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Fuzzy Multi-Objective, Multi-Period Integrated Routing–Scheduling Problem to Distribute Relief to Disaster Areas: A Hybrid Ant Colony Optimization Approach

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Abstract: This paper explores a multi-objective, multi-period integrated routing and scheduling problem under uncertain conditions for distributing relief to disaster areas. The goals are to minimize costs and maximize satisfaction levels. To achieve this, the proposed mathematical model aims to speed up the delivery of relief supplies to the most affected areas. Additionally, the demands and transportation times are represented using fuzzy numbers to more accurately reflect real-world conditions. The problem was formulated using a fuzzy multi-objective integer programming model. To solve it, a hybrid algorithm combining a multi-objective ant colony system and simulated annealing algorithm was proposed. This algorithm adopts two ant colonies to obtain a set of nondominated solutions (the Pareto set). Numerical analyses have been conducted to determine the optimal parameter values for the proposed algorithm and to evaluate the performance of both the model and the algorithm. Furthermore, the algorithm's performance was compared with that of the multi-objective cat swarm optimization algorithm and multi-objective fitness-dependent optimizer algorithm. The numerical results demonstrate the computational efficiency of the proposed method.

Keywords: fuzzy multi-objective integer programming problem; multi-period integrated vehicle routing and scheduling; multi-objective ant colony system; simulated annealing algorithm

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1. Introduction

Given the increasing frequency of disasters, millions of people are affected by natural or man-made events each year, with the number of victims rising significantly in recent decades. Effective planning is crucial in mitigating the impacts of such catastrophes. Logistics play a key role in coordinating the transportation of commodities between regional warehouses and affected areas. However, relief logistics planning involves conflicting objectives, such as minimizing unsatisfied demands, distribution costs, and delays, while maximizing satisfaction and fairness in product distribution [1].

Sudden disasters are unpredictable, presenting significant challenges that underscore the need for an efficient emergency material distribution system. A key challenge for decision-makers is finding a way to swiftly and safely deliver materials to affected areas. Existing research largely focuses on the coordinated transportation of emergency supplies, dynamic distribution, and transport uncertainties [2–4]. To effectively address the complexities of emergency material distribution during crises, it is crucial to integrate all these factors.

In addition, uncertainty plays a crucial role in emergency material distribution, where real-time information is hard to obtain. Accurate demand assessment can improve relief allocation and reduce costs. Furthermore, transportation times may fluctuate due to traffic jams, equipment failures, and other unpredictable events. Researchers explored fuzzy theory and stochastic programming to address uncertain conditions. Considering that the values of these parameters in the affected areas varies over time, the collection of reliable prior data for stochastic programming is challenging. Fuzzy theory is thus more suitable for optimizing these issues [5,6]. In this regard, we propose a fuzzy multi-objective integer programming model.

Furthermore, the routing–scheduling distribution problem is NP-hard [7], and the literature primarily emphasizes the use of metaheuristic algorithms for similar problems [8–11]. By calibrating the metaheuristic algorithm to the specific characteristics of the problem, it can generate effective solutions for planning various operations to address these challenges [6]. Building on the above discussion, we propose a fuzzy multi-objective, multi-period integrated routing–scheduling model and adapt a hybrid algorithm based on a multi-objective ant colony system and simulated annealing algorithm to solve the problem.

2. Literature Review

Research on disaster management is of great importance, and significant studies are being conducted in this field. One of the first studies in the field of transportation in relief logistics was performed by [12]. In the mentioned work, a linear programming model was presented to determine the optimal food transportation schedule. Given the significance of crisis management, several researchers have recently conducted extensive reviews of the studies carried out in this area [1,13–16]. This overview will discuss research in the relief chain response phase with an emphasis on periodic routing, multi-objective routing–scheduling and uncertainty.

2.1. Multi-Period Relief Distribution

Some of the most important aspects of routing problems, which are addressed in this study, are periodic routing problems where customer services must be done periodically during a planning horizon. The aim of periodic routing is to determine the motion paths from the service centers to the customers in each period so that the total routing costs incurred throughout the planning horizon are minimized [17]. The periodic vehicle routing problem was first proposed in [18], while the first mathematical model of the problem was then presented in [19]. Over the past forty-five years, the periodic vehicle routing problem has significantly evolved, leading to applications like the period vehicle routing problem with time windows [20], the multi-depot and periodic vehicle routing problem [21], and the dynamic multi-period vehicle routing problem [22]. Most research has concentrated on using heuristic algorithms to tackle these extended PVRP models.

Li et al. proposed a multi-period vehicle routing problem for emergency perishable materials with uncertain demand, utilizing an improved whale optimization algorithm [23]. Zhang et al. recently proposed a multi-period vehicle routing problem with time windows for drug distribution during epidemics. Their model incorporates virus transmission characteristics and fluctuations in drug demand. They employed an ε-global optimization method with an outer-approximation scheme for achieving global ε-optimal solutions in small instances and introduced a hybrid tabu search algorithm (HTS) for larger instances [24].

2.2. Multi-Objective Relief Distribution

Research on multi-objective optimization problems gained significant popularity in 2002 [25] and has since attracted considerable attention from researchers. Recently, a new multi-objective optimization algorithm, called the multi-objective learner performance-based behavior algorithm, was introduced by Rahman et al. [26]. This algorithm is inspired by the transition of students from high school to college and is evaluated against benchmarks and five real-world engineering optimization problems using various metrics. In a more recent study, Abdullah et al. introduced the multi-objective fitness-dependent optimizer (MOFDO) algorithm, an advanced version of the fitness-dependent optimizer algorithm that combines various types of knowledge [27]. This algorithm was evaluated using ZDT test functions and CEC-2019 benchmarks, showing a better performance than recent methods, like the multi-objective particle swarm optimization, NSGA-III, and multi-objective dragonfly algorithm, in many cases.

