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Optimization of Emergency Logistics Delivery Path based on Guided Local Search Algorithm

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ABSTRACT

Nowadays, the demand for risk response is increasing in countries worldwide, leading to the development of emergency-related industries as strategic emerging sectors. However, the emergency logistics industry is facing increasingly critical distribution issues. This study applies K-means clustering analysis to convert multiple distribution centers into multiple single distribution center problems. It then compares and analyzes the vehicle routing model with time windows for emergency logistics delivery in multiple distribution centers using guided local search(GLS), taboo search (TS), and simulated annealing (SA) algorithm. The results demonstrate that the GLS algorithm outperformed both the SA and TS algorithm in optimizing emergency logistics delivery paths for multiple distribution centers. The GLS algorithm proved to be more effective in solving this problem. This study not only confirms the contemporary value of emergency logistics distribution problems but also offers practical insights into optimizing emergency logistics distribution paths in multiple distribution centers.

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1. Introduction

The distribution problem of emergency logistics has long been a focal point in emergency management. As countries increasingly recognize the importance of emergency logistics, the distribution challenge associated with emergency supplies has gained attention. This has raised the bar for optimizing the efficiency of emergency logistics distribution. The rationale behind this lies in the frequent occurrence of unexpected events in contemporary society, which can give rise to new public crises. Consequently, there is a growing demand for emergency logistics. Throughout this process, national and local governments at all levels are placing greater emphasis *on developing emergency logistics. However, it is important to note that the field is still in its early stages, and it faces common challenges encountered by the wider logistics industry. Currently, a substantial body of literature(Wang et al.,2015;Zhang et al.,2018; Jiang & Yuan,2019; Wang &Ma,2021)addresses the various aspects of emergency logistics. To address the existing limitations of emergency logistics and enhance its quality of development, it has become imperative to achieve "cost reduction and efficiency" in emergency logistics distribution. Previous research on emergency logistics has predominantly focused on areas such as site selection(Boonmeeet al., 2017), optimization models(Baetal., 2021),and evaluation(Yangetal., 2022). However, the discussion on promoting high-quality development within the emergency logistics industry remains fragmented. While some studies have explored emergency logistics distribution, many have primarily employed a single algorithm to improve the logistics path or concentrated solely on the distribution within a single center. Through comprehensive analysis, it becomes evident that analyzing and optimizing emergency logistics distribution paths across multiple distribution centers holds both theoretical and practical significance. It has also emerged as a realistic requirement for the modern emergency and logistics industries.*

The study contributes to the following three aspects: (1) it addresses a gap in previous studies, which often focused on adjusting the emergency logistics distribution path using a single algorithm. This study fills this gap by providing a more scientific and objective approach. (2) It compares and analyzes the applicability of three algorithms for solving the emergency logistics distribution path problem. This analysis helps determine the optimization degree of each algorithm in the context of multi-distribution center scenarios. It also confirms and expands the application scope of each algorithm. (3) This study concludes by identifying the optimal algorithm for optimizing emergency logistics distribution paths in multiple distribution centers. This provides valuable insights and practical recommendations for improving the efficiency and effectiveness of emergency logistics distribution paths in real-world scenarios.

2. Literature Review

Emergency logistics has faced increasing challenges in recent years due to public health crises, large-scale natural disasters, and other emergencies. Unlike conventional cargo distribution, the distribution of emergency cargo encounters more complex and difficult contexts and challenges(Jiang & Yuan,2019). Particularly crucial in terms of site selection and distribution are the issues of ensuring timely supply, meeting the needs of emergency supplies, and optimizing distribution processes(Wang &Ma,2021). Consequently, the location of emergency logistics distribution centers and specific distribution issues have gradually become the focal point of research within the academic community. For instance, Teng et al. (2023) conducted a study on selecting locations for emergency logistics distribution centers and presented a location plan based on earthquake emergency preparedness zoning. This study addresses the challenge of locating distribution centers in earthquake-prone areas. Furthermore, with the growing demand for enhanced logistics and distribution across various industries, adopting the "multi-distribution center" mode of transport has gained traction. This approach aims to optimize the distribution paths of vehicles and improve transport efficiency. The academic community is interested in investigating and developing models and algorithms related to this transportation mode. The focus on the location of emergency logistics distribution centers and the exploration of the multi-distribution centre model underscores the commitment of the academic community to improving emergency logistics practices. By addressing these challenges, researchers strive to enhance the efficiency and effectiveness of emergency logistics, ultimately facilitating better response and recovery during emergencies.

Scholars, both domestically and internationally, have delved deep into studying the problem of path optimization in multi-distribution centers from various perspectives. In the context of emergency logistics, Zhang et al. (2018) investigated the siting and routing problem of emergency logistics with multiple distribution centers, considering the presence of uncertainty. Wang et al. (2020) highlighted the high complexity of the multi-distribution center model and addressed the issue by employing K-means algorithm, effectively resolving the problem of distribution inefficiency. Nguyen et al. (2022) proposed a solution to a novel variant of the vehicle path problem, leading to the generation of solutions and reducing the task duration required. Additionally, Song (2023) established a semi-open multi-distribution center logistics and distribution model, which contributes significantly to cost reduction and efficiency improvement and promotes sustainable development. Emergency logistics distribution in a crisis state possesses several distinctive characteristics, with *the most prominent being the absence of reliable decision-making data(Huang & Song, 2018). Crises are typically abrupt and unpredictable, making emergency logistics uncertain (Zhao et al., 2018).Emergency logistics encounters various challenges, including supply chain disruptions, a shortage of specialized logistics firms, and a low level of informatization. Recognizing these bottlenecks, Zhu et al. (2016) conducted a study on the influence of dual cross-uncertainty factors on delivery strategies in emergency logistics, offering valuable insights for decision-making in this domain. Wang et al. (2017) stated that compared to general logistics, emergency logistics is characterized by suddenness, non-periodicity, and hierarchy, suggesting the application of hierarchical task network planning methods to examine composite emergency logistics distribution problems.*

