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Vehicle Route Planning for Relief Item Distribution under Flood Uncertainty

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Abstract: Flooding, a pervasive and severe natural disaster, significantly damages environments and infrastructure and endangers human lives. In affected regions, disruptions to transportation networks often lead to critical shortages of essential supplies, such as food and water. The swift and adaptable delivery of relief goods via vehicle is vital to sustain life and facilitate community recovery. This paper introduces a novel model, the Vehicle Routing Problem for Relief Item Distribution under Flood Uncertainty (VRP-RIDFU), which focuses on optimizing the speed of route generation and minimizing waiting times for aid delivery in flood conditions. The Genetic Algorithm (GA) is employed because it effectively handles the uncertainties typical of NP-Hard problems. This model features a dual-population strategy: random and enhanced populations, with the latter specifically designed to manage uncertainties through anticipated route performance evaluations, incorporating factors like waiting times and flood risks. The Population Sizing Module (PSM) is implemented to dynamically adjust the population size based on the dispersion of affected nodes, using standard deviation assessments. Introducing the Complete Subtour Order Crossover (CSOX) method improves solution quality and accelerates convergence. The model's efficacy is validated through simulated flood scenarios that emulate various degrees of uncertainty in road conditions, affirming its practicality for real-life rescue operations. Focusing on prioritizing waiting times over travel times in routing decisions has proven effective. The model has been tested using standard CVRP problems with 20 distinct sets, each with varying node numbers and patterns, demonstrating superior performance and efficiency in generating vehicle routing plans compared to the shortest routes, which serve as the benchmark for optimal solutions. The results highlight the model's capability to deliver high-quality solutions more rapidly across all tested scenarios.

Keywords: vehicle routing; relief distribution; uncertainty; genetic algorithms; disasters; floods

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1. Introduction

Natural disasters, arising from uncontrollable natural processes, are events that humans cannot prevent. These incidents typically occur without warning and have profound impacts on human life, the environment, and broader societal structures. Flooding, one of the most common natural disasters, affects both high-risk and low-risk areas indiscriminately [1] and can cause extensive damage to critical infrastructure such as roads, bridges, and public utilities. This damage disrupts the normal flow of people and goods, severely limiting access to essential resources like food and water [2,3]. The resulting shortages can jeopardize the survival of affected individuals and significantly delay the recovery process for entire communities. Consequently, the swift and efficient distribution of relief supplies becomes vital to mitigate these impacts, ensuring that those affected receive the necessary support to survive and rebuild [4].

The distribution of relief resources is pivotal in emergency logistics, facilitating the expedient delivery of essential supplies to areas affected by disasters [5]. However, the orchestration of emergency transportation during flooding is inherently complex and influenced by many unpredictable factors. These include sudden spikes in local demand, extensive damage to transportation infrastructure, and the imminent threat of secondary disasters. Such variables contribute to a multifaceted problem structure in emergency transportation, rendering the planning and execution processes highly intricate [6,7]. This complexity necessitates sophisticated strategies and innovative solutions to address the logistical challenges of emergency scenarios effectively.

A significant challenge in this research is the difficulty of planning routes under flood conditions due to the uncertainty of road conditions which can change over time. This uncertainty results in delays in delivering relief supplies and makes predictions difficult. Most studies frame the problem of distributing emergency resources as a Vehicle Routing Problem (VRP), which is challenging to solve within limited time constraints [8]. Additionally, the distribution patterns of disaster-affected nodes in different flood scenarios add complexity to route planning, such as uniformly distributed nodes versus clustered distributions [9].

Previous studies have introduced various methodologies for routing and scheduling in emergency relief operations. For example, Wohlgemuth et al. [10] developed a Dynamic Vehicle Routing Problem (DVRP) that leverages real-time traffic and demand data to dynamically adjust vehicle routes using GPS data and an Adaptive Large Neighborhood Search (ALNS) algorithm. Hu and Sheng [11] utilized an Immune Evolutionary Algorithm (IEA) to optimize disaster relief schedules for personnel, goods, and vehicles, inspired by the adaptability of the human immune system. Chang et al. [12] combined a Multi-Objective Evolutionary Algorithm (MOEA) with Greedy Search (GS) to enhance emergency logistics scheduling, focusing on optimizing response times, costs, and fuel consumption. Gan et al. [13] designed a scheduling system for emergency vehicles using a time utility function that evaluates factors like injury type, proximity to the incident, and time elapsed since the incident. This system uses an Evolutionary Algorithm (EA) for optimization. Lu et al. [14] proposed a rolling horizon strategy for disaster relief distribution using a State Estimation and Prediction Module (SEPM) and a Relief Distribution Module (RDM) to forecast demand and delivery times from data sources like social media and sensors. Sabouhi et al. [15] introduced a Multi-Objective Mixed Vehicle Routing Problem (MOMVRP) to address the distribution of relief materials, focusing on objectives like travel distance, response time, and aid recipient numbers, using an Evolutionary Algorithm (EA). Gan et al. [16] presented an Emergency Logistics Scheduling (ELS) approach with a Multi-Agent Genetic Algorithm (MA-GA), where each agent has specific roles in optimizing the transportation schedule. However, the mentioned researchs do not consider the uncertainty factors of road conditions resulting from disasters. Moreover, real-time data may not be acceptable if there are issues with communication infrastructure.

Research has demonstrated strategies to handle uncertainty using various transportation modes. Zheng and Ling [17] developed an emergency transportation planning method that integrates air, rail, and road transport to manage uncertainties effectively. They segment the overall problem into sub-components, applying Multi-Objective Tabu Search (MOTS) for task allocation and Multi-Objective Genetic Algorithms (MOGAs) for optimizing delivery schedules and vehicle routes. Ruan et al. [18] introduced a method for planning emergency medical supply deliveries using intermodal transportation, including helicopters and vehicles. They employ a balanced Fuzzy C-Means algorithm to select distribution points and standard Fuzzy C-Means to plan routes, aiming to minimize transportation time.