Rath and Gutjahr presented a three-objective optimization model with a medium-term economic sector, a short-term economic sector, and an accident objective function [28]. To solve the problem, a meta-heuristic scheme based on a genetic algorithm was also provided. Ngueveu et al. introduced a transportation routing model with a stacked capacity where the aim was to minimize the total time required for the vehicle to get applicants [2]. Ahmadi et al. developed a multi-objective multi-depot location-routing model considering network failure, multiple uses of vehicles, and standard relief time. The model was then extended to a two-step stochastic program with a random travel time to determine the locations of distribution centers [29]. Barzinpour et al. proposed a multi-objective model for distribution centers which are located in and allocated periodically to the damaged areas in order to distribute the offered relief commodities [18].

Mohammadi et al. developed a new multi-objective reliable optimization model to organize a humanitarian relief chain that is able to make a broad range of decisions, including reliable facility location–allocation, fair distribution of relief items, assignment of victims, and routing of trucks [30]. Vahdani et al. developed a sophisticated two-stage, multi-objective mixed integer, multi-period, and multi-commodity mathematical model designed for a three-level relief chain [31]. Yu et al. first developed a more general two-echelon multi-objective location routing problem model (2E-MOLRP) in consideration of the inherent similarities in many realistic waste collection applications. Furthermore, to solve the model, an improved non-dominated sorting genetic algorithm with a directed local search (INSGA-dLS) was proposed [32]. Ebrahimi formulated a more comprehensive two-echelon multi-objective location routing problem model (2E-MOLRP), taking into account the inherent parallels in numerous practical waste collection scenarios. Moreover, to tackle the model, they proposed an enhanced non-dominated sorting genetic algorithm with a directed local search (INSGA-dLS) [5]. Zajac and Huber provided an overview of the solving methods for application-oriented multi-objective routing problems [33]. They were also analyzed in terms of algorithmic approaches and implementation strategies [34].

2.3. Relief Distribution with the Uncertain Problem

Given the unpredictable circumstances during and following a crisis, decision-makers frequently grapple with significant uncertainties that compound the complexity of the problem [35]. Inaccurate or delayed information can result in significant casualties and property losses. Various optimization methods in this field are presented in the problem literature. In the following, a number of recent research articles in this field have been reviewed.

Uslu et al. considered a multi-depot vehicle routing problem with stochastic demands and developed a chance-constrained mathematical model to cope with the problem. They also conducted a case study for Ankara city in Turkey [36]. Golabi et al. investigated a stochastic facility location problem for a possible earthquake in Tehran where unmanned aerial vehicles (UAVs) are utilized [17]. Saffarian et al. proposed a bi-objective model for relief chain logistics in an uncertain environment while considering the uncertainty in both traveling times and demands of the damaged areas [37].

Akbarpour et al. created a max–min robust bi-objective optimization model to handle the uncertainty in the pharmaceutical supply chain [38]. Zahedi et al. carried out an empirical study with the aim of creating an optimal model for scheduling resources and vehicles to cater to the needs of disaster-stricken areas with dynamic demands. The research focused on devising a strategic plan for resource allocation during emergencies. This comprehensive model addresses various aspects, including the heterogeneity and fluctuating nature of demands, simultaneous planning for goods distribution and vehicle routing, and a multi-objective model grounded in the essential measures required during emergencies [4].

Rawls and Turnquist presented a two-stage stochastic programming model to tackle the uncertainties in demand and road network availability, facilitating the advanced deployment of emergency relief materials [39]. Liu et al. expanded on this by integrating transportation time uncertainties into their model and using robust optimization techniques to handle these uncertainties [40]. Safaei et al. recognized the fluctuating nature of supply and demand in emergency rescues and proposed a bi-level optimization model, where the upper and lower levels adjust to minimize unmet demands [41]. Additionally, uncertainties may occur during disasters when selecting locations for emergency warehouses [42].

Cao et al. constructed their formulation as a fuzzy tri-objective bi-level integer programming model. They developed a hybrid global criterion method that integrates a primal–dual algorithm, an expected value, and a branch-and-bound approach to solve the model [19]. Wan et al. utilized trapezoidal fuzzy numbers to manage the uncertainty in determining the locations for emergency materials [43]. Fuzzy credibility theory was applied to create a fuzzy chance constraint model incorporating fuzzy demands and unlimited material collection time [44]. Tang et al. utilized trapezoidal fuzzy numbers to represent demand, scheduling time, and satisfaction, ensuring the equitable distribution of disaster relief materials [45].

Our review of the literature shows that the majority of these papers concentrate solely on optimizing specific components. Few studies considered multi-period integrated routing–scheduling, multiple objectives and uncertainty simultaneously. Therefore, this paper investigates the problem of integrated multi-objective, multi-period routing and scheduling under uncertain conditions. To tackle this problem, a multi-objective fuzzy integer programming model is proposed. Considering the intricate nature of the problem, a multi-objective ant colony system algorithm was developed to solve the problem. The rest of the paper is organized as follows. The proposed mathematical model is demonstrated in Section 3. Section 4 is devoted to the multi-objective ant colony system. Numerical analyses are performed in Section 5 to discover the most appropriate parameters for the ant algorithm. Furthermore, several numerical tests are illustrated to demonstrate the main concept and results of the proposed model and algorithm. Section 6 ends the paper with a brief conclusion and future directions.

3. Fuzzy Multi-Objective Multi-Period Integer Programming Model

In this section, a fuzzy multi-objective integer programming model is proposed to formulate the problem. The origin of the model was adapted from [3,46,47], which serves as the foundational source for understanding its development and background. For this aim, the following assumptions were considered:

- Limited number of periods is given;
- Number of depots is fixed;
- Heterogeneous fleet of vehicles is available;
- Capacity of vehicles is predetermined;
- Demand of each customer in each period is specified as a fuzzy parameter;
- Number of customers that should be serviced in each period is defined;
- Customers of each period are different from those of other periods;
- Distance-dependent transportation costs are assumed;
- Each vehicle starts its journey from one depot and ends at another depot, although the starting and ending depots could be also be identical;
- Symmetric transportation network is considered;
- Traversing cost and customer's demand are considered as fuzzy parameters.

