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Original scientific paper

Multivariate Information Collaborative Optimization of Emergency Management Based on Chaos Theory

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Abstracts: Extreme changes in natural climate have led to an increase in waterlogging in urbanization year after year. The study aims to optimize the multivariate information synergy of emergency management and improve the efficiency and effectiveness of disaster response. First, the multi-objective problem model of emergency settlement site selection and material distribution is constructed by means of mathematical modeling. Second, a non-dominated sorting genetic algorithm is used as the basis of the optimization framework, and the Tent chaotic sequence in chaos theory is introduced for the optimization of population initialization and genetic steps. Finally, a multivariate information processing model for emergency management is proposed. The experimental results indicated that the new model has the highest placement point generation rate of 92% and the highest distribution route generation rate of 95% compared to the same type of chaotic model. Compared with the advanced technology models in this field, the new model generated a maximum of 112 settlement schemes and the optimal scheme was 10. The maximum number of distribution route solutions was 121, and the optimal solution was 11. It can be concluded that the introduction of chaotic mapping can significantly improve the global search capability of the model and the efficiency of the algorithm. The study provides a new idea for urban emergency management, which is especially valuable when dealing with complex and dynamic disaster response scenarios.

Keywords: chaos theory; emergency management; settlement; material distribution; nondominated sorting genetic algorithm

1 INTRODUCTION

In recent years, many cities in China have faced increasingly severe urban flooding disasters, which have significantly impacted regional economies and disrupted the daily lives of residents [1]. This situation highlights the urgent need to optimize emergency management (EM) strategies in response to sudden disasters. Current solutions include data analysis and predictive methods powered by artificial intelligence, decision-making support using drone monitoring technology, and coordinated decision-making via cloud data analysis [2]. These technological approaches aim to improve decisions related to resettlement site selection (RSS) and material distribution (MD) through data analysis and real-time monitoring. However, challenges remain, such as the inability to capture key variables and ineffective resource allocation [3]. The introduction of chaos theory (CT) offers new perspectives in EM, particularly in optimizing complex decisions and enhancing the system's ability to respond to sudden changes, showing unique advantages [4]. This study incorporates CT with the non-dominated sorting genetic algorithm II (NSGA-II) to optimize EM by constructing a multi-objective information model that includes contingency RSS and MD. The study's innovation lies in introducing a chaos map (CM) to increase the algorithm's stochasticity and traversal, thereby addressing the limitations of optimization algorithms in complex systems. The research aims to provide more efficient and accurate decision support for urban EM. The research is structured into four parts: the first part analyzes and summarizes previous studies, the second part details the construction of the EM model and the optimized processing model, the third part tests the performance of the new model, and the final part presents a summary of the findings.

2 LITERATURE REVIEW

In recent years, erratic climate changes and the destruction of the natural environment by human activities have led to a surge in urban flooding disasters across China. In response, governments throughout the country have implemented measures to improve urban drainage systems while systematically optimizing emergency management (EM) strategies. For instance, Do-Duy T. et al. explored the allocation of time and efficiency in UAV-assisted deployment scenarios, using the K-means clustering algorithm in emergency situations such as disaster relief and public safety missions. Their experimental results demonstrated that this method effectively addresses resource allocation challenges, particularly in terms of network energy efficiency and execution time [5]. Similarly, Yao Z. et al. identified the growing challenge of secondary disasters, which complicates the deployment of emergency wireless communication networks. To tackle this, they proposed a new EM model that integrates UAV-assisted technology with intelligent reflective surface technology. The experimental outcomes showed that this model offers higher capacity and energy efficiency for post-disaster wireless communication networks compared to traditional channel models [6]. In another study, Arghandeh R. et al. pointed out the shortcomings of existing techniques, particularly the lack of contingency planning and data utilization during sudden disasters. To address this, their research team developed a power management system for extreme weather events by integrating data mining and data processing algorithms. The results indicated that the planned system provided superior stability and operational quality [7]. Kyrkou C. et al. also observed that current EM methods struggle to handle complex data during natural disasters. In response, their research team proposed an EM complex information processing model, incorporating machine learning algorithms. Experimental results revealed that this model could rapidly categorize EM data and effectively provide solutions [8].

Chaos Theory (CT) is a mathematical framework used to describe the complex behavior of nonlinear dynamic systems. Its capacity to understand and predict such intricate systems makes it widely applicable across various fields, including natural sciences, engineering, and biomedical sciences. For instance, Yildiz E. et al. proposed a novel optimization strategy by integrating CT with data mining to investigate the factors contributing to seismic hazard formation. This approach aims to guide the optimization of emergency management (EM) strategies. Their experimental results demonstrated that this strategy effectively categorizes and analyzes historical seismic hazard data, providing valuable insights for disaster managers [9]. Similarly, Fuller R. P. et al. developed a management framework by incorporating CT principles to enhance EM efficiency in post-disaster scenarios. The experimental results revealed that this framework significantly improves the execution and orderliness of EM measures [10]. In another study, Liu R. sought to improve existing EM and information intervention management by proposing an EM information intervention method that combines CT, crisis theory, and life cycle theory. The experimental results indicated that this method exhibited superior information processing efficiency during the 7-20 incident in Zhengzhou, offering a novel approach to EM [11]. Additionally, Wang T. et al. tackled the challenge of emergency material allocation and dispatching by treating it as a combinatorial optimization problem. They introduced an adaptive weighted dynamic differential evolutionary algorithm, enhanced with chaos map (CM) strategies, to address this issue. The experimental results showed that their algorithm possesses stronger global optimization capabilities and faster convergence rates compared to other optimization algorithms, providing significant benefits for smart city research [12].