Additionally, the research integrates multiple specific issues into a single model, focusing on uncertainty. Manopiniwes and Irohara [19] developed a stochastic optimization model for relief supply chain decision making, addressing uncertainties such as demand for relief goods, weather conditions, and transportation delays. The model includes inventory management, allocation of goods, and transportation planning. Sabouhi et al. [20] introduced a mixed-integer linear programming (MILP) model for evacuation and relief distribution planning to minimize vehicle arrival times in affected areas. This model accounts for distance, time, vehicle capacity, and segmented delivery at distribution centers, employing a Memetic Algorithm (MA) for efficiency in large-scale applications. Sakiani et al. [21] tackled the routing problem within the supply chain to minimize blockages and operational costs using a simulated annealing algorithm for vehicle routing and CPLEX for subproblem evaluation. However, the mentioned research requires extensive data and involves complex calculations applied to small-scale problems. Nonetheless, it also introduces metaheuristic algorithms and search operators to address larger-scale issues. This is crucial because disaster relief operations need to be conducted urgently [22].

Genetic Algorithms (GAs) are frequently used in disaster relief to manage environmental uncertainties due to their flexibility in enhancing response quality and low computation requirements [23]. GAs utilize a mechanism known as crossover to explore the search space and maintain solution diversity, which has been adapted across various fields to improve problem-solving efficiency [24].

However, the literature needs a comprehensive exploration of route planning under dynamic road conditions caused by flooding. Additionally, the distribution patterns of disaster-affected nodes add complexity to the routing process, which requires further study [9,25–27].

This paper introduces the VRP-RIDFU model, a vehicle routing plan designed to distribute disaster relief effectively amidst flood-related uncertainties. A Genetic Algorithm (GA), specifically tailored to manage road condition uncertainties, is the primary tool for determining optimal routes. This adjustment includes a risk-based expected value method to part-generate the GA's initial population, integrating flood data and waiting times into this value calculation. The expected values across all routes define the fitness function. The Population Sizing Module (PSM) customizes this population size based on the distribution of disaster-affected nodes, creating a grid that reflects node distribution and uses standard deviation for evaluation. The model employs the Complete Subtour Order Crossover (CSOX), a crossover method noted for its efficiency and low execution time, enhancing the solutions' quality and convergence speed [28]. The optimal solution may be a different route than the shortest one but one that best responds to uncertainties. Therefore, the solutions or planned routes are evaluated against simulated scenarios of road conditions under flood uncertainty. This simulation scenario is designed to accommodate multiple periods of road condition changes. The sum of the waiting times is used to assess the performance of the proposed method.

The paper is structured as follows: Section 2 outlines the problem, Section 3 details the VRP-RIDFU model, Section 4 describes the experiments and simulations, Section 5 discusses the results and comparisons, and Section 6 concludes with future research directions.

2. Problem Formulation

2.1. Relief Items' Distribution under Uncertainty

Information about flood victims is vital in optimizing relief efforts, particularly when planning delivery routes for essential supplies. Knowing the precise locations of the victims, understanding their specific needs, and having accurate details about the road conditions in their area are all critical factors determining the effectiveness of the response operation [29]. However, the uncertainty inherent in flood situations adds significant complexity to this task. Flooding can lead to rapidly changing conditions, where roads that are passable one moment can become obstructed or entirely submerged the next due to sudden increases in water levels. This unpredictability makes maintaining accurate, up-to-date information on road conditions difficult.

Figure 1 shows an example of delivering relief items to 14 flood victims using three vehicles. Each vehicle journeys from the warehouse to different nodes according to the planned route. In route 1, when the vehicle departs from node 3, the road between node 3 and node 4 is flooded. In route 2, the vehicle departs from node 8 but encounters flooding. In both cases, vehicles can continue their journey but must reduce speed for safety, resulting in delays in delivering the aid. Additionally, road conditions may change multiple times on the same road due to the uncertainty of flooding or other environmental factors. Therefore, vehicle speed is adjusted accordingly based on road conditions.

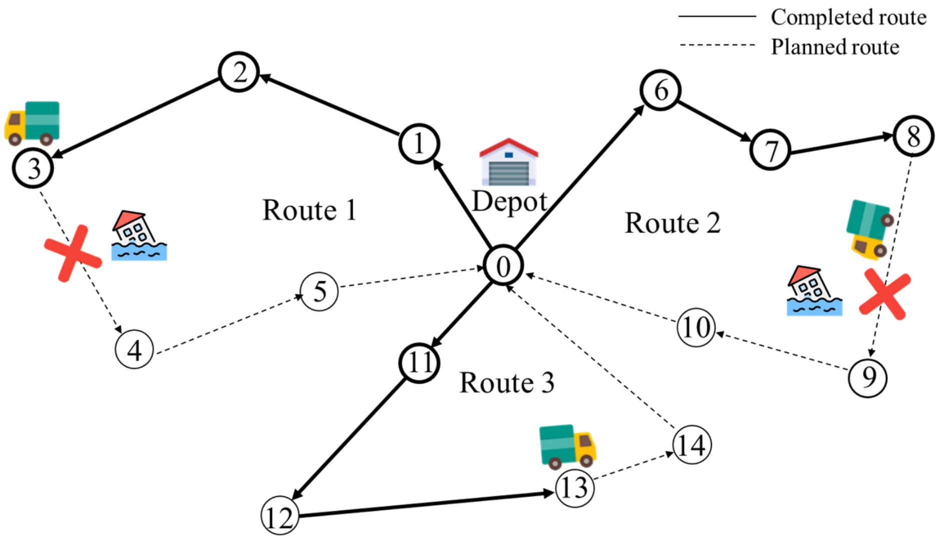


Figure 1. Example of delivery of items under the uncertain flooding situation.

From Figure 2, the road between node 2 and node 3, position U2, indicates a flooded section where the vehicle slows down until it reaches position U3, where the water level decreases, and the vehicle resumes normal speed. The orange line is average speed, and the green line is low speed.