The indices of the model are as follows:

i	An index assigned to customers located at the beginning of an edge ($i = 1, \ldots, N$);
j	An index assigned to customers located at the end of an edge ($j = 1, \ldots, N$ and $j \neq i$);
t	Index of periods ($t = 1, \ldots, T$);
k	Index of vehicles ($k = 1, \ldots, V$);
d	Index of depots ($d = 1, \ldots, D$).

Furthermore, the parameters are listed bellow.

$\widetilde{c}_{ijt}$	Fuzzy transportation cost of edge (i, j) between customers i and j in period t;
$\widetilde{c}'_{dit}$	Fuzzy transportation cost of edge (i, d) or edge (d, i) between customer i and depot d in period t;
$\widetilde{d}_{it}$	Fuzzy demand of customer i in period t;
$\widetilde{w}_{ijt}$	Fuzzy transportation time of edge (i, j) customers i and j in period t;
$\widetilde{w}'_{dit}$	Fuzzy transportation time of edge (i, d) or edge (d, i) between customer i and depot d in period t;
N_t	Number of customers in period t;
c_k	Capacity of vehicle k;
V	Number of available vehicles in each period;
T	Number of periods in the planning horizon;
D	Number of depots;
M	A big number.
B	Subset of customers in each period;
A	Set of depots;
G	Set of all customers and depots in each period.

In the following, the Decision Variables of the model is illustrated.

$x_{ijkt} \in \{0, 1\}$	Equals to 1 if vehicle k traverses edge (i, j) in period t, otherwise 0;
$y_{dikt} \in \{0, 1\}$	Equals to 1 if vehicle k traverses edge (d, i) in period t, otherwise 0;
$z_{idkt} \in \{0, 1\}$	Equals to 1 if vehicle k traverses edge (i, d) in period t, otherwise 0;
$s_{kdt} \in \{0, 1\}$	Equals to 1 if vehicle k is located in depot d at the beginning of period t, otherwise 0;
$f_{kdt} \in \{0, 1\}$	Equals to 1 if vehicle k is located in depot d at the end of period t, otherwise 0;
$time_{it} \geq 0$	Arrival time to customer i in period t.

The fuzzy integer programming model of the problem is as follows:

$$\begin{aligned} \text{Min } f_1 = & \sum_{t=1}^{T} \sum_{i=1}^{N_t} \sum_{j=1, j \neq i}^{N_t} \sum_{k=1}^{V} x_{ijkt} \widetilde{c}_{ijt} \\ & + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{i=1}^{N_t} \sum_{k=1}^{V} y_{dikt} \widetilde{c}'_{dit} \\ & + \sum_{t=1}^{T} \sum_{i=1}^{N_t} \sum_{d=1}^{D} \sum_{k=1}^{V} z_{idkt} \widetilde{c}'_{dit} \end{aligned} \tag{1}$$

$$\text{Min } f_2 = \sum_{d=1}^{D} \sum_{i=1}^{N_t} time_{it} * \widetilde{d}_{it} \tag{2}$$

The model is subjected to the following:

$$\sum_{d=1}^{D} \sum_{k=1}^{V} y_{d,i,k,t} + \sum_{\substack{j=1 \\ j \neq i}}^{N_t} \sum_{k=1}^{V} x_{j,i,k,t} = 1 \quad \forall i, t \tag{3}$$

$$\sum_{j=1, j \neq i}^{N_t} \sum_{k=1}^{V} x_{ijkt} + \sum_{d=1}^{D} \sum_{k=1}^{V} z_{idkt} = 1 \quad \forall i, t \tag{4}$$

$$\sum_{d=1}^{D} \sum_{i=1}^{N_t} y_{dikt} - \sum_{d=1}^{D} z_{jdkt} = 0 \quad \forall k, t \tag{5}$$

$$\sum_{d=1}^{D} \sum_{i=1}^{N_t} y_{dikt} \widetilde{d}_{it} + \sum_{i=1}^{N_t} \sum_{j=1, j \neq i}^{N_t} x_{ijkt} \widetilde{d}_{jt} \preceq c_k \quad \forall k, t \tag{6}$$

$$time_{it} + \widetilde{w}_{ijt} - (1 - x_{ijkt}) M \leq time_{jt} \quad \forall i, j, k, t \tag{7}$$

$$\widetilde{w}'_{djt} - (1 - y_{djkt})M \leq time_{jt} \quad \forall d, j, k, t \tag{8}$$

$$\sum_{d=1}^{D} y_{dikt} + \sum_{j=1, j\neq i}^{N_t} x_{jikt} - \sum_{j=1, j\neq i}^{N_t} x_{ijkt} - \sum_{d=1}^{D} z_{idkt} = 0 \ \forall i, k, t \tag{9}$$

$$\sum_{i=1}^{N_t} \sum_{j=1, j\neq i}^{N_t} x_{ijkt} \leq M\left(\sum_{d=1}^{D} \sum_{i=1}^{N_t} y_{dikt}\right) \ \forall k, t \tag{10}$$

$$\sum_{i\in B}^{N_t} \sum_{j\in B, j\neq i}^{N_t} x_{ijkt} \leq |B| - 1 \ \begin{array}{l} \forall k, t, \forall B \subseteq G \backslash \{A\}, \\ |B| \geq 2 \end{array} \tag{11}$$

$$\sum_{d=1}^{D} \sum_{i=1}^{N_t} y_{dikt} \leq 1 \quad \forall k, t \tag{12}$$

$$\sum_{d=1}^{D} s_{kdt} = 1 \ \forall k, t \tag{13}$$

$$\sum_{d=1}^{D} f_{kdt} = 1 \quad \forall k, t \tag{14}$$

$$\sum_{i=1}^{N_t} y_{dikt} \leq s_{kdt} \ \forall k, d, t \tag{15}$$

$$\sum_{i=1}^{N_t} z_{idkt} \leq f_{kdt} \ \forall k, d, t \tag{16}$$

$$f_{kd(t-1)} = s_{kdt} \ \forall k, d, t \geq 2 \tag{17}$$

The problem is to determine optimal routes for vehicles to service customers in a post-disaster logistics network, aiming to minimize total costs while maximizing customer satisfaction under uncertain conditions. The first objective function (1) focuses on minimizing transportation costs, which consist of three components: transportation between customers, between depots and customers, and between customers and depots. Due to the inclusion of fuzzy cost parameters, the objective function is fuzzy. The second objective function (2) aims to enhance customer satisfaction by ensuring that service is expedited for the most demanding customers.