In summary, while technologies such as AI, UAV monitoring, and cloud data analysis have led to significant progress in emergency management (EM), particularly in optimizing resettlement site selection (RSS) and material distribution (MD), challenges remain. These include deficiencies in resource allocation effectiveness, system flexibility, and real-time data processing. To address these issues, this study seeks to apply Chaos Theory (CT) to EM for urban flooding. Unlike previous approaches, this study will combine CT with advanced optimization algorithms to develop a new processing model aimed at enhancing the effectiveness and real-time response capabilities of disaster management.

3 RESEARCH METHODOLOGY

The emergency management (EM) requirements for sudden-onset disasters are particularly demanding, especially regarding the siting of resettlement sites and the distribution of emergency relief materials. To address these challenges, the study first constructs a multi-objective problem model through mathematical modeling for these two critical aspects. Following this, an optimization strategy is introduced to solve the problem, leading to the proposal of a novel Emergency Management Multivariate Information (EMMI) processing model. This model leverages Chaos Theory (CT) to enhance optimization, aiming to improve the overall efficiency and effectiveness of disaster response.

3.1 Modeling of Emergency Settlement Points and Emergency Material Distribution Multi-Objective Problems

Emergency management (EM) is crucial for effectively responding to sudden urban flooding, as it involves a range of complex decisions and resource coordination. In such scenarios, selecting appropriate emergency resettlement sites and optimizing the distribution of emergency supplies are essential tasks to ensure the safety of lives and maintain social stability [13, 14]. Typically, resettlement sites are chosen from large facilities like hospitals, schools, and gymnasiums. However, given the limited availability of such sites within a city, it is vital that selected resettlement sites are in close proximity to the affected victims, ensuring convenient and efficient relocation [15]. At this point, the disaster victims' resettlement transfer schematic, as illustrated in Fig. 1, provides a visual representation of the process.

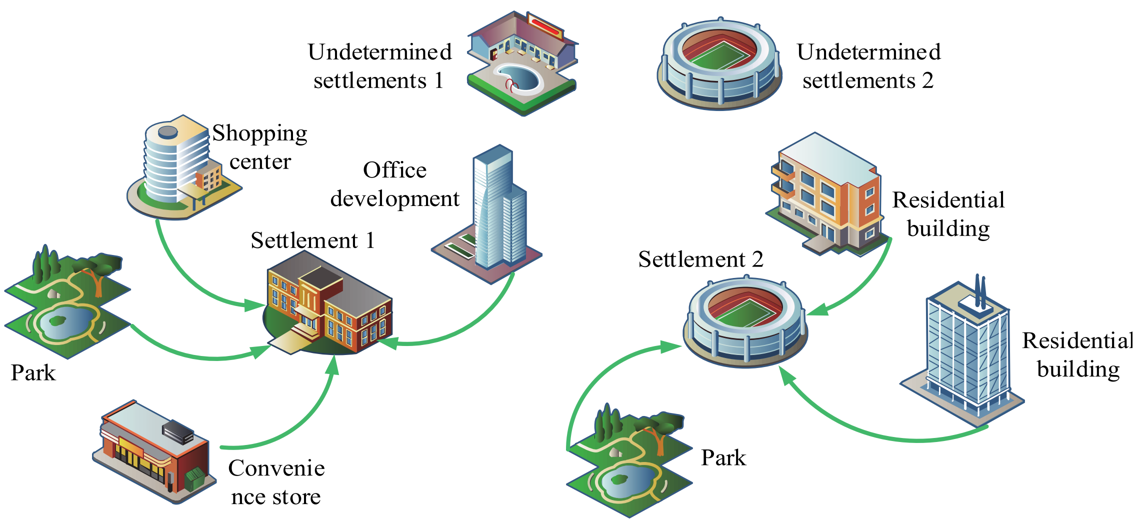


Figure 1 Schematic diagram of resettlement management for the affected population

In Fig. 1, to achieve large-scale resettlement of urban residents, it is crucial not only to consider the resettlement routes but also to search for and identify previously unknown rescue resettlement sites. The study assumes that the locations of the affected sites within a given area are known, and each affected site requires at least one resettlement site. Given the limited capacity of these resettlement sites, the study emphasizes the need to maximize the capacity of each site. Additionally, it is important to minimize the distance between neighboring resettlement sites and to reduce the overall number of resettlement sites, which would help to avoid complications in subsequent material distribution (MD) for rescue operations. Based on these assumptions, the study proposes a multivariate information problem model for emergency resettlement site selection (RSS) using the concept of radius radiation. This model aims to optimize the placement of resettlement sites by minimizing the average distance between resettlement points and affected points. The computational formula for this minimization is presented in Eq. (1).

$$Q_1 = \frac{1}{N}\sum_{i=1}^{N}\min_{j\in J} d_{ij} \tag{1}$$

In Eq. (1), N represents the number of affected points, while J denotes the set of candidate resettlement points, with $j \in J$. The variable d_{ij} represents the distance from the affected point i to the resettlement point j. The formula for maximizing the capacity utilization of the resettlement points is provided in Eq. (2).

$$Q_2 = \sum_{j\in J}\frac{u_j}{c_j}, u_j \le c_j, \forall_j \in J \tag{2}$$

In Eq. (2), u_j represents the actual number of occupants at resettlement site j. c_j denotes the maximum capacity of resettlement site j. The formula for minimizing the number of resettlement sites is provided in Eq. (3).

$$Q_3 = \min|J| \tag{3}$$

In Eq. (3), all algebraic meanings remain consistent with the previous explanations. At this stage, the constraints related to the service area and distance limitations for individual resettlement sites are presented in Eq. (4).

$$\begin{cases} \sum_{j\in J} x_{ij} \ge 1 \\ d_{ij} \le D, \forall_i \text{ where } x_{ij} = 1 \end{cases} \tag{4}$$

In Eq. (4), D represents the distance threshold, and x_{ij} denotes a binary variable. If the affected point i is covered by resettlement site j, then $x_{ij} = 1$; otherwise, $x_{ij} = 0$. After constructing the multivariate information management model for resettlement site selection, the study considers typical urban flooding scenarios where city houses are generally less damaged but poorly suited for resettlement. In such cases, the suburbs are often chosen as resettlement sites for displaced populations [16]. To address these challenges, the study proposes a three-point distribution network that integrates material storage depots, material transfer centers, and resettlement sites. This network utilizes coordinated distribution methods, including water, land, and air transport, to optimize the distribution path as much as possible. The schematic diagram illustrating the multiple distribution channels for emergency material management is presented in Fig. 2.