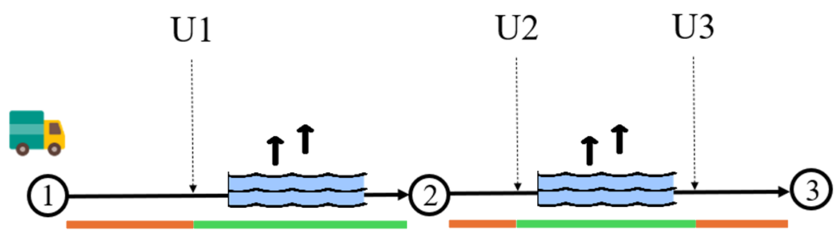


Figure 2. An example of uncertain road conditions affecting vehicle speed.

2.2. The Waiting Time

When planning for disaster relief, minimizing distance or travel time is often prioritized. In emergencies such as flooding, the urgency to alleviate conditions makes waiting time a crucial dimension that cannot be overlooked. The longer individuals wait, the more stress and uncertainty they face, impacting their mental well-being and ability to recover from the situation. Figure 3 illustrates the difference between two routes of equal distance.

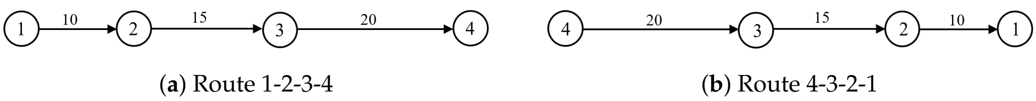


Figure 3. Difference in travel time and waiting time.

Routes 1-2-3-4 have a total travel time of 45, the same as route 4-3-2-1. However, they are different when considering the total waiting time of both routes. Route 1-2-3-4 has a total waiting time of 10 + (10 + 15) + (10 + 15 + 20) = 80, while route 4-3-2-1 has a total waiting time of 20 + (20 + 15) + (20 + 15 + 10) = 100. Therefore, route 1-2-3-4 is the preferable choice.

2.3. Mathematical Model

The format and constraints of this research problem are similar to the Capacitated Vehicle Routing Problem (CVRP), which is one type of VRP with limitations on vehicle capacity [30]. This model has the following mathematical formula:

Variables and Parameters:

- n: Total number of victims.
- m: Total number of vehicles.
- $I = \{1, 2, \ldots, n\}$: Set of victims.
- $J = \{0\} \cup I$: Set of all nodes including the depot (depot indexed as 0).
- $K = \{1, 2, \ldots, m\}$: Set of vehicles.
- t_{ij}: Travel time from victim i to victim j.
- Q_k: Capacity of vehicle k.
- q_i: Demand of victim i.

Decision Variables:

- x_{ijk}: Binary variable indicating whether vehicle k travels from victim i to victim j (1 = yes, 0 = no).
- w_i: Continuous variable representing the waiting time for victim i to receive deliveries.

Objective Function:

$$\min \sum_{i \in I} w_i \tag{1}$$

Constraints:

- Service Constraint. Each victim is visited exactly once by exactly one vehicle:

$$\sum_{j \in J, j \neq i} \sum_{k \in K} x_{ijk} = 1, \quad \forall i \in I \tag{2}$$

- Capacity Constraint. The demand of all victims served by a vehicle does not exceed its capacity:

$$\sum_{i \in J} q_i x_{ijk} \leq Q_k, \quad \forall k \in K \tag{3}$$

- Flow Conservation. Ensuring vehicles leave a victim after arriving:

$$\sum_{i \in J, i \neq j} x_{ijk} = \sum_{h \in J, h \neq j} x_{jhk}, \quad \forall j \in J, \forall k \in K \tag{4}$$

- Waiting Time Calculation. The waiting time for each victim takes into account the travel times from the previous victim:

$$w_i \geq t_{ji} + w_j - M(1 - x_{jik}), \quad \forall i, j \in J, i \neq j, \forall k \in K \tag{5}$$

where M is a large number.

- Probability Constraint. Ensure that travel is only scheduled on paths with acceptable feasibility under uncertain conditions:

$$p_{ij} \geq \theta x_{ijk}, \quad \forall i, j \in J, i \neq j, \forall k \in K \tag{6}$$

where θ is the minimum acceptable probability for a path to be considered feasible. p_{ij} represents the probability that the road condition between nodes i and j is passable during the planning period.

- Non-Negativity and Integrality.

$$x_{ijk} \in \{0, 1\}, \quad \forall i, j \in J, \forall k \in K \tag{7}$$

$$w_i \geq 0, \quad \forall i \in I \tag{8}$$

3. The Proposed Model

3.1. VRP-RIDFU Model

This model employs a GA as the primary algorithm to find suitable solutions. Although several research studies have suggested that a GA may not be the best algorithm for vehicle routing problems, a GA has mechanisms to handle uncertainty or changing data. The mechanisms for generating and updating solutions within a GA can create diversity within the population in each generation. A GA selects individuals with good fitness values in changing situations to improve and adapt solutions efficiently until meeting the specified conditions. The operation of VRP-RIDFU is illustrated in Figure 4.

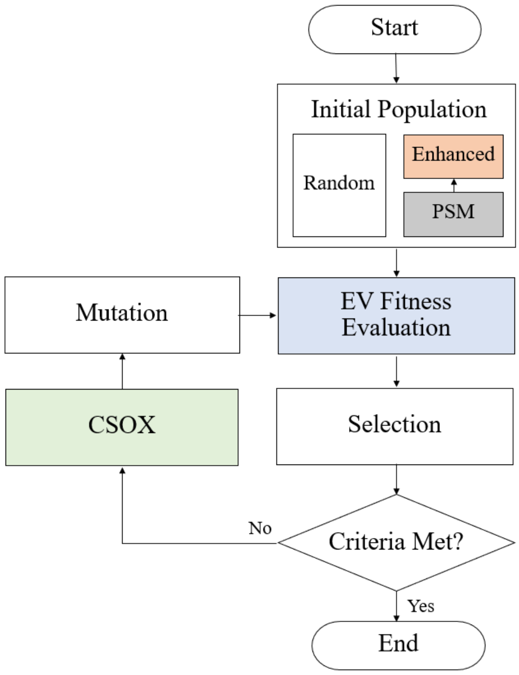


Figure 4. VRP-RIDFU flowchart.