Constraints (3) and (4) guarantee that each customer is served exactly once per period. Constraint (5) stipulates that each vehicle's route begins at one depot and ends at the other one, which is not necessarily the initial depot. Fuzzy constraint (6) requires that the total demand from customers on a vehicle's route must not exceed its capacity. Constraints (7) and (8) ensure the vehicle's route is feasible based on travel times between customers and between customers and depots. Flow conservation is addressed in (9), while (10) specifies that the vehicle's route must begin at a depot. Constraint (11) prevents subtours. Constraint (12) allows for a number of idle vehicles during each time period. Constraints (13) and (14) specify that each vehicle is at one depot at the start and end of each time period. Constraint (15) and (16) show the relationship between variables y_{dikt}, s_{kdt}, z_{idkt}, and f_{kdt}. Also, the relationship between variables f_{kdt} and s_{kdt} is stated in constraint (17).

To overcome fuzziness, the concept of ranking functions is proposed. A Ranking function is a function $\Re : F(R) \rightarrow R$, where $F(R)$ is a set of fuzzy numbers defined on set of real numbers, which maps each fuzzy number into a real line, where a natural order exists. If we let $\widetilde{A} = (a, b, c)$ be a triangular fuzzy number, then $\Re(\widetilde{A}) = \frac{a+2b+c}{4}$. In addition, arithmetic operations between two triangular fuzzy numbers defined on the real set are presented as follows:

If $\widetilde{A}_1 = (a_1, a_2, a_3)$ and $\widetilde{A}_2 = (b_1, b_2, b_3)$ are two triangular fuzzy numbers, then

$$\widetilde{A}_1 + \widetilde{A}_2 = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \tag{18}$$

$$\widetilde{A}_1 \approx \widetilde{A}_2 \Leftrightarrow a_i = b_i, i = 1,2,3. \tag{19}$$

$$\widetilde{A}_1 \preceq \widetilde{A}_2 \Leftrightarrow a_i \leq b_i, i = 1,2,3. \tag{20}$$

4. Hybrid Multi-Objective Ant Colony System and Simulated Annealing Algorithm

The multi-objective, multi-period integrated routing–scheduling problem is NP-hard, as noted in the Introduction. As a result, many researchers have focused on metaheuristic algorithms to tackle similar challenges. Notably, the ant colony optimization algorithm is a prominent method for addressing various vehicle routing problems [48]. Recently, hybrid metaheuristic algorithms have gained traction for leveraging the strengths of multiple approaches to solve complex optimization issues. This paper proposes a hybrid multi-objective ant colony system combined with a simulated annealing algorithm to tackle the problem.

Ants communicate using pheromones, which are chemical substances they release and detect. When foraging, ants move randomly until they encounter a pheromone trail, which they may choose to follow. The likelihood of an ant selecting a path is influenced by the pheromone density; a higher density increases the chance of selection [40].

In the ant colony optimization (ACO) algorithm, artificial ant colonies work together to tackle complex optimization problems. Ants traverse a network marked by artificial pheromones. The nest represents the initial state, and food signifies the final state. Each vehicle's route begins and ends at a depot, corresponding to the nest and food. Ants probabilistically select adjacent vertices based on pheromone levels on the various edges. Pheromones are stored in a multidimensional matrix reflecting the quantity on each edge over time. Each ant deposits pheromones on its path, which is influenced by the value of the objective function. To prevent local optima, pheromone levels gradually evaporate. Constraints are checked whenever an ant selects a new customer to ensure compliance with problem requirements. Additionally, heuristic information is employed to avoid stagnation in local optima.

To apply the ant colony optimization algorithm for multi-objective problems, multiple ant colonies sequentially explore the solution space to find better solutions. Each ant searches the network to generate a solution. These solutions are then compared, resulting in a set of nondominated solutions referred to as the colony's optimal Pareto set [49]. Assuming S1 and S2 to be two feasible solutions for a multi-objective minimization problem, if none of the objective functions achieved by S1 are larger than the objective functions corresponding to S2 and at least one objective function achieved by S1 is smaller than S2, S1 dominates S2. The pheromone of the edges belonging to the optimal Pareto set is increased so that the next colony can better discover the solutions found by the current colony. Part of the pheromone also evaporates regularly on all edges. The main operators of the multi-objective ant colony system are stated in the following.

4.1. Pheromone Structure

This algorithm employs two distinct pheromone trails for two objective functions, which are updated separately at the end of each iteration. The use of multiple pheromone trails to address various multi-objective problems has been explored in several studies, including unequal area facility layout, secure routing for wireless sensor networks, minimizing total completion time and energy costs in single-machine preemptive scheduling, and mixed-load school bus routing [49,50].

4.2. Heuristic Information

The heuristic information is determined based on three factors:

The travelling cost between customers i and j;

The travelling time $time_{it}$;

The amount of demand $\widetilde{d}_{jt}$ of customer j;

For ant k located at customer i, two separate pieces of heuristic information corresponding to the two objective functions of the problem are defined as follows:

$$\eta_{ijt}^{C} = \frac{1}{c_{ijt}} \tag{21}$$

$$\eta_{ijt}^{S} = \frac{1}{time_{jt} d_{jt}} \tag{22}$$

4.3. Quasi-Random Probability Rule

When ant k is at the location of customer i, the next customer from the neighborhood of customer i in period t is selected based on the following quasi-random probability rule:

$$j = \begin{cases} \text{argmax}_{l \in N_i^{kt}} \left\{ \left[\left(\tau_{ijt}^{C}\right)^{\alpha} \left(\eta_{ijt}^{C}\right)^{\beta} \right]^{\lambda} \left[\left(\tau_{ijt}^{S}\right)^{\alpha} \left(\eta_{ijt}^{S}\right)^{\beta} \right]^{1-\lambda} \right\} & N_i^{kt} \neq \varnothing, q \leq q_0 \\ j^* & o.w. \end{cases} \tag{23}$$