Moreover, in various emergency scenarios, the effectiveness of emergency logistics response is hindered by obstacles such as disrupted transportation routes, inadequate logistics capacity, and delayed information synchronization caused by the initial and subsequent secondary crises(Chenet al.,2023). To address these challenges, numerous scholars have developed diverse models for emergency logistics, aiming to mitigate real-world difficulties like limited rescue time and high demand for post-disaster materials. For instance, Song et al. (2020) proposed a dynamic emergency logistics distribution optimization model in their research, which focuses on establishing an efficient distribution process from distribution centers to disaster sites while considering the psychological impact of material destruction. Alternatively, the GERT network model provides a clear description of the entire process of emergency logistics distribution. This model enables decision-makers to make informed decisions regarding emergency logistics distribution by considering the dynamics and complex random situations during the distribution process(Luet al., 2021). In addition, Zhu & Tang (2022) have developed an optimization model that integrates the simulated annealing method with the Floyd optimization algorithm. Their model aims to identify optimal paths for emergency logistics and distribution in different contexts, offering practical insights for effectively managing the complexities of this field.

Previous research in emergency logistics has primarily focused on qualitative studies of sudden crises. While some studies touch upon the location of emergency logistics and distribution centers and distribution paths, there is a need to enrich further and enhance the research content in this area. Specifically, there is a lack of research that combines the "multi-distribution center model" and "emergency logistics distribution," leaving space for investigating the optimization of emergency logistics distribution paths for multi-distribution centers. Additionally, when it comes to quantitative research, there are limited studies directly comparing the GLS, TS, and SA algorithm for studying the distribution problem in emergency logistics. To address this gap, this study adopts these three algorithms individually to solve the problem. Feasible optimal path schemes are derived through data comparison. The study suggests that using the GLS algorithm can optimize the emergency logistics and distribution path for multi-distribution centers, thereby promoting the rationalization and scientific advancement of emergency logistics and distribution services.

3. Methodology

In the context of crises, it is essential to expedite the process of making optimal choices from multiple emergency logistics distribution centers. Additionally, emergency supplies must be efficiently transported from the chosen center along a designated path to reach the location of the affected population. This study randomly selected a disaster-stricken area as the research object, which consists of 3 distribution centers and 100 locations of affected people. The coordinates of the distribution centers and affected people were randomly generated. It is assumed that each of the three distribution centers has sufficient emergency supplies and five vehicles (V1~V5) with the same configuration. Additionally, in the emergency logistics process, each vehicle departs from the distribution center once in a cycle, eventually returning to the same distribution center. The transportation of emergency supplies can be completed in one go.

Since there are multiple distribution centers in the area for emergency logistics, the affected people may not solely rely on a single distribution center to receive their emergency supplies within one distribution cycle. Thus, in this study, weat tempted to propose an optimization approach that considers not only the "transportation distance" between each distribution center and the affected people but also the "collaborative scheme" among the distribution centers. We aim to achieve an efficient and rational allocation of emergency supplies by devising different algorithms *to optimize the division of labour among the multiple distribution centers. This will ultimately enhance the efficiency of emergency logistics distribution and ensure effective materials delivery to the affected people.*

3.1. Distribution Centre and Affected People Coordinate Generation

Since the study focuses on optimizing the distribution paths for emergency logistics with multiple distribution centers, the first step is to establish a model that includes the coordinates of the distribution centers and the affected people. To accomplish this, a computer randomly generates the location coordinates for three distribution centers and 100 affected people.

The three distribution centers were assigned the numbers C1~C3 with the following specific coordinates. C1: (3.67235026, -5.3110362), C2: (12.3887512, -20.21946007), C3: (-1.04149501, 5.5187255).

The 100 affected people are numbered R0 to R99; their location coordinates are listed in Table 1.Due to the large amount of data, only a portion of the affected people's coordinates are shown in Table 1. And the coordinates are expressed in scientific notation.

Resident number (Ri)	Coordinate (x,y)
R0	(-2.07876826e+00, -8.10520594e+00)
R1	(6.80172331e+00, -6.35086542e+00)
R2	(8.77175822e+00, -7.90945268e+00)
R3	(1.08838516e+01, 5.83782019e+00)
R4	(-2.52888433e+00, 1.55191434e+00)
R5	(-1.22772367e+00, 7.58360937e+00)
R6	(1.15321022e+01, -1.17463104e+00)
R7	(1.42427900e+01, -4.69196362e+00)
R8	(2.79880566e+00, 1.39006620e+00)
R9	(8.70025735e+00, -2.31730233e+00)
…	…
R90	(5.89444995e+00, -5.42041440e+00)
R91	(-1.66880372e+01, 1.10853800e+01)
R92	(1.80670243e+00, 8.75523915e+00)
R93	(-6.85570792e+00, 8.46539350e+00)
R94	(9.17048963e-01, 7.57088898e-01)
R95	(-1.15096332e+01, -2.09150162e+00)
R96	(0.00000000e+00, 0.00000000e+00)
R97	(3.67235026e+00, -5.31103620e+00)
R98	(1.23887512e+01, -2.02194601e+01)
R99	(-1.04149501e+00, 5.51872550e+00)

Table 1. The location coordinates of affected people

Furthermore, Figure 1 illustrates the distribution of the distribution centers and the locations of the affected people. In this figure, it can be observed that three distribution centers and 100 affected people are randomly assigned within a square area. The locations of the distribution centers are represented by red dots labelled as "Centers", while the locations of each affected person are denoted by blue dots labelled as "Residents".