The operation of VRP-RIDFU consists of five main steps. The first step involves creating the initial population of solutions. The solution represents the sequence of nodes for the delivery by three vehicles. Node 0 represents the depot, while nodes 1 to 6 represent the disaster sites. The initial population comprises individuals generated through randomization and enhanced individuals. Enhanced individuals represent a subset of the population that has been enhanced for efficiency in addressing uncertain problems. The proportions of these two groups within the population are defined, as depicted in Figure 5, which will be discussed in Sections 3.2 and 3.3. Step 2, evaluating the quality of each individual in the population, will include the fitness value for assessment in the form of the sum of expected values, as elaborated in Section 3.4. Step 3, the population selection, involves ordering and selecting individuals according to predefined percentages. The method selects the best-performing individuals from the current generation to form the next generation's population. If the quality of solutions does not improve after evaluation in step 3 according to the specified rounds, enhanced individuals are generated and substituted for the least fit individuals in sequence. These enhanced individuals are created in proportion to the predefined ratio. Steps 4 and 5 involve enhancing the quality of solutions through crossover and mutation. Crossover is performed using the CSOX operator, which will be discussed in Section 3.5. As for mutation, the swap method is selected. Finally, the termination criterion is defined by the specified number of generations.

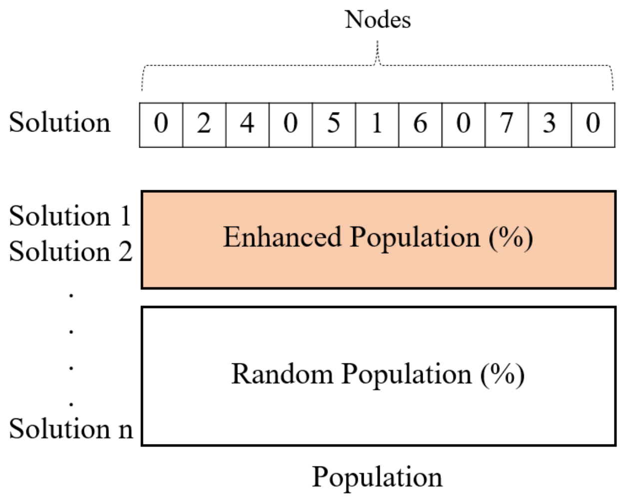


Figure 5. An example of solution and population representation.

3.2. Enhanced Population

In general, initializing the population for a GA using randomization may not be efficient for solving specific problems. Therefore, a portion of the initial population is enhanced to be more effective in addressing uncertainties. This enhanced population is referred to as the enhanced population.

Creating solutions for the enhanced population involves sequencing cities while considering the impact of selecting one city over another. This impact is the expected outcome value from selecting a city sequence under the uncertainty of road conditions. The total waiting time for assistance from unreached disaster victims and the uncertainty of road conditions must be considered. The reflection of this concept can be observed in Equations (9), (10), and (11), respectively.

$$w_{i,j} = \sum_{i=0}^{n} \sum_{j=0}^{n-1} \left(t_{i,j}^{n} + \Delta t \right) \quad , \tag{9}$$

$$\Delta t = \begin{cases} t_{i,j}^{f} - t_{i,j}^{n} & \text{, if the road is flooded} \\ 0 & \text{, otherwise} \end{cases} \quad , \tag{10}$$

where $w_{i,j}$ represents the waiting time for nodes that have not yet received assistance when selecting the route from node i to j, $t_{i,j}^{n}$ denotes the travel time from node i to j under normal road conditions, $t_{i,j}^{f}$ denotes the travel time from node i to j when the road is flooded, and Δt represents the additional time incurred when the road is flooded.

$$E_{i,j} = w_{i,j} \cdot \left(1 - p_{i,j}\right) + w'_{i,j} \cdot p_{i,j} \quad , \tag{11}$$

where $E_{i,j}$ represents the expected outcome value in traveling from node i to node j, $w'_{i,j}$ represents the waiting time for nodes if the road between i and j is flooded, and $p_{i,j}$ represents the probability of road flooding between nodes i and j.

3.3. Population Sizing Module

The allocation of the size of the enhanced population has an impact on the quality of the solutions and the processing speed. The allocation proportions are 25%, 50%, 75%, and 100% of the total population. It is found that setting the allocation proportions at 25% and 75% yields good solution quality for problems where node distributions are evenly spread and clustered [31], respectively. However, because victim location data are given in coordinate positions, the actual distribution pattern of the nodes is unknown, making it difficult to determine an appropriate enhanced population size. This section presents a technique for selecting an appropriate population size by analyzing the node distribution pattern. This module is referred to as the Population Sizing Module (PSM). In the first step, a grid of suitable size for node distribution is generated. The second step uses the standard deviation (SD) to analyze the distribution pattern. This article assumes that a uniform distribution means that within each grid cell, there is one node, and the standard deviation value is 0. Similarly, if the SD > 1.0, it indicates that the nodes are clustered, meaning that more than 68.2% of the nodes are close to each other, as illustrated in Algorithms 1–3.

Algorithm 1 Generate Spatial Grid.

Input: List of nodes xy with their (x, y) coordinates
Output: A grid with each cell containing the count of nodes assigned to it
  $minX, minY, maxX, maxY \leftarrow \min(xy), \max(xy)$
  $width \leftarrow maxX - minX$
  $height \leftarrow maxY - minY$
  $n, m \leftarrow$ OptimizeGridDimensions(length of xy, $width$, $height$) ▷ Call Algorithm 2
  $cellWidth \leftarrow width/n$
  $cellHeight \leftarrow height/m$
  $grid \leftarrow$ Initialize an $m \times n$ matrix with all values set to 0
  for each node in xy **do**
    $xIndex \leftarrow \lfloor (node.x - minX)/cellWidth \rfloor$
    $yIndex \leftarrow \lfloor (node.y - minY)/cellHeight \rfloor$
    $grid[yIndex][xIndex] \leftarrow grid[yIndex][xIndex] + 1$
  end for
  Return grid

Algorithm 2 Optimize Grid Dimensions.