in which $0 \leq q_0 \leq 1$ is a random parameter and j^* is a random variable selected based the following random probability rule:

$$p_{ij}^{t} = \frac{\left[\left(\tau_{ijt}^{C}\right)^{\alpha} \left(\eta_{ijt}^{C}\right)^{\beta} \right]^{\lambda} \left[\left(\tau_{ijt}^{S}\right)^{\alpha} \left(\eta_{ijt}^{S}\right)^{\beta} \right]^{1-\lambda}}{\sum\limits_{j' \in N_i^{k,t}} \left[\left(\tau_{ij't}^{C}\right)^{\alpha} \left(\eta_{ij't}^{C}\right)^{\beta} \right]^{\lambda} \left[\left(\tau_{ij't}^{S}\right)^{\alpha} \left(\eta_{ij't}^{S}\right)^{\beta} \right]^{1-\lambda}} \quad j \in N_i^{kt} \tag{24}$$

in which α, β and λ are parameters. The value of λ is obtained based on the following relation:

$$\lambda = \begin{cases} 0 & k \leq a \\ \frac{k}{b-a} - \frac{a}{b-a} & a < k < b \\ 1 & k \geq b \end{cases} \tag{25}$$

where a and b are two parameters. According to the definition of λ, some ants use only information about one of the objective functions, while others use information about both objective functions.

The decision rule to service customer j after i in period t is defined as follows:

$$p_{(i,j)}^{t} = \begin{cases} \frac{\left[\left(\tau_{ijt}^{C}\right)^{\lambda} \left(\tau_{ijt}^{S}\right)^{1-\lambda} \right]^{\alpha} \left[\eta_{ijt}\right]^{\beta}}{\sum\limits_{j' \in N_i} \left[\left(\tau_{ij't}^{C}\right)^{\lambda} \left(\tau_{ij't}^{S}\right)^{1-\lambda} \right]^{\alpha} \left[\eta_{ij't}\right]^{\beta}} & j \in N_i \\ 0 & o.w. \end{cases} \tag{26}$$

in which $\lambda \in (0, 1)$ indicates the relative importance of the objective functions. Also, α and β are two parameters that indicate the ant's relative tendency to follow the path using pheromone information and heuristic information, respectively.

4.4. Pheromone Update

The pheromone level of each link is updated through two mechanisms. The evaporation rule reduces the pheromone of each selected link according to the following evaporation rate:

$$\tau_{ijt}^{C} \leftarrow (1 - \xi) \tau_{ijt}^{C} \tag{27}$$

$$\tau_{ijt}^{S} \leftarrow (1 - \xi) \tau_{ijt}^{S} \tag{28}$$

in which $0 < \xi < 1$ is a parameter. In this way, after selection of customer j after i in period t, its corresponding pheromone trail is reduced by a ratio of $1 - \xi$ and its desirability is reduced for subsequent selections.

The pheromone levels on the links of the colony's Pareto-optimal solutions are updated in each iteration as follows:

$$\tau_{ijt}^{C} = \min\left\{1, \tau_{ijt}^{C} \cdot \rho + \frac{Q}{C}\right\} \tag{29}$$

$$\tau_{ijt}^{S} = \min\left\{1, \tau_{ijt}^{S} \cdot \rho + \frac{Q}{S}\right\} \tag{30}$$

in which C is the sum of the cost of Pareto-optimal solutions and S is the sum of $time_{it} * d_{it}$ where customer i is located in one of the Pareto-optimal solutions.

In each iteration of the multi-objective ant colony system, a set of feasible solutions was generated, which were then evaluated using the simulated annealing algorithm. This optimization technique, inspired by the gradual cooling of metals, helps the system reach its lowest-energy state by reducing atomic movements. It is effective in identifying global optimal solutions, as it prevents getting stuck in local optima within the search space. The steps of the proposed hybrid algorithm are as follows:

Step 1: Initialize all parameters of the multi-objective ant colony system.

Step 2: Initialize the computational temperature T to a great value.

Step 3: For each colony c and ant k, construct a solution s.

Step 4: If the constructed solution s is non-dominated by the current Pareto set (PS), accept it. Otherwise, evaluate the solution based on Equation (31) and accept it with the probability $P = -\frac{E(s)}{T}$.

$$E(s) = \min_{s^* \in PS} \sqrt{(f_1(s) - f_1(s^*))^2 + (f_2(s) - f_2(s^*))^2} \tag{31}$$

Step 5: Update the pheromone trail.

Step 6: Update the temperature T according to the cooling schedule (32) and repeat steps 3–6 until the temperature is small according to the following formula:

$$T(n) = \frac{1}{\rho + 1}(\rho + \tanh(\gamma^n))T(n-1), \tag{32}$$

where $\rho = 4$ and γ is a parameter between 0.8 and 0.99.

In the following section, various numerical experiments have been carried out to assess the effectiveness of the proposed algorithm.

5. Numerical Results

This section provides numerical examples illustrating the effectiveness of the proposed hybrid multi-objective ant colony system and simulated annealing algorithm, along with a discussion on model validation. The algorithm was implemented on a computer with 8 GB of RAM and a 1.6 GHz CPU.

In the first experiment, we selected the optimal algorithm parameters. The number of ants varied based on the number of customers across different periods; as customer numbers increase, the solution space expands, necessitating more ants for an effective search. According to the introduced quasi-random probability law, some ants rely solely on the first objective function, while others focus exclusively on the second, generating Pareto-optimal solutions. The remaining ants utilize a combination of both objective functions. In our tests, the number of ants using information from both objective functions was fewer than those using either function individually. This occurs because finding a Pareto-optimal solution is considerably more complex for ants relying on a single objective function. Other parameter values were determined experimentally and are listed in Table 1.

Table 1. The values of the parameters of the algorithm.

Parameter	a	b	q_0	ρ	ξ	α	β	T
Value	1.2	2.25	0.9	0.9	0.1	2	1	100

The second experiment presents a small example demonstrating the key concepts and results of the proposed model and solution approach. It involves a two-objective, two-period fuzzy vehicle routing and scheduling problem with seven disaster centers and two distribution centers. The problem's parameters are detailed in Tables 2–4.