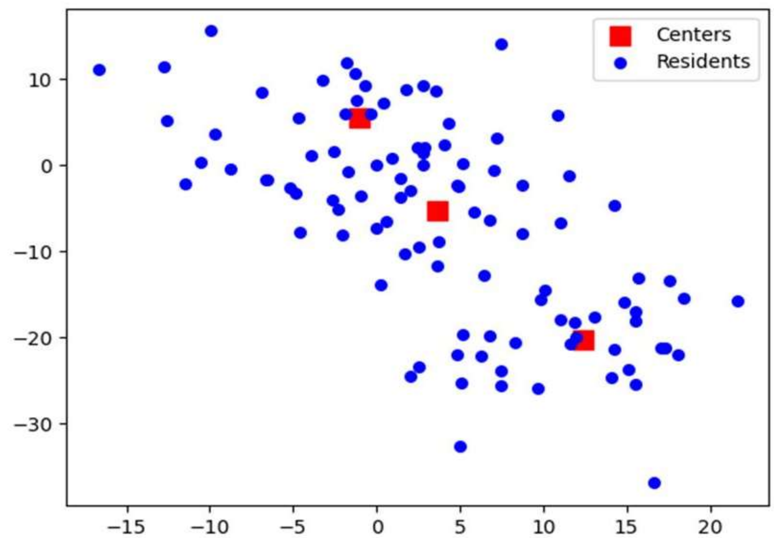

Figure 1. The location coordinates of distribution centres and affected people

3.2. Clustering of affected people based on K-means

3.2.1. Introduction to K-means Algorithm

The k-means algorithm is indeed one of the earliest clustering algorithms. It takes the input parameter k, where n data objects are divided into h clusters. The algorithm aims to achieve higher similarity among objects within the same cluster and lower similarity between objects in different clusters. Clustering similarity is an important indicator of the quality of clustering results as it helps evaluate the performance of clustering algorithms and select the best model.

The clustering similarity measure is typically calculated by assessing the similarity or distance between samples. In this study, we use the "distance" measure, aiming for samples within the same cluster to be as close as possible while samples from different clusters are farther apart. The algorithm has gained popularity and has been widely applied in various domains, including data mining, due to its well-established techniques and high implementation feasibility.

3.2.2. Adaptability Analysis

In this study, the vehicle path optimization problem involves many affected people outlets in a certain region. Since the demand of a single affected person is within the carrying capacity or volume constraint of the distribution vehicle, it is necessary to approach the problem differently to handle the dense distribution of affected people. To address this, we propose integrating the affected people regionally and transforming the original large-scale multi-distribution center multi-point distribution path optimization problem into multiple single-distribution center multi-point distribution path optimization problems. This transformation reduces the problem size and computational complexity and improves decision-making efficiency.

Thus, to allocate each affected person's point to the appropriate logistics centre, we can utilize the K-means algorithm for clustering. By considering the similarity of the data's features, each affected person's location can be clustered with its corresponding distribution centers. This allows for better allocation of tasks among the distribution centers. The algorithm is highly suitable for analyzing the relationship between emergency logistics distribution centers and the locations of affected people.

3.2.3. Clustering Implementation

The k-means algorithm aims to divide data samples into k clusters through an iterative process. The clustering result is determined by minimizing the cost function, also known as the loss function, which minimizes the distance between each sample and the center of its corresponding cluster. This process continues until the error of each point from its center is minimized, resulting in the final clustering result.

The cost function in K-means is defined as the sum of squared errors of each sample from the center of its cluster. It can be calculated using Equation (1):

$$J(c,\mu) = \sum_{i=1}^{N} \| x_i - \mu_{Ci} \|^2 \qquad (1)$$

Where, x_i represents the i^{th} sample, c_i represents the cluster to which it belongs, μ_{Ci} represents the centroid (mean)of the cluster, and N represents the total number of samples.

K-means algorithm iterates to find the cluster centers that minimize the overall cost function, effectively grouping similar data points together. Through this process, the algorithm provides an efficient way to analyze the relationship between distribution centers in emergency logistics and the locations of affected people.

The algorithm aims to group the affected people into appropriate clusters based on their proximity to the distribution centers. Figure 1 shows three distribution centers (C1, C2 and C3) and 100 affected people (R0 to R99).To cluster these affected people using the K-means algorithm, Python software was utilized. Obtain the final clustering result with the affected people grouped into three clusters corresponding to the three distribution centers.

After the K-means algorithm operation ended, we obtained the following clustering results, and the affected people were divided into three sets:

***(1)** The distribution CenterC1 will provide distribution services to 39 affected people: Ri = { i | i = 0, 1, 2, 3, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19, 21, 23, 24, 25, 26, 27, 28, 31, 32, 67, 68, 72, 73, 76, 77, 78, 83, 85, 88, 93, 97, 99}.*

***(2)** The distribution CenterC2 will provide distribution services to 35 affected people: Ri = {i | i = 29, 30, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65}.*

***(3)** The distribution CenterC3 will provide distribution services to 26 affected people: Ri = { i | i = 4, 5, 16, 20, 22, 66, 69, 70, 71, 74, 75, 79, 80, 81, 82, 84, 86, 87, 89, 90, 91, 92, 94, 95, 96, 98}.*