Input: Total number of nodes (*nodes*), area width (w), and height (h)
Output: Optimized grid dimensions (*grid_w*, *grid_h*) that best fit the area's aspect ratio
  $ratio \leftarrow w/h$
  $grid\_w \leftarrow \lceil \sqrt{nodes} \rceil$
  $grid\_h \leftarrow \lceil nodes/grid\_w \rceil$
  $bestDiff \leftarrow \infty$
  $bestDimensions \leftarrow (grid\_w, grid\_h)$
  while true do
    $newGridW \leftarrow grid\_w + 1$
    $newGridH \leftarrow \lceil nodes/newGridW \rceil$
    $newRatio \leftarrow newGridW/newGridH$
    $ratioDiff \leftarrow |newRatio - ratio|$
    if $ratioDiff < bestDiff$ **then**
      $bestDiff \leftarrow ratioDiff$
      $bestDimensions \leftarrow (newGridW, newGridH)$
      $grid\_w \leftarrow newGridW$
    else
      break
    end if
  end while
  if $h > w$ **then**
    return $(bestDimensions[1], bestDimensions[0])$
  else
    return *bestDimensions*
  end if

Algorithm 3 Analyze Distributions.

Input: Total number of nodes $(nodes)$, area width (w), and height (h)
Output: Statistical analysis of the node distribution within the grid
$diff\_grid \leftarrow$ (Number of rows in grid $*$ Number of columns in grid) $-$ Length of xy
$count \leftarrow 0$
for each row in grid **do**
    while $count < diff\_grid$ and there is a zero in the row **do**
        Remove a zero from the row
        Increment count by 1
    end while
end for
$sd \leftarrow$ Calculate standard deviation from all cell counts in the grid

3.4. EV Fitness Evaluation

Evaluating solution quality from this perspective differs from general vehicle routing problems. While assessing solution quality based on the shortest distance may expedite reaching the affected individuals, the flood scenario necessitates considering the risk of flooded routes. Hence, this perspective proposes evaluating solution quality using the expected value of the combined results in route selection and the waiting time, as Equation (12) describes.

$$Minimize \sum_{k=1}^{K} \sum_{i=0}^{N-1} \sum_{j=i+1}^{N-1} E_{i,j}^{k}(w_{i,j}, p_{i,j}), \quad (12)$$

where $E_{i,j}^{k}$ represents the expected value of the outcome when selecting a route, considering both waiting time and flood risk factors, from node i to j using vehicle k.

The solutions or routes obtained through evaluation using this technique demonstrate the ability to handle uncertainty or changes in road conditions. The best route identified will be tested for performance against simulated scenarios with uncertain conditions occurring more than once, as outlined in Section 4.

3.5. CSOX

Crossover is a mechanism in a GA that enhances the quality of solutions. In this process, CSOX is chosen and tested for efficiency with TSP problems [28]. Results show that CSOX accesses solutions faster and produces higher-quality solutions than other operators. Furthermore, CSOX demonstrates a computation time comparable to other operators. CSOX maintains the sequence of cities in parts that contribute to good solution quality, such as the solution's front, middle, and end parts. Consequently, the new population generated from crossover comprises six individuals, but the processing time is similar to other methods, which produce only two individuals. With these properties, CSOX enhances the efficiency of the VRP-RIDFU model.

4. Experiment

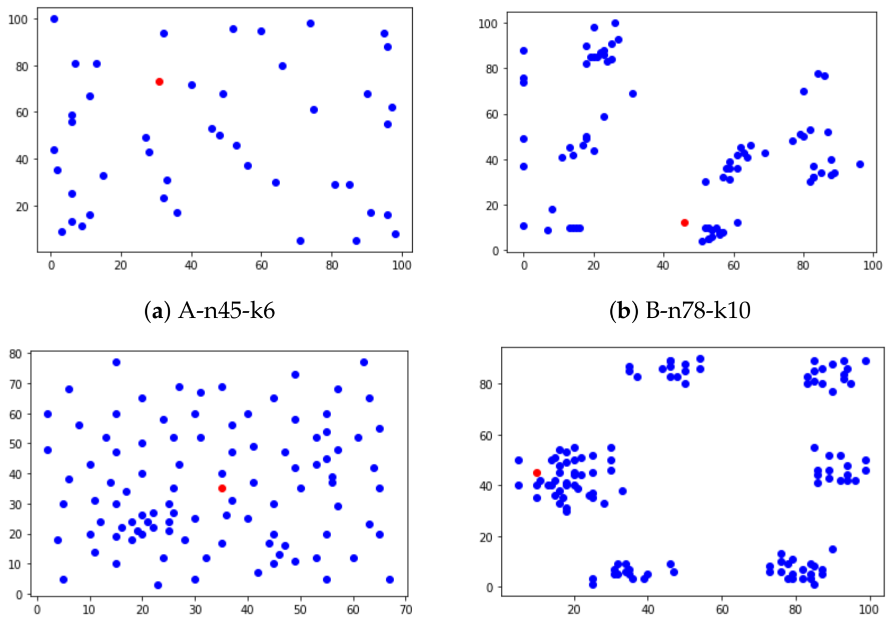
This section outlines the method and steps used to test the performance of the developed model, VRP-RIDFU, designed for planning delivery routes to assist disaster victims under uncertain flood conditions. The benchmark problem used to test model performance is CVRP [30]. The simulated flood scenario dataset includes additional flood risk data along the routes. The experiments are meticulously designed to assess the model's capability to produce efficient results, focusing on reducing the waiting time for disaster victims' assistance to mitigate potential losses due to food and water shortages.