Table 2. The values of parameters $\widetilde{c}_{ijt}$, $\widetilde{c}'_{dit}$, $\widetilde{w}_{ijt}$, and $\widetilde{w}'_{dit}$ for $t = 1$.

		Customers						
		1	2	3	4	5	6	7
Customers	1		(9,12,15) (12,13,14)	(20,19,22) (13,16,19)	(28,30,33) (23,24,26)	(17,21,22) (14,18,19)	(15,17,19) (21,23,25)	(20,22,23) (21,23,25)
	2	(9,12,15) (12,13,14)		(13,15,16) (17,19,20)	(33,36,38) (6,7,9)	(20,21,24) (9,11,13)	(28,29,30) (16,18,20)	(34,35,36) (11,12,14)
	3	(20,19,22) (13,16,19)	(13,15,16) (17,19,20)		(45,48,50) (17,18,20)	(33,35,36) (13,14,18)	(34,35,37) (12,13,15)	(32,35,38) (12,14,15)
	4	(28,30,33) (23,24,26)	(33,36,38) (6,7,9)	(45,48,50) (17,18,20)		(18,20,23) (12,13,15)	(18,20,23) (15,18,19)	(33,34,37) (18,19,21)
	5	(17,21,22) (14,18,19)	(20,21,24) (9,11,13)	(33,35,36) (13,14,18)	(18,20,23) (12,13,15)		(24,25,26) (9,11,13)	(37,38,41) (9,11,14)
	6	(15,17,19) (21,23,25)	(28,29,30) (16,18,20)	(34,35,37) (12,13,15)	(18,20,23) (15,18,19)	(24,25,26) (9,11,13)		(15,18,20) (17,18,19)
	7	(20,22,23) (21,23,25)	(34,35,36) (11,12,14)	(32,35,38) (12,14,15)	(33,34,37) (18,19,21)	(37,38,41) (9,11,14)	(15,18,20) (17,18,19)	
Depots	1	(12,16,18) (7,9,12)	(10,13,14) (14,16,18)	(13,14,17) (12,16,20)	(21,22,24) (21,23,25)	(16,20,21) (12,15,16)	(5,7,8) (14,17,18)	(13,16,21) (19,22,24)
	2	(15,17,19) (13,14,16)	(12,15,16) (5,7,8)	(27,30,32) (13,15,19)	(18,23,24) (11,14,15)	(8,10,12) (25,26,27)	(18,19,21) (10,14,15)	(12,15,17) (16,18,20)

Table 3. The values of parameters $\widetilde{c}_{ijt}$, $\widetilde{c}'_{dit}$, $\widetilde{w}_{ijt}$, and $\widetilde{w}'_{dit}$ for $t = 2$.

		Customers						
		1	2	3	4	5	6	7
Customers	1		(32,35,36) (14,15,16)	(42,45,47) (8,10,12)	(21,23,25) (13,16,17)	(28,30,33) (32,34,36)	(43,44,45) (18,19,21)	(25,27,28) (10,12,17)
	2	(32,35,36) (14,15,16)		(10,12,15) (24,25,26)	(11,12,15) (18,19,23)	(18,20,24) (11,13,15)	(45,47,48) (6,8,9)	(40,43,44) (10,12,13)
	3	(42,45,47) (8,10,12)	(10,12,15) (24,25,26)		(20,22,23) (18,19,20)	(21,23,25) (15,18,19)	(44,45,47) (22,24,25)	(43,44,46) (19,20,22)
	4	(21,23,25) (13,16,17)	(11,12,15) (18,19,23)	(20,22,23) (18,19,20)		(12,13,15) (24,26,27)	(38,40,42) (15,17,18)	(28,30,31) (10,13,14)
	5	(28,30,33) (32,34,36)	(18,20,24) (11,13,15)	(21,23,25) (15,18,19)	(12,13,15) (22,24,25)		(21,23,27) (18,19,21)	(19,20,22) (23,25,26)
	6	(43,44,45) (18,19,21)	(45,47,48) (6,8,9)	(44,45,47) (22,24,25)	(38,40,42) (15,17,18)	(21,23,27) (18,19,21)		(15,16,18) (13,15,16)
	7	(25,27,28) (10,12,17)	(40,43,44) (10,12,13)	(43,44,46) (19,20,22)	(28,30,31) (10,13,14)	(19,20,22) (23,25,26)	(15,16,18) (13,15,16)	

Table 3. *Cont.*

		Customers						
Depots	1	(6,8,9) (14,16,18)	(12,15,18) (12,17,18)	(9,10,12) (14,15,16)	(14,16,18) (11,15,18)	(14,15,19) (12,15,16)	(7,9,10) (10,13,15)	(25,26,28) (10,13,15)
	2	(10,13,14) (10,13,15)	(23,24,26) (15,18,19)	(7,12,13) (9,10,12)	(8,11,12) (21,23,24)	(12,14,16) (17,18,20)	(13,14,17) (14,17,18)	(18,23,24) (10,13,15)

Table 4. Fuzzy demand of disaster centers in two periods.

	Periods	
Customers	**1**	**2**
1	(4,9,12)	(12,13,17)
2	(16,18,22)	(17,18,20)
3	(7,11,13)	(12,15,16)
4	(13,15,18)	(16,18,19)
5	(8,12,13)	(10,13,16)
6	(15,18,20)	(12,17,22)
7	(14,15,18)	(12,15,16)

Table 5 displays the Pareto-optimal solutions for the small example, detailing the vehicle routes that include both distribution and disaster centers. Figure 1 illustrates Pareto-optimal solution #1. The last column of Table 5 outlines the service schedules for disaster centers. The small example was also solved using AMPL (A Mathematical Programming Language) for comparison. While the objective function values from AMPL matched those from the proposed approach, the execution time in AMPL was over three times longer.

