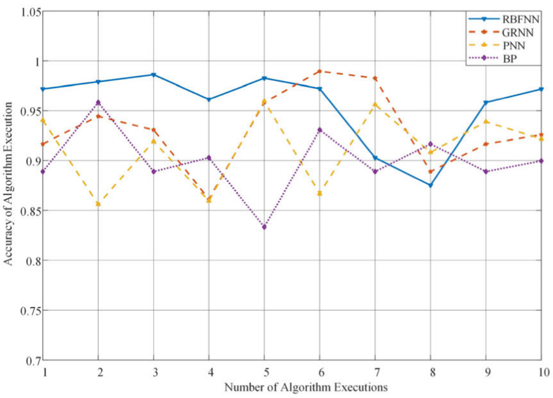
Based on the analysis of Figure 13(a), Figure 13(b), and Table 4, it is evident that RBFNN exhibits distinct advantages in terms of accuracy and computational efficiency. In contrast, the BP neural network lags behind significantly due to its reliance on the error back propagation algorithm for training. As both PNN and GRNN are derived from RBFNN, their outcomes demonstrate certain similarities. However, GRNN combines RBFNN with linear neurons while PNN incorporates competitive neurons; thus, RBFNN proves more suitable for addressing the requirements outlined in this paper.

In the process of model construction and training, the central vector of the hidden unit is formed by aggregating all training samples based on deductive data from emergency rescue plans, thereby constraining the performance of conventional neurons. At the same time, as the number of samples increases, the artificial evaluation analysis becomes increasingly complex. Therefore, in order to utilize the advantages of RBFNN, we propose a radial neural network evaluation model.

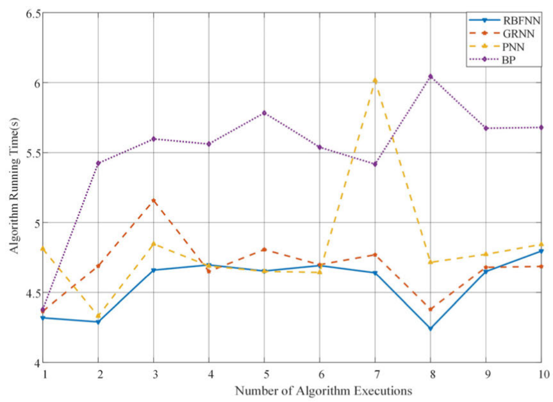
The RBF neural network and BP neural network can be employed for predicting and analyzing the efficacy of emergency schemes. However, in terms of specific network training, the RBF neural network offers distinct advantages in approximation ability, classification ability, and learning speed by requiring adjustment of only one propagation speed parameter. Ultimately, the network converges to an optimal regression surface with the largest accumulation of samples while also demonstrating superior performance when data is limited.

C. DISCUSSION

We compare our analysis with recent state-of-the-art studies, such as Nafei et al. [37], who used a multiple quasi-metric decision making research approach to address corporate sustainable sourcing. They used the TOPSIS method as a criterion for measuring supplier preferences and evaluated their rankings. While this scheme has technical advantages in ana-



(a) Accuracy of four algorithms running 10 times



(b) Running time of four algorithms running 10 times

FIGURE 13. **The experiments were conducted by running each of the four algorithms ten times.**

lyzing rankings for small samples, it proves to be inadequate when dealing with urgent urban flooding decision making, which requires the immediate generation of preferences and rankings for emergency solutions. Specifically, our study is based on projected data pertaining to urban flood emergency solutions, wherein the magnitude of data samples and the dimensions of attributes in multiple quasi-measurement decisions present challenges to conventional evaluation analysis programs. The literature [38] provides a comprehensive questionnaire for exploring the intricate domain of sustainable supply chain time, and establishes a dynamic and transformative connection between sustainable supply chain management and machine intelligence. This article addresses the convergence of artificial intelligence and machine learning, providing valuable insights and considerations that direct our focus towards an in-depth exploration of machine intelligence in emergency management. Furthermore, it enhances our understanding of the disruptive potential of machine intelligence in the field of emergency management. At the same time, this research also addresses the challenges of combining machine intelligence with emergency management, such as data complexity, facilitating rapid decision support for emergency personnel, and considering emerging technology trends and technological innovations that will continue to drive advancements in the field.

VI. CONCLUSION

The present study proposes an evaluation methodology for urban waterlogging emergency rescue plans, utilizing wargames to enhance cost-effectiveness and improve response capabilities, while identifying deficiencies in current strategies. An index system is developed to assess emergency rescue operations by utilizing a radial basis function neural network and conducting wargame experiments for data collection and capability measurement. This suggested approach holds practical significance in enhancing urban emergency response plans through the application of intelligent techniques like wargaming and neural networks. It eliminates unnecessary delays or deliberations and enables real-time data processing and adaptation that mimic expert assessments. The result is saving valuable time and resources, while enabling emergency responders to quickly evaluate and improve response strategies.

Research on future urban waterlogging rescue services includes several interesting areas of investigation, such as using game theory to evaluate the effectiveness of multi-scenario operations and optimize resource allocation for improved response times. Another area of interest is developing a game theory-based emergency reasoning system to enhance response efforts by considering multiple factors and potential outcomes. Additionally, researchers are exploring methods for modeling emergency response databases in situations with incomplete disaster information.

The objective of this study is to investigate the use of advanced analytical tools, such as wargame simulation and neural network learning optimization algorithms, to improve emergency services in urban waterlogging scenarios. Through this research effort, we aim to provide valuable insights into implementing these methodologies in real-world situations, with the ultimate goal of enhancing emergency response capabilities and mitigating the impacts of urban waterlogging on public safety and infrastructure. By utilizing these sophisticated analytical tools, we can gain a deeper understanding of urban waterlogging dynamics and develop targeted emergency services that have the potential to save lives and protect communities.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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