Optimization of Humanitarian Aid Distribution Using the Bee Colony Algorithm

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Abstract– This study addresses the optimization of humanitarian logistics during natural disasters by implementing the Artificial Bee Colony (ABC) algorithm. Natural disasters frequently disrupt infrastructure and supply chains, complicating aid distribution. The paper reviews bio-inspired and metaheuristic algorithms, with a focus on ABC, which mimics the foraging behavior of bees to explore and exploit optimal solutions efficiently. The ABC algorithm is compared against a genetic algorithm using statistical tests, including Shapiro-Wilk, F-test, and Z-test, confirming ABC's superior performance in resource distribution. The research identifies key challenges such as uncertain data, limited transportation capacity, and the need for equitable aid allocation. Numerical experimentation demonstrates that the ABC algorithm delivers higher efficiency and effectiveness in planning relief operations. Additionally, the study presents a software interface to facilitate parameter configuration and result visualization. This work contributes to the field by introducing the ABC algorithm in a new context, offering a reliable tool for disaster response planning.

Keywords-- Humanitarian Logistics, Bee Colony Algorithm, Optimization, Disaster Response, Bioinspired Algorithms.

I. INTRODUCTION

Humanity has continually experienced the devastating effects of natural disasters such as earthquakes, tsunamis, and tornadoes, the impact of which varies by geographical location. According to the WMO (World Meteorological Organization), between 1970 and 2019, these events caused more than 2 million lives lost and an economic impact valued at 3.64 trillion dollars [1]. Given these effects, there is a need to mitigate and prepare for action before, during, and after these disasters [2]. However, given that disasters are inevitable and difficult to predict [3], organizations face challenges coordinating logistic efforts, complicating the timely delivery of aid to impacted areas due to roadblocks and scarce resources. Humanitarian logistics involves multiple sectors, each with its own capabilities and limitations [4], [3]. Coordination difficulties between these actors can delay aid delivery, which is exacerbated when infrastructure is destroyed and more efficient management of available resources is required [5]. This underscores the importance of identifying priority needs and optimizing distribution, especially in the first days after a disaster, when survival depends on essential resources [6].

Furthermore, logistical challenges in the delivery of food, medicine, and other supplies have a considerable impact on public health, both in the short and long term, due to the lack of basic services and exposure to disease [7]. In case emergency

situations, many people are forced to move in search of aid, which also contributes to the crisis. Logistics planning is essential for aid distribution in major disasters and involves solving optimization problems, such as warehouse location, distribution, and inventory planning. This is complex due to capacity and cost constraints [8].

Humanitarian logistics involves multiple sectors, each with its own capabilities and limitations [4], [10]. Coordination difficulties among these actors can delay aid delivery, particularly when infrastructure is destroyed, requiring more efficient resource management [5]. This underscores the importance of identifying priority needs and optimizing distribution, especially in the first days following a disaster, when survival depends on essential resources [6]. Additionally, logistical problems in delivering food, medicine, and other supplies significantly impact public health in the short and long term due to a lack of basic services and exposure to diseases [7]. During emergencies, many people are forced to relocate in search of aid, further contributing to the crisis.

Logistics planning is essential for aid distribution in major disasters and involves solving optimization problems such as warehouse location, distribution, and inventory planning. This is complex due to capacity constraints and costs [8]. One proposed solution to this distribution problem was developed by engineer Robert Aduviri Choque in 2018, who implemented a genetic algorithm, a biology-inspired method, to provide optimal solutions. This study seeks to improve that solution by employing another bio-inspired algorithm to achieve better results with shorter response times

II. BEE COLONY ALGORITHM

The Artificial Bee Colony (ABC) algorithm, developed by Dervis Karaboga in 2005, is an optimization method based on the cooperative behavior of bees. In this algorithm, each solution is represented as a food source that artificial bees explore in a multidimensional search space. The algorithm seeks a balance between exploration and exploitation to identify optimal solutions, both locally and globally. It begins with randomly generated solutions, where employed bees optimize options, and observer bees select and improve the best sources based on shared information. Scout bees, meanwhile, introduce new solutions, replacing those that have not improved over a given time [9]. The effectiveness of ABC is determined by parameters such as the number of food sources, the trial limit, and the number of cycles, which affect its efficiency and ability to find optimal solutions, although tuning them correctly can be challenging.