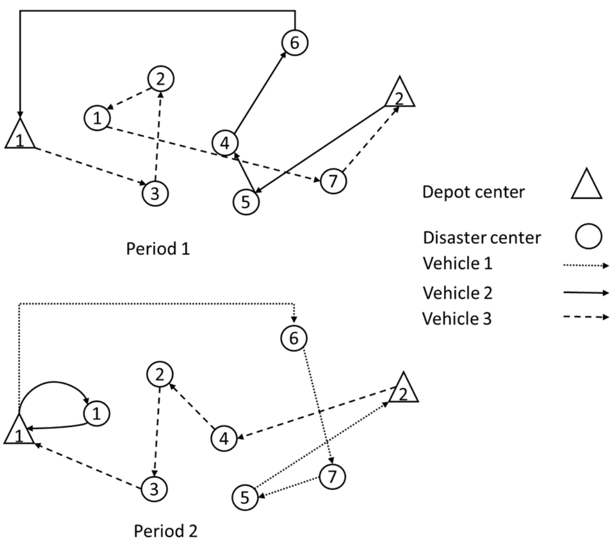

Figure 1. Graphical representation of Pareto-optimal solution #1.

In the third experiment, benchmark examples were utilized to evaluate the performance of the proposed model and solution approach for medium and large problems. These examples were created by combining the standard benchmarks of the multi-depot vehicle routing problem, which are available at http://www.bernabe.dorronsoro.es/vrp/ (accessed on November 2006). The details of the generated examples are presented in Table 6.

Table 5. The set of Pareto-optimal solutions.

Solution	Values of Objective Functions	Routes of Vehicles	Customer Service Schedule
1	$f_1 = 256.2$ $f_2 = 8040$	$t = 1, k = 3: 1 \to 3 \to 2 \to 1 \to 7 \to 2$ $t = 1, k = 2: 2 \to 5 \to 4 \to 6 \to 1$ $t = 2, k = 3: 2 \to 4 \to 2 \to 3 \to 1$ $t = 2, k = 1: 1 \to 6 \to 7 \to 5 \to 2$ $t = 2, k = 2: 1 \to 1 \to 1$	$time_{11} = 48$, $time_{12} = 16$ $time_{21} = 35$, $time_{22} = 42$ $time_{31} = 16$, $time_{32} = 67$ $time_{41} = 39$, $time_{42} = 23$ $time_{51} = 26$, $time_{52} = 53$ $time_{61} = 57$, $time_{62} = 13$ $time_{71} = 71$, $time_{72} = 28$
2	$f_1 = 257.7$ $f_2 = 8000$	$t = 1, k = 1: 1 \to 3 \to 2 \to 1 \to 7 \to 1$ $t = 1, k = 2: 2 \to 5 \to 4 \to 6 \to 1$ $t = 2, k = 1: 1 \to 3 \to 2 \to 4 \to 2$ $t = 2, k = 2: 1 \to 6 \to 7 \to 5 \to 2$ $t = 2, k = 3: 1 \to 1 \to 1$	$time_{11} = 48$, $time_{12} = 16$ $time_{21} = 35$, $time_{22} = 40$ $time_{31} = 16$, $time_{32} = 15$ $time_{41} = 39$, $time_{42} = 63.3$ $time_{51} = 26$, $time_{52} = 53$ $time_{61} = 57$, $time_{62} = 13$ $time_{71} = 71$, $time_{72} = 28$
3	$f_1 = 267.6$ $f_2 = 7000$	$t = 1, k = 3: 1 \to 1 \to 2 \to 3 \to 1$ $t = 1, k = 2: 2 \to 5 \to 4 \to 6 \to 1$ $t = 1, k = 1: 2 \to 7 \to 1$ $t = 2, k = 1: 1 \to 3 \to 2 \to 4 \to 2$ $t = 2, k = 2: 1 \to 6 \to 7 \to 5 \to 2$ $t = 2, k = 3: 1 \to 1 \to 1$	$time_{11} = 9$, $time_{12} = 16$ $time_{21} = 22$, $time_{22} = 40$ $time_{31} = 41$, $time_{32} = 15$ $time_{41} = 42.64$, $time_{42} = 59$ $time_{51} = 26$, $time_{52} = 53$ $time_{61} = 60.64$, $time_{62} = 13$ $time_{71} = 18$, $time_{72} = 28$
4	$f_1 = 270$ $f_2 = 6500$	$t = 1, k = 3: 2 \to 4 \to 5 \to 2$ $t = 1, k = 2: 1 \to 1 \to 2 \to 3 \to 1$ $t = 1, k = 1: 2 \to 7 \to 6 \to 1$ $t = 2, k = 1: 1 \to 6 \to 7 \to 5 \to 2$ $t = 2, k = 2: 1 \to 1 \to 1$ $t = 2, k = 3: 1 \to 4 \to 2 \to 3 \to 2$	$time_{11} = 9$, $time_{12} = 16$ $time_{21} = 22$, $time_{22} = 42$ $time_{31} = 41$, $time_{32} = 67$ $time_{41} = 14$, $time_{42} = 23$ $time_{51} = 28$, $time_{52} = 54.4$ $time_{61} = 36$, $time_{62} = 13$ $time_{71} = 18$, $time_{72} = 29.4$

Table 6. The specification of the benchmark examples.

Instance	Number of Periods	Number of Depots	Number of Vehicles
P01, P02	2	5	10
P01, P03	2	5	10
P01, P04	2	5	10
P02, P03	2	5	10
P02, P04	2	5	10
P03, P04	2	5	10
P01, P02, P03	3	5	10
P01, P02, P04	3	5	10
P01, P03, P04	3	5	10
P02, P03, P04	3	5	10
P01, P02, P03, P04	4	5	10

This section compares the performance of the proposed hybrid multi-objective ant colony system and simulated annealing algorithm with the multi-objective cat swarm optimization (MCSO) algorithm [51,52] and multi-objective fitness-dependent optimizer (MOFDO) algorithm [27]. Table 7 presents the average values of the two objective functions for the nondominated solutions identified by each algorithm in every instance. The fifth and seventh columns of Table 7 indicate the percentage differences between the nondominated solutions produced by the algorithms.

Table 7. Comparing the performance of the proposed hybrid algorithm with the MCSO and MOFDO algorithms.