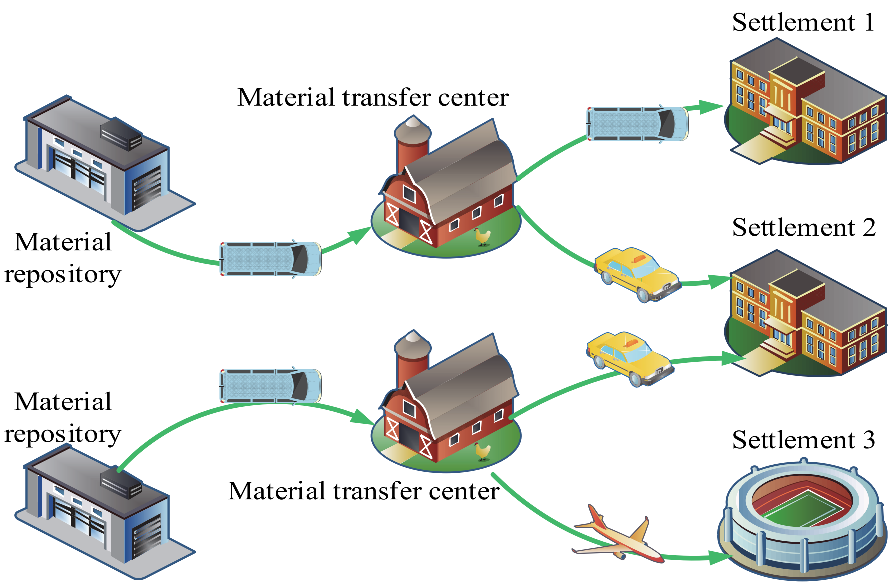


Figure 2 Schematic diagram of the distribution of multifaceted information materials for emergency management

In Fig. 2, the distribution process begins with the material storage depot receiving the distribution request. The depot then transfers the materials directly to the transit center for storage, following the prioritized path. Next, after planning and determining the resettlement points, distribution paths, and materials to be delivered, the relevant distribution information is transmitted to the transit center, which then undertakes the deployment and coordination of the distribution. During this phase, depending on road conditions, distribution can be carried out using land, air, or water transport to maximize efficiency and effectiveness. To facilitate this multi-modal material distribution, the study makes several assumptions about the model. First, the distribution process considers only one-way trips, meaning that the return journey after distribution is not calculated. Second, the material storage capacity at the transit center is limited, and each distribution tool also has a limited carrying capacity. Third, the carrying capacity and average running speed of the distribution tools are fixed. The objective function for Emergency Management Multivariate Information (EMMI) material distribution is provided in Eq. (5).

$$Z_1 = \sum_{a \in A} \sum_{b \in B} \sum_{c \in C} (t_{abc} \cdot g_{abc} \cdot x_{abc}) \tag{5}$$

In Eq. (5), a, b and c represent the material repository, transshipment center, and placement point, respectively. The variable x_{abc} denotes the distribution task from repository a to placement point c via transshipment center b. The variable t_{abc} represents the time cost of the entire distribution task, while g_{abc} denotes the path cost of the distribution task. At this stage, it is crucial to ensure that the handling capacity of each transshipment center and the materials received by each placement point do not exceed their maximum capacities. The constraints related to these conditions are provided in Eq. (6).

$$\begin{cases} \sum_{a \in A} \sum_{c \in C} x_{abc} \le C_b, \forall_b \in B \\ \sum_{a \in A} \sum_{b \in B} x_{abc} \le C_c, \forall_c \in C \end{cases} \tag{6}$$

In Eq. (6), C_b and C_c represent the maximum processing capacity of the transshipment center b and the maximum receiving capacity of the placement point c, respectively. The coverage constraint and distribution integrity constraint at this stage are provided in Eq. (7).

$$\begin{cases} \sum_{a \in A} \sum_{c \in C} x_{abc} \ge 1, \forall_b \in B \\ x_{abc} \le y_{ab} \wedge x_{abc} \le z_{bc}, y_{ab}, z_{bc} \in [0,1] \end{cases} \tag{7}$$

In Eq. (7), y_{ab} and z_{bc} indicate whether the paths from repository a to transit center b and from transit center b to placement site c are selected, respectively. In summary, the study integrates the multivariate information problem model for emergency resettlement site selection (RSS) with the EMMI material distribution problem model to construct a comprehensive Emergency Management Multivariate Information (EMMI) model. The structure of this model is illustrated in Fig. 3.