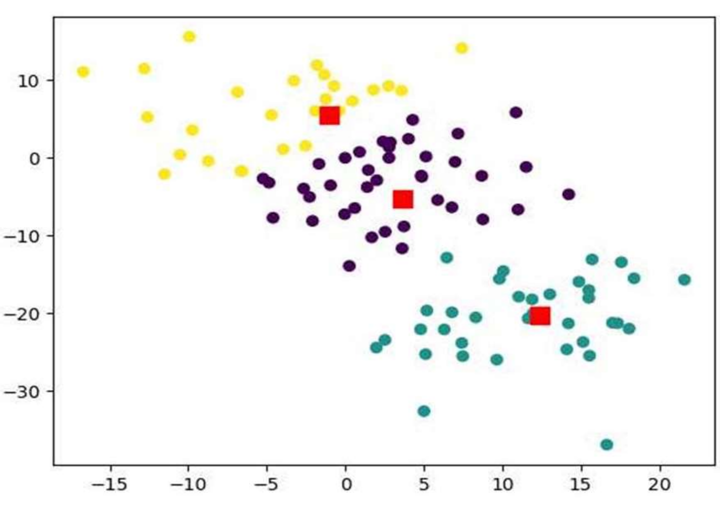

Figure 2. Clustering results of affected people based on distribution centers

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3.3. Solution Method for Optimal Path

In this study, the criterion for evaluating the advantages and disadvantages of emergency logistics distribution routes is the time taken to complete the distribution. Since time can be represented as the ratio of distance and speed, and the vehicle configurations are the same, the equation is simplified to finding the "shortest total distance." This problem can be solved using various algorithms such as the GLS, TS and SA algorithms.

Equation (2) represents the formula used to calculate the total path distance:

$$\text{Total Distance} = \sum_{j=1}^{5} S_j \qquad (2)$$

Where, S *denotes the distance traveled by a vehicle, and* j *denotes the number of vehicles. The constraint is that "the distance cannot exceed the boundary".*

3.3.1. Guided Local Search Algorithm

The GLS algorithm is a heuristic algorithm developed for solving combinatorial optimization problems. It aims to leverage both local and global search techniques by incorporating an auxiliary function that guides the search process towards better solutions. The key idea behind the GLS algorithm is to introduce an auxiliary function, also known as an objective or penalty function, into the local search process. This function evaluates the quality of the current solution and directs the search towards more promising directions. The design of the auxiliary function typically takes into account the problem's constraints and characteristics. The search process is guided towards finding improved solutions by assigning different weights or penalties based on the current solution's quality. The GLS algorithm operates as follows. The specific process is shown in Figure 3.

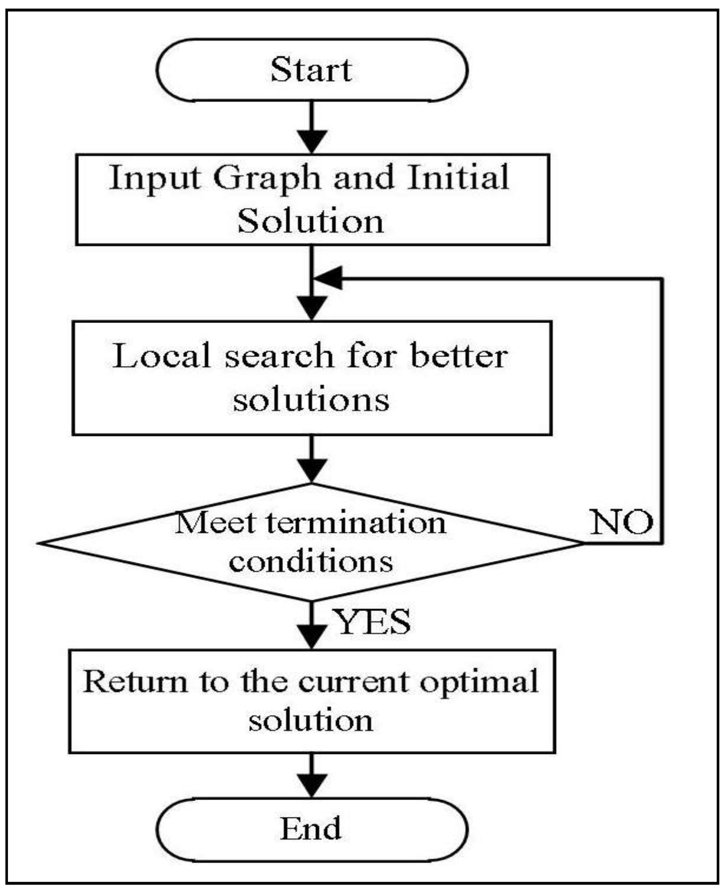

Figure 3. Flowchart of the GLS algorithm

Step 1: *Initialization. An initial solution is set as the current solution.*

Step 2: *Iterative improvement. In each iteration, the quality of the current solution is evaluated using the auxiliary function. The set of neighboring solutions is generated, and a neighboring solution is selected as the next current solution based on certain rules. The current solution is updated accordingly, and the search direction or weight is adjusted based on the evaluation result of the auxiliary function.*

Step 3: *Termination. The stopping condition is checked, and the search process ends if satisfied. Otherwise, it returns to the second step for further iterations.*

Step 4: *Solution retrieval. The algorithm returns the optimal or near-optimal solution.*

The GLS algorithm leverages auxiliary functions to effectively guide the search process, discovering improved solutions. The algorithm's remarkable flexibility and adaptability render it suitable for solving diverse combinatorial optimization problems. Its ability to find higher-quality solutions within a shorter period is unparalleled by other algorithms. Additionally, adjusting the design and parameters of the auxiliary function allows for further enhancements in the algorithm's performance and search effectiveness. Therefore, the GLS algorithm is particularly well-suited for addressing vehicle path optimization problems with multiple centers, as it satisfactorily incorporates domain-specific knowledge and effectively guides the search towards optimal or near-optimal solutions.