Due to the specificity of the problem model, it is not easy to compare methods in other studies. The shortest distance or best solution to the CVRP problem is compared under the assumption that choosing the shortest route may take less time to travel, even if that road is flooded. This test reduces the vehicle's speed when traveling on a flooded road. On the other hand, if the route is less likely to be flooded but has a long distance, it may take more time to travel.

Python version 3.7.7 is the language used to develop this model. It runs on a notebook computer with Intel® core TM i7-9750H CPU (2.60 GHz), 8 G RAM, and Windows 11 operating system.

4.1. Dataset and Parameter Settings

The CVRP dataset for testing comprises 20 problems from CVRPLIB (accessed on 20 January 2024). http://vrp.atd-lab.inf.puc-rio.br/index.php/en/, which are widely recognized standard problems for VRP. Each problem's size ranges from 22 to 200 cities. The dataset includes city coordinates, demands, the number of vehicles, and the capacity of each vehicle. Each dataset has uniform and clustered node distribution patterns, as depicted in Figure 6.



(**a**) A-n45-k6 (**b**) B-n78-k10 (**c**) E-n101-k14 (**d**) M-n121-k7

Figure 6. The example of CVRP instances' characteristics.

In Figure 6, the red points (node 0) represent depots, and the blue points represent the locations of disaster victims. The problem codes have the following meanings: A, B, E, and M, which denote the problem set. N denotes the number of cities. K denotes the maximum number of vehicles. An additional factor introduced into the problem to test the efficiency of the developed model is the level of flood risk on each road segment.

The adjustment of parameters for evaluating the performance of VRP-RIDFU consists of the GA and environmental parameters, as shown in Table 1.

Table 1. Parameter setting.

GA Parameters		Environment Parameters	
Population size:	20–30	Flooded probabilities:	0.0–1.0
Generation:	100–2000	Uncertainty situation:	1–10 times
Crossover rate:	0.7–1.0	Vehicle speed:	3–88 km/h [32]
Mutation rate:	0.1–0.3		
Selection rate:	0.5		
Number of runs:	20		

4.2. Simulation of Flood Uncertainty

The effectiveness of the route plans produced using VRP-RIDFU is evaluated by simulating the uncertainty of flood conditions. This uncertainty relates to the likelihood that each section of the road will flood. Reduced travel speeds may result in longer wait times if the route plan under evaluation has several sections of flooded roads.

This uncertainty is simulated to occur over time, with the time intervals generated randomly according to a uniform distribution. In this test, the number of occurrences of uncertainty ranges from 1 to 10 times. The maximum travel time of the optimal solution's route is used to define the time intervals for the occurrence of uncertainty. In other words, if there are five vehicles or five routes, the travel time of the route with the most extended duration is used to determine the time intervals for uncertainty occurrence. The road conditions in the simulated scenarios will vary randomly, making it challenging to predict.

5. Experimental Results

This section will present the results of developed model performance testing based on the objectives of the paper, divided into three parts: comparing the efficiency of routes in terms of waiting time, assessing route efficiency when adjusting the population size appropriately for each problem, and evaluating the use of CSOX for improving solution quality compared to other popular crossovers.

5.1. Efficiency Comparison Based on the Waiting Time

The waiting time is the performance metric to be measured from the routes obtained from the developed model compared to the Shortest Routes from the Optimal Solution (SROS). The best, average, and worst waiting times will be compared. Additionally, the tests demonstrate the total distance, total travel time, and the number of flooded roads from all roads for both solutions, as shown in Table 2.

Table 2. Comparison of the performance of vehicle route plans under flood uncertainty obtained from SROS and VRP-RIDFU.