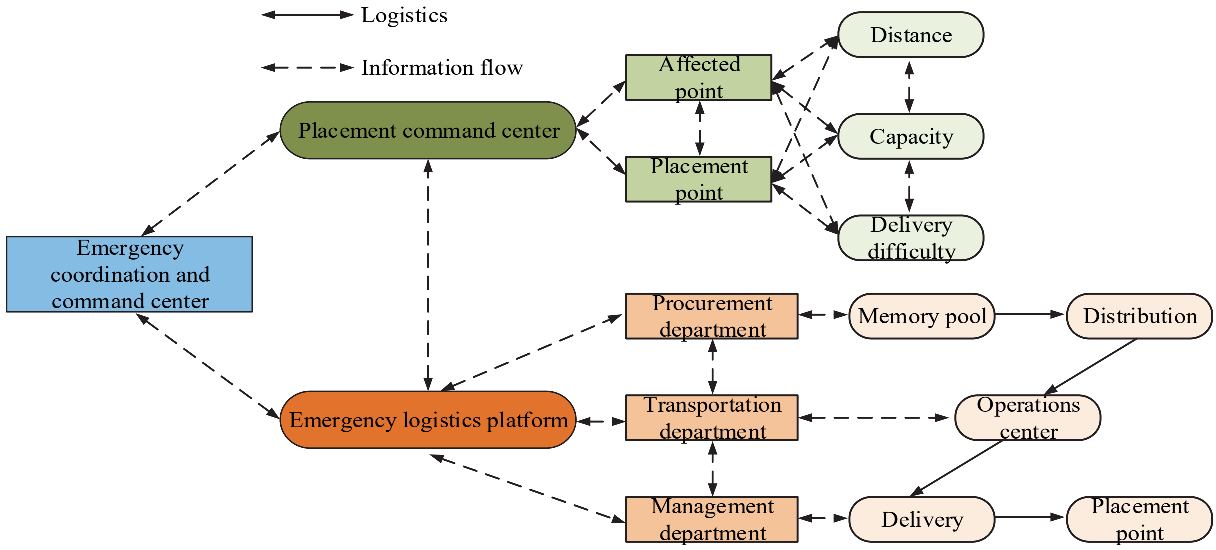


Figure 3 Emergency management multivariate information modeling structure

In Fig. 3, the emergency coordination command center oversees both the resettlement command center and the emergency logistics platform, facilitating real-time data reporting through the information flow. The resettlement command center is responsible for directly coordinating the planning between the disaster site and the resettlement site. This coordination takes into full consideration factors such as the transfer distance for disaster victims, the capacity of the resettlement sites, and the challenges associated with subsequent material distribution (MD). Additionally, the emergency logistics platform manages the procurement department, transportation department, and management department under its jurisdiction. The materials involved are first distributed from the storage warehouse to the transfer center, and from there, they are transported to the various resettlement sites as needed.

3.2 Emergency Multi-Objective Information Coordination Strategy Based on Chaos and NSGA-II

After constructing the comprehensive EMMI model for urban flooding, the study aims to introduce heuristic algorithms to solve this multi-objective problem. Existing solution algorithms can be broadly classified into three categories: algorithms that convert the problem into a single objective by applying weights, optimization algorithms that prioritize objectives based on the importance of weights, and algorithms that compute the Pareto front of the problem [17, 18]. Given the post-disaster context, where information flow is disrupted and assessing the importance of individual objectives is challenging, the study opts to use the third type of algorithm. Among these, the Non-dominated Sorting

Genetic Algorithm II (NSGA-II) is a Pareto-based computational algorithm known for its superior running speed and convergence properties. NSGA-II has been widely applied in various fields of multi-objective problem-solving and has produced significant results [19, 20]. The algorithm flow of NSGA-II is depicted in Fig. 4.

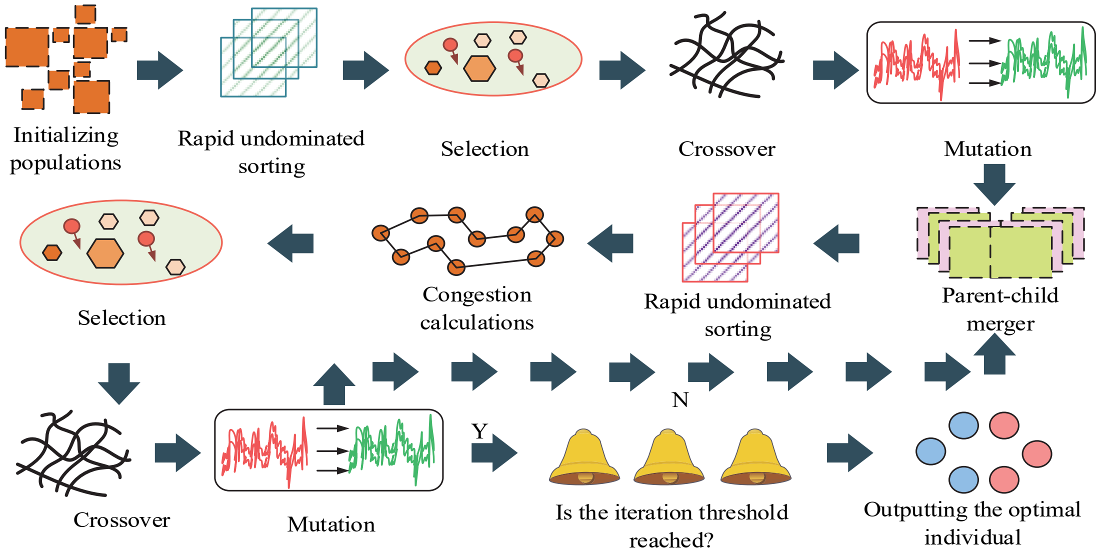


Figure 4 NSGA-II arithmetic flow

In Fig. 4, the NSGA-II algorithm begins by randomly generating an initial population, which is then sorted using a fast non-dominated sorting method. This process assigns individuals to different non-dominated fronts. Next, the crowding distance of individuals within each front is calculated to maintain population diversity. After this, a selection operation is performed to create a new parent population. The selected parents then undergo crossover and mutation operations to produce offspring. The parent and offspring populations are merged, followed by another round of fast non-dominated sorting and crowding distance calculations to determine the best individuals for the next generation. This iterative process continues until a predetermined number of iterations is reached, resulting in a near-optimal solution set that completes the multi-objective optimization. However, when applied to dynamic EM scenarios, the performance of NSGA-II can degrade significantly due to the constant changes in environmental data, which reduces its multi-objective optimization search capabilities. To address this, the study introduces Chaos Theory (CT) to enhance the algorithm. CT helps increase the stochasticity and diversity within the NSGA-II algorithm, enabling it to escape local optima and improve its ability to search for global optimal solutions. Chaos Map (CM) is a key concept in CT, often employed in optimization algorithms to enhance the generation of initial populations, parameter adjustments, and diversification of search strategies, thanks to its nonlinear dynamic properties. The Tent map, a classic CM sequence, is used in this context. The distribution curve of the Tent map is illustrated in Fig. 5 [21].