3.3.2. Tabu Search Algorithm

The TS algorithm employs a tabu table or tabu list to keep track of explored solutions during the search process. This helps prevent getting trapped in local optima while facilitating a global search. The fundamental concept of the TS algorithm is to iteratively find a better solution by exploring neighboring solutions in the solution space and continuously updating the current solution. To avoid local optima, the algorithm considers constraints specified in the tabu table when selecting the next solution.

The TS algorithm starts with an initial solution set as the current solution. A termination condition and an iteration limit are defined. In each iteration, the following steps are performed:

Step 1: *Generate the set of neighboring solutions from the current solution.*

Step 2: *Select a neighboring solution as the next current solution based on specific evaluation criteria.*

Step 3: *Update the tabu table by adding the current or neighboring solution.*

Step 4: *Update the current solution.*

Step 5: *Check if the termination condition is satisfied. If yes, end the search. Otherwise, go back to step 2 to continue the iteration.*

Step 6: *Return the optimal or near-optimal solution.*

Figure 4 illustrates the specific process. The TS algorithm can be applied to address vehicle path optimization problems with multiple centers, providing potential solutions.

3.3.3. Simulated Annealing Algorithm

The SA algorithm is an optimization algorithm that is inspired by the physical process of annealing in metallurgy. It aims to find the global optimal or near-optimal solution in complex problem spaces. The algorithm mimics the cooling of atoms in a metal, where they gradually converge to a stable state with the lowest energy. The core idea of the SA algorithm is to accept poorer solutions with a certain probability that decreases as the search progresses. This strategy allows the SA algorithm to explore beyond local optima and move towards the global optimum. The SA algorithm consists of several steps:

Step 1: *Initialization. An initial solution is randomly generated, and the initial and termination temperatures are set.*

Step 2: *Cyclic process. The SA algorithm iterates through a series of temperature-decreasing steps until the temperature reaches the termination temperature.*

Step 3: *Solution generation. A new solution is generated by applying a small random perturbation to the current solution at the current temperature.*

Step 4: *Energy difference calculation. The energy difference, which measures the solution's superiority, is calculated between the new and current solutions.*

Step 5: *Solution acceptance. The new solution is accepted based on a probability determined by comparing the energy difference with the current temperature. This allows for accepting worse solutions, preventing the algorithm from getting stuck in local optima.*

Step 6: *State update. If the new solution is accepted, it is updated; otherwise, it is kept unchanged.*

Step 7: *Temperature lowering. After each iteration, the current temperature is decreased using a cooling function, gradually reducing the temperature.*

Step 8: *Termination and return. The SA algorithm terminates when the temperature reaches the termination temperature or a certain number of iterations have been reached. It then returns the obtained optimal or near-optimal solution. The specific process is shown in Figure 5.*