Instance		Hybrid Algorithm (This Paper)	MCSO Algorithm		MOFDO Algorithm	
				Difference (Percent)		Difference (Percent)
P01, P02	f_1	1362.74	1362.74	0	1358.25	−0.33
	f_2	4017.75	4145.76	3.08	4103.41	2.08
	Time(s)	78	53		79	
P01, P03	f_1	1356.09	1359.93	0.28	1356.09	0
	f_2	4829.72	4857.84	0.57	4834.67	0.1
	Time(s)	85	89		98	
P01, P04	f_1	1789.09	1799.18	0.56	1795.76	0.37
	f_2	6439.96	6521.84	1.25	6524.67	1.29
	Time(s)	87	83		93	
P02, P03	f_1	2061.18	2156.87	4.43	2174.57	5.21
	f_2	5582.74	5879.67	5.05	5634.25	0.91
	Time(s)	91	95		94	
P02, P04	f_1	1937.3	1987.56	2.52	1954.37	0.87
	f_2	6939.07	6921.23	−0.25	6930.14	−0.12
	Time(s)	123	111		131	
P03, P04	f_1	2154.91	2161.76	0.31	2152.45	−0.11
	f_2	6302.44	6412.56	1.71	6401.27	1.54
	Time(s)	145	156		163	
P01, P02, P03	f_1	2459.97	2598.76	5.34	2540.31	3.16
	f_2	5581	5987.3	6.78	5772.13	3.31
	Time(s)	234	254		250	
P01, P02, P04	f_1	2885.83	2956.87	2.4	2871.76	−0.48
	f_2	7542.17	7823.18	3.59	7792.54	3.21
	Time(s)	257	261		260	
P01, P03, P04	f_1	3055.55	3167.67	3.53	3047.75	−0.25
	f_2	6664.19	6718.19	0.8	6692.14	0.41
	Time(s)	247	259		264	
P02, P03, P04	f_1	3321.51	3478.98	4.52	3214.73	−3.32
	f_2	8597.18	9783.45	12.12	8673.54	0.88
	Time(s)	298	345		367	
P01, P02, P03, P04	f_1	4689.39	4893.91	4.17	4713.98	0.52
	f_2	8853.29	8976.76	1.37	8852.73	−0.01
	Time(s)	376	671		895	

The comparison of the proposed hybrid multi-objective ant colony system and simulated annealing algorithm with the MCSO algorithm demonstrates that the hybrid approach is highly effective in achieving lower objective function values, as indicated in Table 7.

Additionally, in 8 out of 11 test instances, the hybrid algorithm provided solutions in less CPU time than the MCSO algorithm.

While it is evident that our proposed hybrid algorithm typically demonstrates superior performance overall, the MOFDO algorithm outperforms it in some instances. Specifically, in 4 out of a total of 11 different cases analyzed, the MOFDO algorithm produced an f_1 value that was lower than the corresponding f_1 value generated by our proposed algorithm. Furthermore, when examining the accuracy of the f_2 values, we discovered that in 2 of the 11 cases, the MOFDO algorithm yields more precise results compared to our proposed algorithm. This shows that although our algorithm is generally more effective, the MOFDO algorithm can still excel in particular scenarios.

Figure 2 compares the execution times of the three algorithms. The results show that the proposed algorithm consistently outperforms the MCSO algorithm in execution time. Furthermore, the MOFDO algorithm has consumed longer execution times in all cases. In general, the proposed hybrid algorithm typically produces results that are better or at least comparable to those of the MCSO and MOFDO algorithms, according to the findings reported.

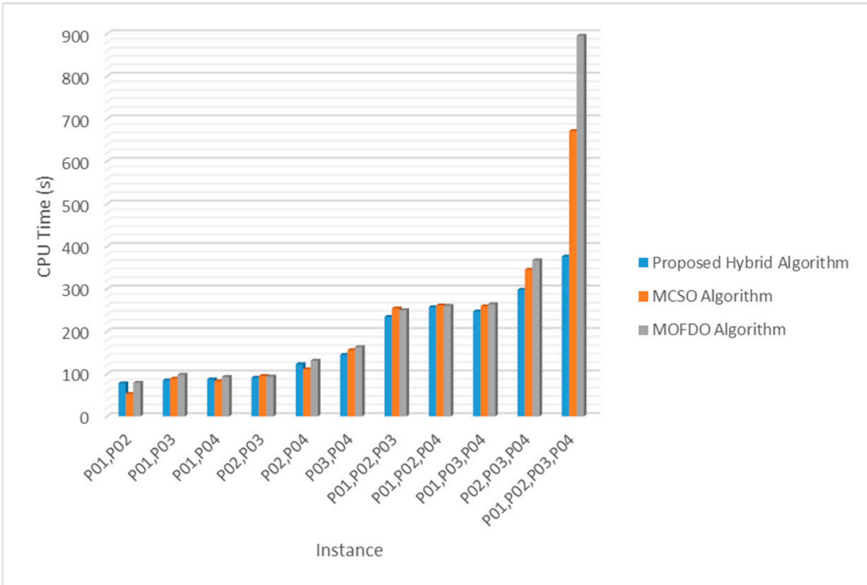

Figure 2. Comparing the execution times of the algorithms.

6. Conclusions and Future Directions

This paper addresses the multi-objective, multi-period integrated routing and scheduling problem for distributing relief to disaster areas under uncertain conditions. We propose a fuzzy multi-objective integer programming model to formulate the problem. To solve it, we developed a hybrid multi-objective heuristic algorithm that combines a multi-objective ant colony system with a simulated annealing algorithm. A small example illustrated the key concepts of our model and solution approach. Additionally, benchmark instances were used to evaluate the performance of the hybrid algorithm, comparing the results to those of a multi-objective cat swarm optimization algorithm and multi-objective fitness-dependent optimizer algorithm. The findings indicate that our hybrid algorithm effectively finds solutions with lower objective function values in a relatively short computation time in most cases. Future research could explore problem decomposition and customer selection strategies to enhance algorithm performance, along with the implementation of more powerful heuristic operators. Additionally, due to the limited supply and time in the early periods, it is applicable to expand the model to distribute relief based on specific periods.

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