In Fig. 5, the curve distribution of the Tent Chaos Map (CM) sequence is characterized by its uniformity and high traversal ability. Additionally, the Tent map shows linear growth and decline across various intervals, forming a pattern resembling a tent. This characteristic suggests that the chaotic nature of the sequence is preserved even with slight changes in parameters, making it robust and reliable for optimization purposes.

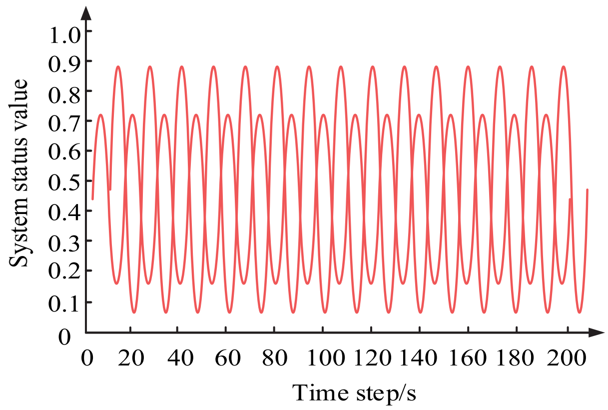


Figure 5 Tent chaos distribution curve

The computational formula for the Tent chaos is provided in Eq. (8).

$$T(x) = \begin{cases} \mu \cdot x, if\, 0 \le x < 0.5 \\ \mu \cdot (1-x),\ \text{if}\ 0.5 \le x < 1 \end{cases} \tag{8}$$

In Eq. (8), $T(x)$ represents the output of the Tent mapping, where x denotes the current state, with values ranging between [0, 1]. The parameter μ represents the Tent mapping parameters, which can take values between [0, 2]. When applying Tent chaos in the stochastic generation of the initial population for NSGA-II, the optimized initial population is calculated using the formula shown in Eq. (9).

$$X_i^0 = T^{(i)}(x_0) \tag{9}$$

In Eq. (9), X_i^0 represents the initial value of the i-th individual and x_0 denotes the initial condition of the Tent mapping. The notation $T^{(i)}$ indicates the application of the Tent mapping i times. During the selection phase, a chaotic sequence is generated using the Tent mapping, and individuals are selected based on the sequence values to participate in the subsequent crossover and mutation processes, thereby increasing the diversity of the population. The computational formula for this selection process is shown in Eq. (10).

$$S_{i+1}=T(S_i) \tag{10}$$

In Eq. (10), S_i and S_{i+1} denote the i-th and i + 1-th chaotic states, respectively. In the crossover phase, the output of the Chaos Map (CM) can be used as a dynamic adjustment factor for the crossover probability, enhancing the diversity of solutions. The crossover computation equation for this stage is provided in Eq. (11).

$$p_c = \min(p_{c,\max}, T(S_i)) \tag{11}$$

In Eq. (11), p_c denotes the crossover probability and $p_{c,\max}$ denotes the upper limit of the crossover probability. For the mutation operation, the sequence generated by the Tent mapping is used to adjust the mutation probability of an individual. The computational equation for this adjustment is provided in Eq. (12).

$$P_{mut}(t) = TentMap(P_{mut}(i)) \tag{12}$$

In Eq. (12), $P_{mut}(i)$ denotes the variance probability of the i-th individual and *TentMap* refers to the Tent Chaos Map function. In summary, the study introduces an EMMI model processing approach that combines the improved NSGA-II algorithm with Tent chaos. The flow of this model is illustrated in Fig. 6.

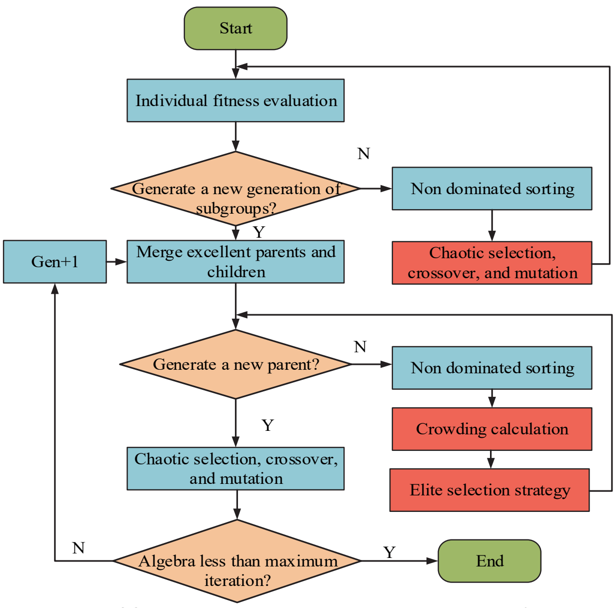


Figure 6 NSGA-II-Tent emergency management multivariate information processing flow

In Fig. 6, after constructing the EMMI model, the model information is input into NSGA-II as initial data. The process begins with generating initial population individuals, such as placement points and distribution paths, using the Tent Chaos Map (CM). Next, the fitness evaluation of these individuals is conducted, which involves calculating the location of the placement points and the length of the distribution paths. If a new generation of individuals is generated at this stage, the best individuals are selected and merged with the parent generation. If not, non-dominated sorting and chaotic inheritance - comprising chaotic selection, chaotic crossover, and chaotic mutation - are performed until a new generation of individuals is produced. Once the merging is complete, if a new parent generation is formed, chaotic inheritance is repeated. Otherwise, non-dominated sorting, crowding distance calculation, and individual selection optimization, combined with an elite selection strategy, are executed again until a new parent generation is created. Finally, if the number of iterations reaches the specified threshold, the optimal placement locations and material distribution paths are output. If the threshold has not been reached, the number of generations is incremented by one, and the merging of parent and child generations and subsequent operations continue.