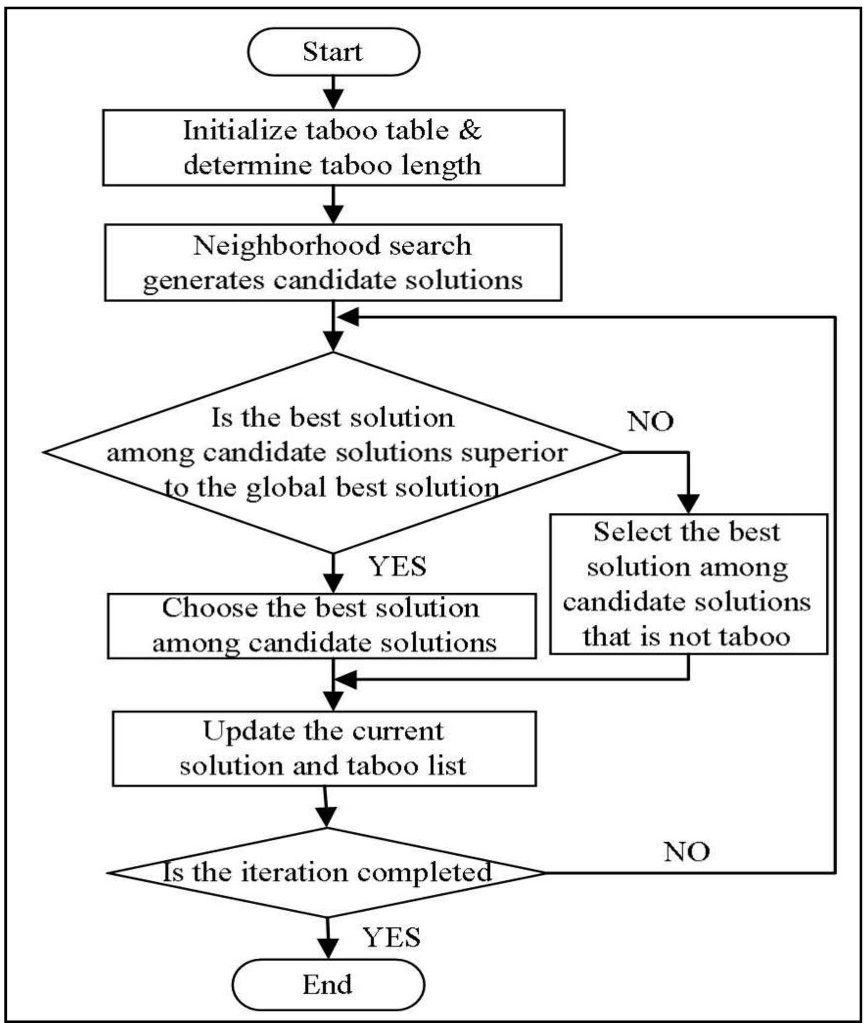

Figure 4. Flowchart of the TS algorithm

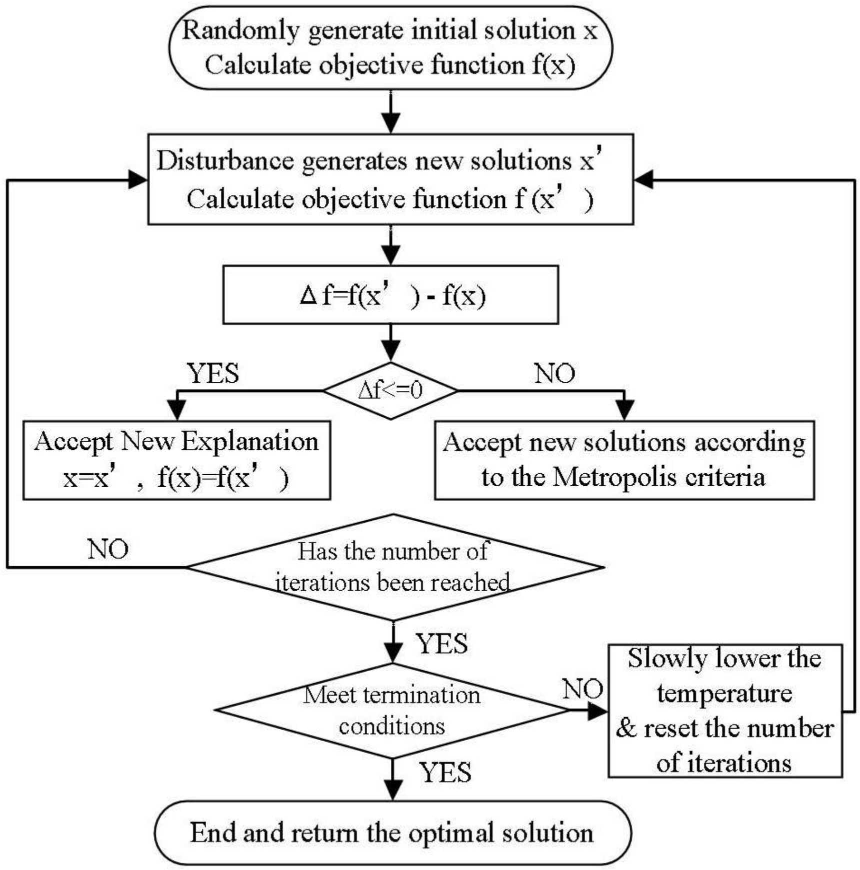

Figure 5. Flowchart of the SA algorithm

4. Result Analysis

4.1. Simulation Results for Different Algorithms

Based on our analysis of the three algorithms mentioned above, we have obtained optimal results for each algorithm and conducted an analysis of these results. The following presents the shortest distance routes for the hypothesized problem after applying the GLS, TS and SA algorithms. These routes represent the optimal paths for each of the five vehicles in the three emergency logistics distribution centers under different algorithms. It is evident that all three algorithms successfully generate their respective routing schemes when dealing with the vehicle path optimization problem involving multiple centers.

(1) *The results of the GLS algorithm are as follows: the distance from distribution center, C1 is 107 m, from C2 is 119 m, and from C3 is 120 m. The total distance is 346 m. The specific distribution routes are shown in Table 2.The total distance travelled by vehicles in the three centers under the GLS algorithm is 346 m.*

(2) *The results of the TS algorithm are as follows: the distance from distribution center, C1 is 109 m, from C2 is 119 m, and from C3 is 120 m. The total distance is 348 m. The specific distribution routes are shown in Table 3.The total distance traveled by vehicles in the three centers under the TS algorithm is 348 m.*

(3) *The result of the SA algorithm is as follows: the distance from distribution center, C1 is 109 m, from C2 is 119 m, and from C3 is 120 m. The total distance is 348m. The specific distribution routes are shown in Table 4.The total distance traveled by vehicles in the three centers under the SA algorithm is 348 m.*

		Specific Path	Distance (m)	Total (m)
	V1	C1→9→6→7→14→2→1→93→C1	22	
	V2	C1→76→21→27→72→24→67→8→97→99→73→17→C1	22	
C1	V3	C1→77→11→13→32→31→C1	17	107
	V4	C1→19→68→3→88→18→12→C1	25	
	V5	C1→25→85→0→28→23→26→10→78→83→15→C1	21	
	V1	C2→57→45→65→46→58→39→41→35→63→48→47→44→43→54→C2	27	
	V2	C2→C2	0	
C2	V3	C2→56→40→37→36→C2	32	119
	V4	C2→51→52→33→C2	28	
	V5	C2→53→59→55→50→38→34→61→60→64→42→29→30→49→62→C2	32	
	V1	C3→75→91→84→C3	21	
	V2	C3→69→70→89→90→80→5→C3	25	
C3	V3	C3→16→66→86→71→95→81→C3	20	120
	V4	C3→94→74→96→79→C3	30	
	V5	C3→4→87→82→22→98→92→20→C3	24	