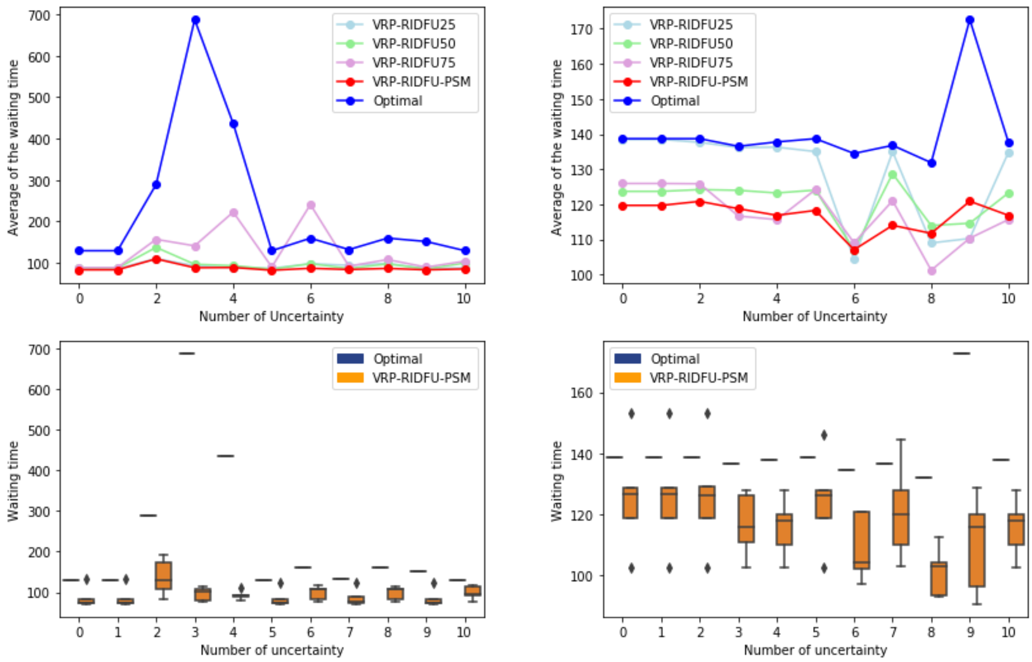
Instance	SROS				VRP-RIDFU							
	Distance	Flooded Roads	Travel Time	Waiting Time	Distance	Flooded Roads	Travel Time	Waiting Time				
								Best	Avg.	Worst	SD	Runtime
A-n32-k5	787.808	21/37	40.564	148.72	1307.367	**14/37**	42.144	**74.165**	**111.956**	163.941	28.488	0.952
A-n45-k6	944.876	20/51	41.023	154.026	1745.027	**10/51**	52.277	**106.621**	**151.285**	181.846	25.852	1.34
A-n54-k7	1171.784	34/61	62.181	247.615	2180.315	**16/61**	67.244	**143.125**	**217.528**	385.937	66.433	1.421
A-n69-k9	1165.995	42/78	56.515	190.01	2256.247	**24/78**	75.391	**151.121**	**181.329**	209.124	20.387	13.371
A-n80-k10	1766.5	43/90	79.954	338.92	2917.092	**22/90**	102.727	**200.575**	**260.959**	**305.785**	45.491	14.957
B-n31-k5	1020.04	17/36	35.918	114.065	1199.534	**9/36**	39.714	**44.801**	**71.096**	**90.342**	14.999	0.871
B-n44-k7	915.84	26/51	47.076	136.302	1504.949	**20/51**	60.758	**91.352**	**132.654**	289.601	60.521	1.228
B-n50-k8	1322.562	35/58	66.325	194.469	2087.358	**21/58**	70.646	**101.165**	**160.11**	232.626	36.936	1.463
B-n64-k9	869.316	39/73	42.451	125.108	1515.499	**16/73**	87.691	**95.518**	**123.403**	176.111	29.226	13.97
B-n78-k10	1229.273	39/88	85.564	347.652	2344.841	**25/88**	150.854	**207.544**	451.637	981.318	168.77	14.761
E-n22-k4	375.28	16/26	185.051	446.137	654.092	**8/26**	**27.453**	**29.852**	**98.034**	**292.458**	74.576	8.464
E-n33-k4	838.721	16/37	78.219	315.045	1336.702	**6/37**	**51.996**	**96.878**	**167.547**	**249.985**	45.291	9.415
E-n51-k5	524.944	28/56	47.921	214.457	1280.486	**7/56**	**42.593**	**123.625**	246.471	541.688	116.322	11.612
E-n76-k7	687.603	43/83	63.001	368.738	1755.087	**15/83**	76.137	**277.151**	**350.894**	490.428	72.637	13.199
E-n101-k8	826.908	56/108	79.466	537.964	2562.869	**20/109**	106.201	**351.809**	**435.996**	**493.801**	49.223	16.631
M-n101-k10	819.811	56/111	1047.49	6972.741	2630.86	**29/111**	**101.015**	**342.304**	**614.708**	**1167.073**	279.548	17.296
M-n121-k7	1045.16	54/128	1912.189	16205.98	3239.154	**29/128**	**351.658**	**794.176**	**1741.898**	3841.707	964.342	20.309
M-n151-k12	1030.756	80/163	371.393	2819.523	3459.861	**32/163**	**147.623**	**529.622**	**1355.167**	5625.328	1556.315	24.946
M-n200-k16	1294.666	82/216	2962.126	20472.488	4603.015	**43/216**	**1815.141**	**2553.844**	**6115.756**	**14,210.947**	4769.317	48.504
M-n200-k17	1294.894	108/217	116.34	793.822	4716.01	**43/217**	193.205	**554.435**	1493.736	4676.866	1347.315	73.215

Table 2 shows that in terms of overall performance, VRP-RIDFU provides better quality solutions than the shortest path under uncertain conditions, even when the uncertainty occurs only five times during the journey. Numbers are highlighted in bold to emphasize the superior performance metrics of VRP-RIDFU compared to the shortest path approach. Both the best and average values show that, in some instances, VRP-RIDFU produces solutions of better quality despite having a higher total distance. The number of flooded roads indicates that the model encounters fewer flooded roads.

The experiment utilizes 100 generations to solve problems with around 50 nodes, achieving solutions within 2 s on average. For problems with approximately 120 nodes, 500 to 1000 iterations are necessary. Except for the 200-node problem, which uses 30 generations, all other issues require 2000 iterations. A consistent population size of 20 is applied across all problems except for the 200-node scenario. The minimum time to generate effective solutions is about 2 min. This experiment initially shows the impact of road condition uncertainties occurring five times, highlighting the model's initial response. Upcoming tests will further explore how the model handles different frequencies of uncertainty and evaluate the PSM approach for adjusting to various node distribution patterns.

5.2. Efficiency Comparison Based on the Impact of Enhanced Population Size Variation

This test demonstrates the impact of enhanced population size on the models' performance in coping with different node distribution patterns. VRP-RIDFU25, VRP-RIDFU50, and VRP-RIDFU75 are models that have enhanced population ratios of 25%, 50%, and 75%, respectively. The VRP-PSM model uses PSM to optimally adjust the enhanced population size based on the node distribution pattern. Optimal refers to the shortest path solution for the problem. Additionally, each model is tested over 20 runs to evaluate its robustness against uncertainty fluctuations ranging from 1 to 10 occurrences, as depicted in Figures 7 and 8.