4 RESULTS AND DISCUSSION

The study establishes a controlled testing environment to first evaluate the performance of the NSGA-II Chaos Improvement Algorithm. Following this, the study compares the algorithm with other leading algorithms in this field to identify the most effective approach. Finally, a simulation test is conducted using a real-world case from Kunming City to verify the validity and feasibility of the proposed model.

4.1 Emergency Management Multivariate Information Processing Model Performance Testing

The testing environment is equipped with an Intel® Core i7-9700 CPU @ 3.00GHz ×16, and a GPU of NVIDIA GeForce RTX 3060. The batch size is set to 2000, the update frequency to 10, and the test weight to 0.6. The datasets used for testing are sourced from the Federal Emergency Management Agency (FEMA) and the Global Disaster Alert and Coordination System (GDACS). The FEMA dataset contains historical disaster event information, totaling more than 30,000 data entries. GDACS, provided by the United Nations, includes over 30,000 pieces of information related to disaster event data and early warning information. Additionally, the relevant parameter settings for Resettlement Site Selection (RSS) and Material Distribution (MD) are detailed in Tab. 1.

Table 1 Parameter configuration

Parameters	Numerical value
Transfer speed	6 km/h
Rescue time frame	30 min
Number of settlements	≤ 3
Average speed of vehicles	40 km/h
Average speed of aircraft	200 km/h
Maximum vehicle load	5000 kg
Maximum aircraft load	2000 kg
Material 1 unit weight	30 kg
Substance 2 unit weight	50 kg
Number of transit centers	≤ 4

Based on the parameters set in Tab. 1, the study first conducted a comparative test of the proposed method against similar multi-objective optimization algorithms.

This comparison was done using a Pareto frontier test, with time as the independent variable and the placement point generation rate and distribution route generation rate as the dependent variables. The algorithms compared included Logistic-NSGA-II, Sine-NSGA-II, Chebyshev-NSGA-II, and Henon-NSGA-II. The results of these tests are illustrated in Fig. 7.

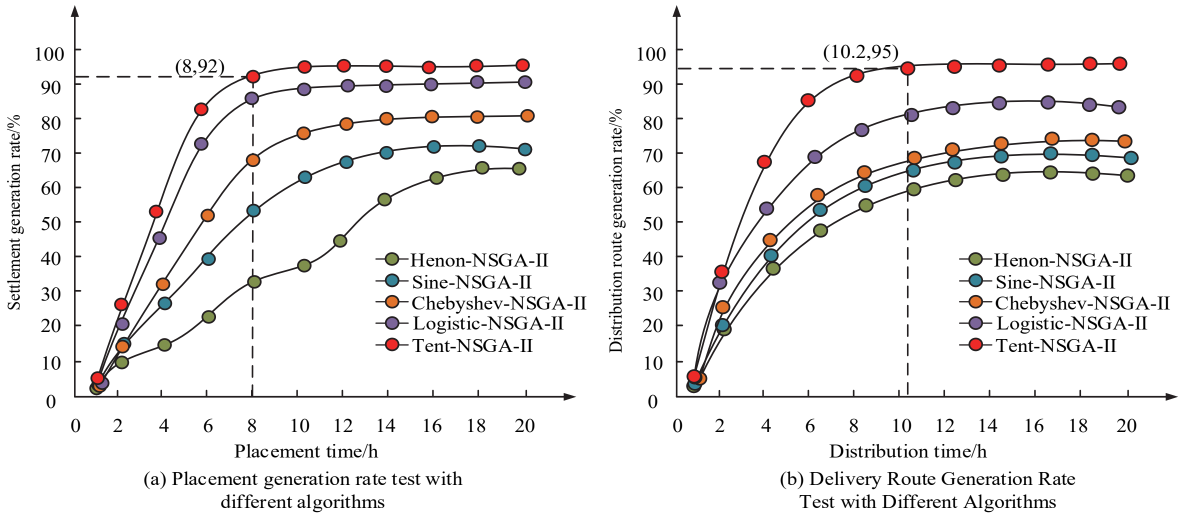


Figure 7 Placement generation rate and distribution route generation rate testing

Fig. 7 presents the results of the comparative tests of different algorithms. Specifically, Fig. 7a shows the comparative test results for the placement point generation rate, while Fig. 7b displays the results for the distribution route generation rate. In these tests, the Henon-NSGA-II and Sine-NSGA-II algorithms exhibited lower productivity, with the placement point generation rate dropping to as low as 65% and the distribution route generation rate to 70%. In contrast, the Tent chaotic optimized NSGA-II algorithm demonstrated significantly better performance, achieving a placement point generation rate of up to 92% and a distribution route generation rate of up to 95%, with an average computation time of 9 hours. This improved performance can be attributed to the Tent mapping's cleaner structure and higher stochasticity in generating chaotic sequences, which effectively mitigates issues such as premature convergence and local optima during the optimization process. Following these tests, the study further introduced more advanced multi-objective algorithms, including the Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D), the Strength Pareto Evolutionary Algorithm (SPEA), and the Non-Dominated Sorting Particle Swarm Optimization (NSPSO). The results of these comparative tests are presented in Tab. 2.