Table 2. Optimal paths based on the GLS algorithm

		Specific Path	Distance (m)	Total (m)
	V1	C1→9→6→7→14→2→1→93→C1	22	
	V2	C1→76→21→27→72→24→67→8→97→99→73→17→C1	20	109
C1	V3	C1→77→11→13→32→31→C1	17	
	V4	C1→19→68→3→88→18→12→C1	25	
	V5	C1→25→85→0→28→23→26→10→78→83→15→C1	25	
	V1	C2→57→45→65→46→58→39→41→35→63→48→47→44→43→54→C2	27	
	V2	C2→C2	0	119
C2	V3	C2→56→40→37→36→C2	32	
	V4	C2→51→52→33→C2	28	
	V5	C2→53→59→55→50→38→34→61→60→64→42→29→30→49→62→C2	32	
	V1	C3→75→91→84→C3	21	
	V2	C3→69→70→89→90→80→5→C3	25	
C3	V3	C3→16→66→86→71→95→81→C3	20	120
	V4	C3→94→74→96→79→C3	30	
	V5	C3→4→87→82→22→98→92→20→C3	24	

Table 3. Optimal paths based on the TS algorithm

		Specific Path	Distance (m)	Total (m)
C1	V1	C1→9→6→7→14→2→1→93→C1	22	109
	V2	C1→17→23→28→10→85→25→C1	20	
	V3	C1→77→11→13→32→31→C1	17	
	V4	C1→19→68→3→88→18→12→C1	25	
	V5	C1→76→21→27→72→24→67→8→97→99→73→26→10→78→83→15→C1	25	
C2	V1	C2→57→45→65→46→58→39→41→35→63→48→47→44→43→54→C2	27	119
	V2	C2→C2	0	
	V3	C2→56→40→37→36→C2	32	
	V4	C2→51→52→33→C2	28	
	V5	C2→53→59→55→50→38→34→61→60→64→42→29→30→49→62→C2	32	
C3	V1	C3→75→91→84→C3	21	120
	V2	C3→69→70→89→90→80→5→C3	25	
	V3	C3→16→66→86→71→95→81→C3	20	
	V4	C3→94→74→96→79→C3	30	
	V5	C3→4→87→82→22→98→92→20→C3	24	

Table 4. Optimal path based on the SA algorithm

4.2. Comparison of Results of Different Algorithms

The partitioning of the initial disaster-affected population and logistics distribution centers is based on the K-means clustering algorithm mentioned earlier. Subsequently, three algorithms are employed to solve each individual distribution centre after partitioning. The obtained comparison results showcase the optimal solutions for the distance traveled by logistics distribution vehicles in the three distribution centers, as demonstrated in Table 5 and Figure 6.

Algorithms \ Centers	C1 (m)	C2 (m)	C3 (m)	Total Distance (m)
The GLS algorithm	107	119	120	346
The TS algorithm	109	119	120	348
The SA algorithm	109	119	120	348

Table 5. Comparison of different algorithms for optimal total distance

It can be observed that the SA and TS algorithm both yield a total distance of 348m, while the GLS algorithm achieves a total distance of 346m. This indicates that the GLS algorithm performs the best in this simulation. Therefore, under the given conditions, the GLS algorithm is more effective in solving the multi-distribution center vehicle path optimization problem. In real-world problem-solving scenarios, the solutions proposed by the three algorithms may also exhibit greater differences due to variations in distance scales.

5. Conclusions

This study specifically focuses on applying the K-means clustering algorithm and three path

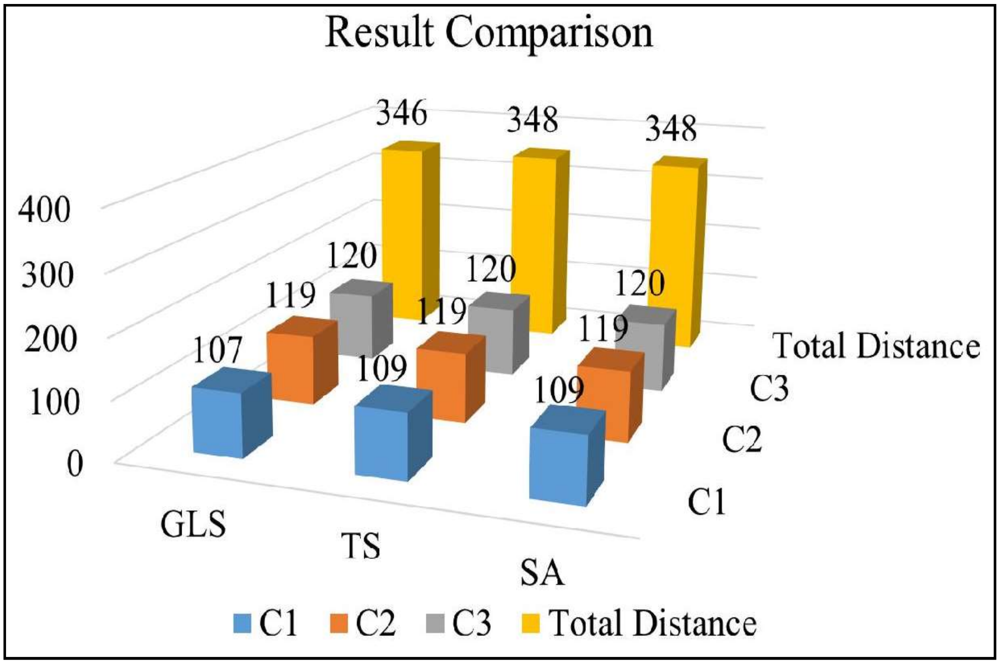

Figure 6. Comparison of different algorithms for optimal total distance

optimization algorithms to solve the real-world problem of VRPTW. Through an extensive comparative analysis of the emergency logistics distribution path optimization problem in multi-distribution centers, we have obtained the following research conclusions:

Firstly, in real-world scenarios, this study provides a solution to how to pair affected people with multiple distribution centers. It is that the K-means clustering algorithm is employed as a classification method to group individuals with a higher correlation to each centre point, establishing reasonable pairings. This approach facilitates the efficient distribution of resources and enables the formation of regional mesh distribution routes for different distribution centres.