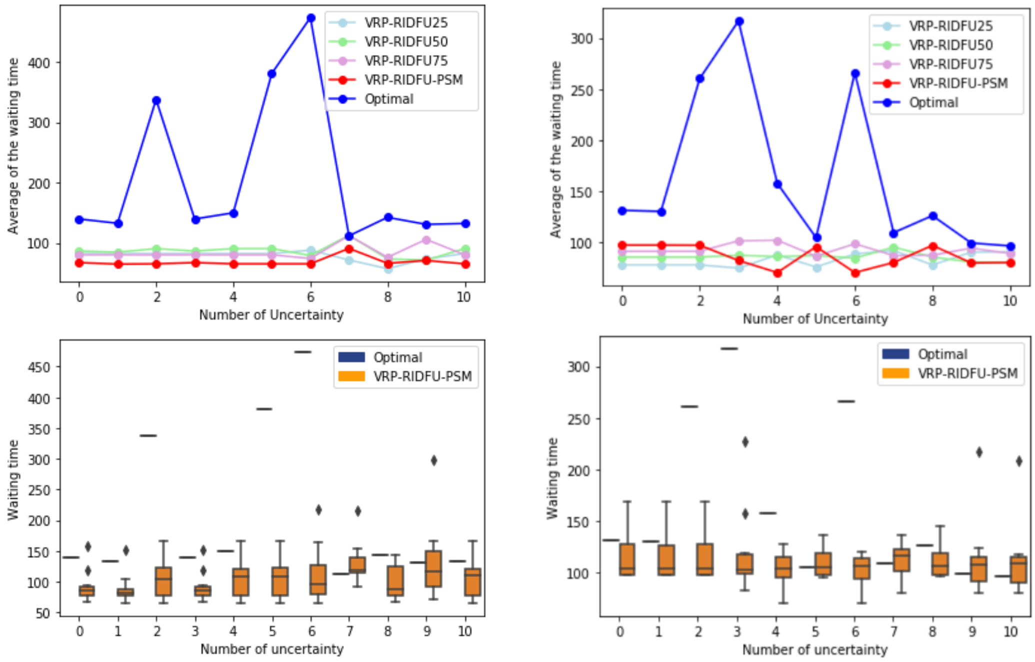


(**a**) A-n32-k5 (**b**) B-n50-k8

Figure 7. Graphs of the performance response to the number of times uncertainty occurs for problem sets A and B.

Figure 7 shows the testing results of the models on problem sets A and B. In contrast, Figure 8 shows the testing results for problem sets E and M. Each problem set has a distinct number of nodes and distribution patterns. The x-axis represents the number of uncertainty occurrences, and the y-axis shows the average waiting time. The performance testing indicates that the total waiting time obtained from the VRP-RIDFU models is less than optimal in all scenarios. The graph from the VRP-RIDFU models exhibits notable stability, particularly for the models utilizing the PSM approach. Additionally, the boxplot demonstrates minimal variation in the results, emphasizing the models' resilience to uncertainties in the developed routing plans. However, the optimal boxplot graph is non-distributed because it is the shortest path, so the results are the same every time it is run.

Moreover, most of the outliers in the VRP-RIDFU's boxplot graph are few and far from the median of the results, represented by rhombuses. Outliers identify situations where the model significantly underperforms or outperforms compared to expected results.



(**a**) E-n50-k8 (**b**) M-n151-k12

Figure 8. Graphs of the performance response to the number of times uncertainty occurs for problem sets E and M.

5.3. Efficiency Comparison Based on the Crossover Operator

This test evaluates the effectiveness of the quality improvement mechanism of the GA selected for the CSOX model. CSOX will be compared with the conventional operator's OX and PMX, which are widely recognized [24]. The impact of increasing problem node numbers on operator performance will be assessed. The parameter values are as follows: population size = 10, generation = 1000, crossover rate = 0.8, and mutation rate = 0.2.

Figure 9 shows that in all problems, CSOX outperforms the other two operators regarding solution quality. However, more is needed as the error bars also indicate that the solutions provided by CSOX are consistently less variable than the other two operators.

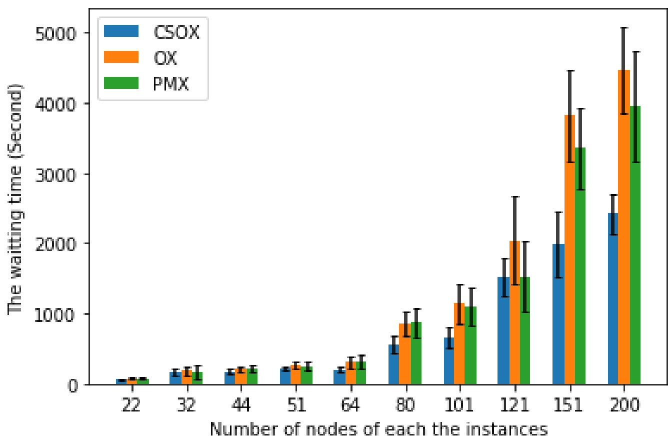


Figure 9. Comparing the performance concerning the number of nodes of the operators CSOX, OX, and PMX.

6. Conclusions

This research successfully develops and tests a model named the Vehicle Routing Problem for Relief Item Distribution under Flood Uncertainty (VRP-RIDFU), which employs Genetic Algorithms (GA) as the principal mechanism for generating and enhancing the quality of routing plans. A subset of the GA population, enhanced population, is specifically crafted to handle uncertainties in flooding-related road conditions. This achievement is realized by utilizing expected outcomes based on waiting times and flood risk assessments to select routes, effectively increasing resilience to unpredictable circumstances. The enhanced population's proportion significantly influences the routes' effectiveness when applied to various disaster-affected population distributions. The Population Sizing Module (PSM) is introduced to accommodate these distributions with grid generation techniques and standard deviation assessments for node dispersion. Moreover, the Complete Subtour Order Crossover (CSOX) is selected as the crossover operator because it produces high-quality routes, facilitates quick solution convergence, and reduces operational times. Testing demonstrates that the developed model efficiently plans vehicle routes that reduce unpredictable waiting times caused by flooding uncertainties compared to the shortest routes from standard CVRP problems. Furthermore, the developed model requires less time to generate these routing plans. Implementing the VRP-RIDFU model for planning vehicle routes for disaster relief significantly decreases the waiting time for aid, enhancing both the route creation efficiency and the delivery's effectiveness amidst flood uncertainties. Communities benefit from quicker relief and the expedited restoration of their quality of life. However, a limitation of this model is its dependency on accurate flood risk data, which, if precise, dramatically enhance the model's effectiveness in producing efficient vehicle routes. Such data can be sourced from relevant governmental and private sector information repositories. Additionally, the current PSM only allows the enhanced population proportion to be set in uniform and clustered distributions. Future developments in PSM could enable finer adjustments to accommodate various dispersion patterns, further refining the model's applicability and performance.

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