Table 2 Test comparison of optimization schemes for different algorithms

Data set	Algorithm	Settlement	Distribution routes
FEMA	MOEA/D (Generation Policy/Optimal Policy)	88 (5)	89 (4)
	SPEA (Generation Policy/Optimal Policy)	87 (6)	82 (3)
	NSPSO (Generation Policy/Optimal Policy)	90 (4)	80 (3)
	Tent-NSGA-II (Generation Policy/Optimal Policy)	98 (6)	91 (4)
GDACS	MOEA/D (Generation Policy/Optimal Policy)	96 (7)	101 (8)
	SPEA (Generation Policy/Optimal Policy)	107 (7)	112 (10)
	NSPSO (Generation Policy/Optimal Policy)	102 (5)	110 (7)
	Tent-NSGA-II (Generation Policy/Optimal Policy)	112 (10)	121 (11)

In Tab. 2, the results of comparing the four advanced algorithms across two datasets reveal slight differences. The MOEA/D algorithm produces up to 96 placement generation schemes, with 7 identified as optimal. It generates a maximum of 101 distribution route solutions, with 8 being optimal. The SPEA algorithm achieves a maximum of 107 resettlement generation schemes, with 7 optimal solutions, and 112 distribution route schemes, with 10 being optimal. The NSPSO algorithm generates up to 96 placement point schemes, with 7 optimal, and a maximum of 110 distribution route schemes, with 7 being optimal. In comparison, the Tent-NSGA-II algorithm stands out, achieving a maximum of 112 placement point generation schemes, with 10 identified as optimal, and 121 distribution route schemes, with 11 optimal solutions. These results indicate that the method proposed in the study demonstrates notable superiority and reliability compared to other advanced algorithms.

4.2 Emergency Management Multivariate Information Processing Model Simulation Testing

The study uses the heavy rainfall and subsequent urban flooding in Kunming's main city in July 2023 as the test background. According to a report by Yunnan Daily, during this rainfall event, the city recorded 190 stations with light rain, 133 stations with moderate rain, 95 stations with heavy rain, 59 stations with very heavy rain, and 6 stations with extremely heavy rain. The average rainfall within Kunming's second ring area was 90 millimeters. In response, Kunming Drainage Company urgently issued an alert warning and escalated to a Level I emergency response. The emergency resettlement and material distribution (MD) situation during this event is depicted in Fig. 8.

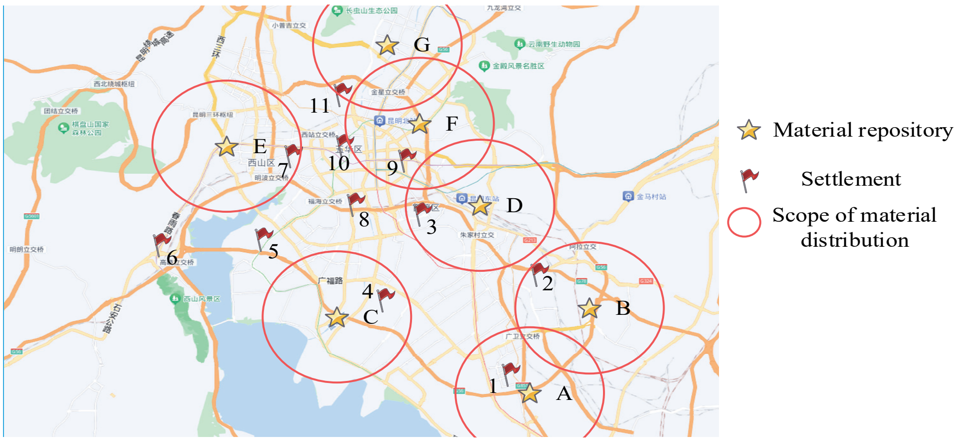


Figure 8 Schematic diagram of resettlement points and material distribution points for flooding in Kunming city

In Fig. 8, following the urban emergency flooding, the urban area of Kunming was more severely impacted compared to the suburban areas. Points 1, 2, and 6 are notably farther from the urban center. The material storage depots are also located at a considerable distance from the emergency resettlement points. Due to the limited capacity and range of material distribution (MD), some resettlement points, such as resettlement points 8, 5, and 6, experienced delays in receiving timely subsidies. To address these challenges, the study also compares the effectiveness of different algorithms, including MOEA/D, SPEA, and NSPSO, in optimizing resettlement site selection (RSS) and material distribution routes. The results of these tests are presented in Fig. 9.