We have also reached conclusions regarding acquiring a relatively optimal distribution path for emergency logistics within a specific region. To obtain detailed paths, we applied various algorithms to simulate different scenarios. Consequently, we have identified the GLS algorithm as the ideal solution for optimizing emergency logistics distribution across multiple distribution centers. Notably, the implementation of this algorithm resulted in an actual solution distance of 346 meters.

Furthermore, this study focuses on solving and comparing the results obtained from different algorithms used to address this problem. It was found that the GLS algorithm slightly outperforms the TS and SA algorithms in the path optimization problem of emergency logistics distribution across multiple distribution centers. This finding aligns with the characteristic strengths of the GLS algorithm, which excels in generating optimal solutions within a relatively fixed population.

Finally, there are two limitations to the research that need to be addressed in the future. First, since the K-means algorithm relies on the "distance" measure for division, the mean and variance of high-dimensional clusters can significantly impact the clustering results. Therefore, it is necessary to normalize the data. Outliers or noise can also affect the mean and potentially cause a shift in the cluster centre, so they should be pre-processed. Second, our simplified emergency logistics and distribution model does not consider external constraints such as roadblocks and buildings that may exist in reality, which is also an improvement direction for future research.

Declarations of Interest

All authors disclosed no relevant relationships.

References

[1] Wang, H. J., Du, L. J., Hu, D., et al. (2015). Location-Routing problem for relief distribution in emergency logistics under uncertainties. *Journal of Systems & Management*, 24(06), 828-834.

[2] Zhang, B., Li, H., Li, S. G., et al. (2018). Sustainable multi-depot emergency facilities location-routing problem with uncertain information. *Applied Mathematics and Computation*, 333, 506-520.

[3] Jiang, Y. P., Yuan, Y. F. (2019). Emergency logistics in a large-scale disaster context: achievements and challenges. *International Journal of Environmental Research and Public Health*, 16(5), 779.

[4] Wang, H. C., Ma, X. Y. (2021). Research on multi objective location of urban emergency logistics under major emergencies. *Mathematical Problems in Engineering*, 2021, 5577797.

[5] Boonmee, C., Arimura, M., Asada, T. (2017). Facility location optimization model for emergency humanitarian logistics. *International Journal of Disaster Risk Reduction*, 24, 485-498.

[6] Ba, Y. L., Feng, C. X., Jia, W. P., et al. (2021). A multi-scenario optimization model for emergency cold chain logistics distribution. *Mathematical Problems in Engineering*, 2021, 1628162.

[7] Yang, Y. X., Guo, Z. X., He, Z. F. (2022). Multi-attribute decision making method based on probabilistic linguistic term sets and its application in the evaluation of emergency logistics capacity. *Journal of Intelligent & Fuzzy Systems*, 42(3), 2157-2168.

[8] Teng, H. J., Shu, Z. L., Zhang, X., et al. (2023). Study on model optimization method of emergency logistics distribution system in earthquake disaster. *Journal of Safety Science and Technology*, 19(04), 160-167.

[9] Wang, Y., Zhang, S. L., Guan, X. Y., et al. (2020). Collaborative multi-depot logistics network design with time window assignment. *Expert Systems with Applications*, 140, 112910.

[10] Pham, D. Q., Nguyen, H. T., et al. (2022). Modeling and solving a multi-trip multi- distribution center vehicle routing problem with lower-bound capacity constraints. *Computers & Industrial Engineering*, 172(A), 108597.

[11] Song, Q. (2023). Semi-open multi-distribution center path planning with time windows. *Sustainability*, 15(6), 4800.

[12] Huang, X. X., Song, L. Y. (2018). An emergency logistics distribution routing model for unexpected events. *Annals of Operations Research*, 269(1), 223-239.

[13] Zhao, H. P., Niu, C. C., Zhang, T. T., et al. (2018). Review and prospect of emergency logistics under uncertainty conditions. *Journal of Risk Analysis and Crisis Response*, 08(02), 101-109.

[14] Zhu, J. X., Tan, Q. M., Cai, J. F., et al. (2016). Emergency logistics distribution strategy based on double uncertainty. *Systems Engineering*, 34(03), 1-8.

[15] Wang, Z., Wang, S. C., Li, M. L., et al. (2017). Research on application of HTN planning in emergency logistics program formulation. *Safety and Environmental Engineering*, 24(05), 15-20.

[16] Chen, R. R., Ma, R., Li, J., et al. (2023). Reflection on urban emergency logistics distribution of livelihood necessities during the COVID-19 pandemic prevention. *Traffic & Transportation*, 39(02), 66-70.

[17] Song, Y. H., Song, Y. H., Li, C. X., et al. (2020). Emergency supplies distribution model considering psychological impact of supplies damage. *China Safety Science Journal*, 30(07), 173-179.

[18] Lu, L., Yang, L. G., Luo X. C., et al. (2021). Graph evaluation and review technique for emergency logistics distribution in complex environment. *Discrete Dynamics in Nature and Society*, 2021, 1-10.

[19] Zhu, G. N., Tang, X. P. (2022). Research on rural emergency logistics distribution path based on simulated annealing method and Floyd optimization algorithm. *Software Engineering*, 25(12), 9-12+8.