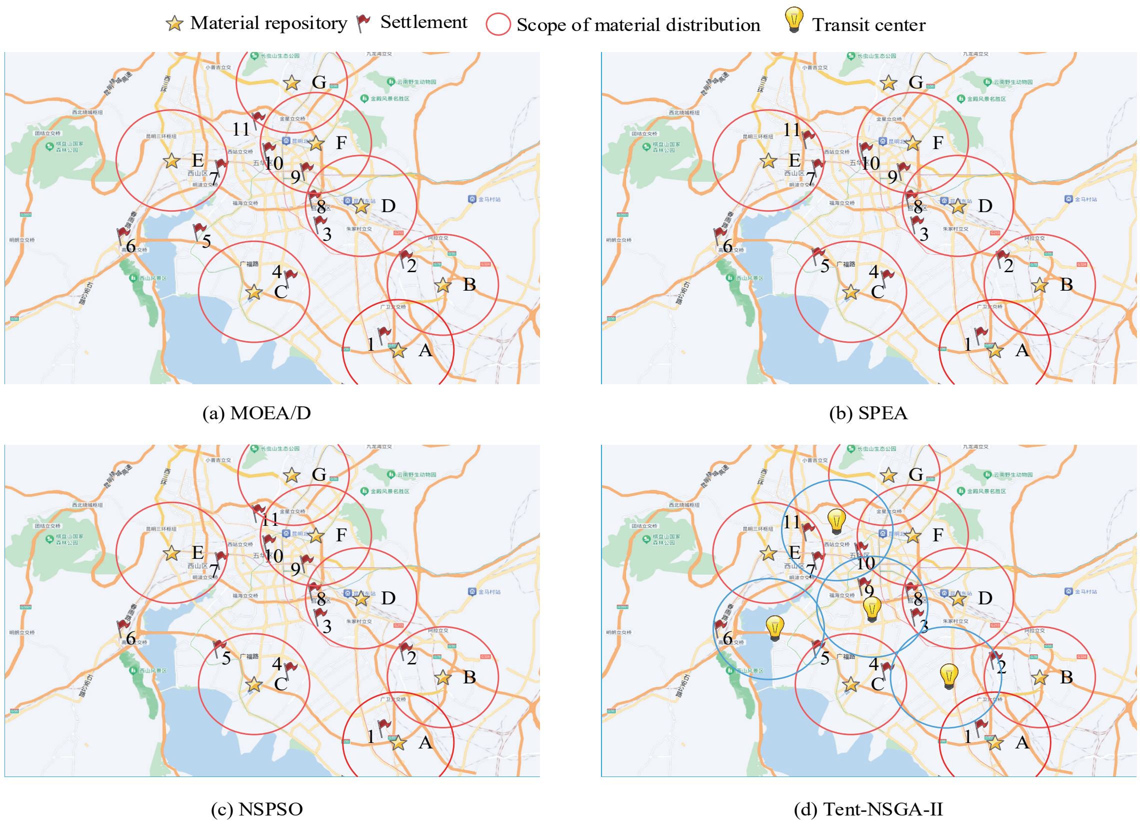
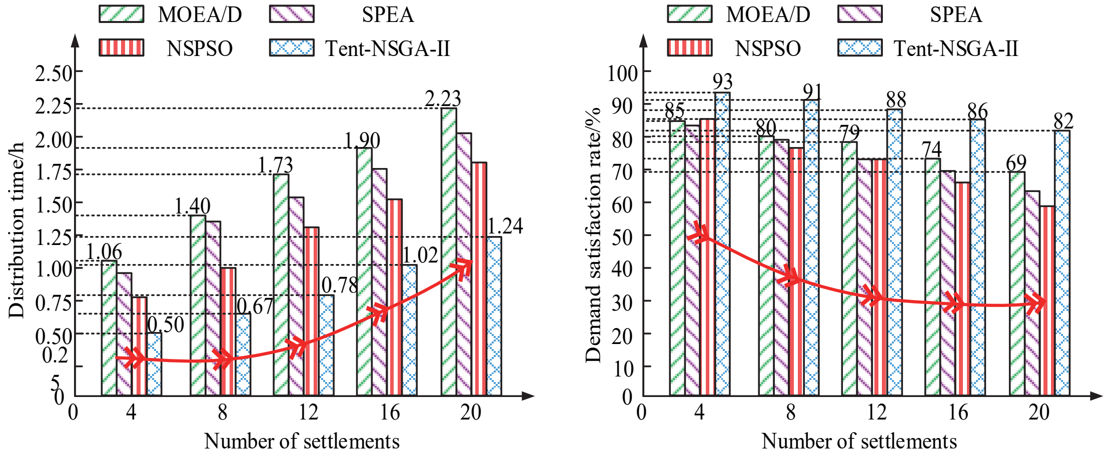


Figure 9 Settlement points and material distribution programs under different algorithms

Fig. 9 presents the RSS and MD planning results for various algorithms: Fig. 9a shows the results under the MOEA/D algorithm, Fig. 9b displays the outcomes using the SPEA algorithm, Fig. 9c illustrates the planning results with the NSPSO algorithm, and Fig. 9d presents the results achieved by the Tent-NSGA-II algorithm. Compared to the first three algorithms, the proposed method using the Tent-NSGA-II algorithm effectively addresses the MD challenges at edge placement points, such as point 6, by incorporating a transit center. This approach also eases the distribution burden on individual material repositories, with each transshipment point efficiently serving two resettlement locations. The study further evaluates these four algorithms based on distribution time and demand fulfillment rate indicators, with the test results shown in Fig. 10.



(a) Delivery time testing
(b) Requirements satisfaction testing

Figure 10 Delivery time and demand satisfaction rate tests with different algorithms

Fig. 10 presents the test results for the four algorithms: Fig. 10a shows the delivery time, while Fig. 10b illustrates the demand fulfillment rate. The results indicate that as the number of placement points increases, the material distribution (MD) time gradually rises, and the demand fulfillment rate steadily declines across all four algorithms. Upon comparison, the proposed algorithm demonstrates the smallest increase in distribution time and the slowest decline in satisfaction rate. Specifically, its delivery time ranges from a low of 0.5 hours to a high of 1.24 hours, while the demand satisfaction rate varies between 93% and 82%. These results suggest that the proposed algorithm is more suitable for subsequent emergency resettlement site selection and MD tasks, offering a high degree of credibility and feasibility compared to the other algorithms tested.

5 CONCLUSION

Urban flooding, as a sudden and widespread natural disaster, has caused significant damage to many cities in China. In response, this study focuses on addressing the challenges of Resettlement Site Selection (RSS) and Material Distribution (MD) through multivariate information processing in emergency management (EM). The approach begins by mathematically modeling the RSS and MD problems. The NSGA-II algorithm serves as the foundational framework, enhanced by the introduction of a Tent chaotic sequence for optimization, culminating in the development of an Emergency Management Multivariate Information (EMMI) processing model. Experimental results demonstrate that this model outperforms similar chaotic models, achieving a placement point generation rate of up to 92% and a distribution route generation rate of up to 95%. When compared to advanced algorithms in the field, the Tent-NSGA-II algorithm generated up to 112 placement schemes, with 10 identified as optimal, and a maximum of 121 distribution route schemes, with 11 optimal solutions. Simulation tests further confirmed the model's efficacy, particularly in managing MD challenges at marginal placement points by incorporating transit centers, which also helped to alleviate distribution pressure on individual material storage depots. The model achieved a distribution time ranging from 0.5 to 1.24 hours, with a demand satisfaction rate between 82% and 93%. In summary, the proposed model has proven effective in the practical application of flood response in Kunming City, providing robust decision support for urban disaster management. However, the study does acknowledge certain limitations, such as the need for further investigation into the algorithm's stability in extremely complex environments. Future work will focus on enhancing the model's real-time dynamic adjustment capabilities and exploring its generalizability across different regions to meet a broader range of EM needs.

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