The pseudocode of the classic ABC algorithm is detailed in Figure 1. In the bee colony algorithm, SN represents food sources, *Cmax* is the total number of algorithm cycles, and *Limit* defines the number of cycles without improvement before replacing the solution with a new one from a scout bee. These algorithms leverage the collective intelligence of artificial bees to find optimal or near-optimal solutions. They are computationally efficient as they require fewer evaluations of the objective function compared to other optimization methods. However, a downside is that the algorithm can get stuck in local minimum, limiting its ability to explore potentially better solutions [9]. For experimental and comparative purposes, a genetic algorithm was also developed as part of this project.

1. Initialize the solution population $x_{ij;0}$; i= 1, … , SN
2. Evaluate the population
3. **For** c = 1 **up to** Cmax **do**
4. Generate new solutions u_{ij} for the employed bees
5. Keep the best solution between x_{ij} and u_{ij}
6. Select the solutions that will be visited by the observer bees
7. Generate new solutions u_{ij} for the observer bees
8. Keep the best solution between x_{ij} and u_{ij}
9. Check for abandoned sources (if the Limit has already been reached) and replace them with solutions randomly generated by the scout bees
10. Keep the best solution found so far
11. **End For**
12. Return the best solution

Fig. 1 Pseudocode of the BCA.

III. Research Questions

During and after natural disasters, several factors must be considered for aid distribution. The main factors identified in the reviewed documents are detailed below:

A. Cost

This includes the need to reduce total costs, including production, procurement, plant and distribution center openings, transportation, and poor-quality costs (evaluation and prevention costs) [11]. It also considers integrated factors such as time cost, penalties for resource shortages, alternative supply sources, and multiple types of resources [12].

B. Time

Another crucial factor is the transportation used to distribute resources. The distribution time of resources and fairness in aid allocation are considered [13].

C. Environmental Effects

The environment plays a significant role, as weather conditions can cause disruptions in resources or hinder natural mobility [28].

D. Equity and Uncertainty

Equity ensures that communities with the same level of priority receive fair aid distribution. Additionally, uncertainty is considered regarding demand locations and the possibility that disasters may partially destroy facilities [14].

E. Distribution Centers

Finally, humanitarian aid distribution centers (HADC) play a crucial role in bridging the gap between stranded beneficiaries and relief aid during disasters [15].

The results indicate that various parameters influence the design of a relief supply network during a disaster. Many factors must be controlled to significantly mitigate the catastrophe and save lives by delivering relief products on time [16]. The main problems identified are described below:

1) Ecological Impact: Natural disasters affect infrastructure and transportation routes, posing a significant challenge for humanitarian logistics. Disasters can block routes, affect response times and require adjustments in distribution routes to safe areas [11], [17]. In practice, difficulties also arise in finding the shortest route to meet logistical needs in disaster areas [18].

2) Lack of Updated Information: Another major problem is that, due to the unpredictable nature of disasters, much of the data is uncertain, making it difficult to consider all scenarios to make the best possible decisions. The demand for supplies and acquisition and transportation costs are considered uncertain parameters [14].

3) Time: The time required to complete aid activities is also a critical factor, as assistance must be provided as quickly as possible [19].

F. Principal studies

Additionally, various other challenges include damaged road networks, high demand for multiple materials, resource shortages, multiple supply and demand sites, and limited transportation capacity [13]. Currently, various solutions are applied to address these challenges, each with specific considerations based on the model used. Some of the solutions found include:

A model designed to reduce total travel time, overall environmental impact, and total demand loss. A robust fuzzy stochastic optimization approach is used to han- dle uncertain data arising in disaster conditions. Given the problem's complexity, a hybrid approach integrating multi-objective programming and a heuristic algorithm is adopted for efficient resolution [20].

An effective model for assigning and scheduling rescue units can reduce economic and human losses in natural disasters. This study proposes a mixed-integer linear programming model to minimize weighted completion times and delays in relief operations [19].

A nonlinear mixed-integer programming model to maximize demand coverage and reduce operational costs and distances traveled [21].

A proposed model that addresses two related problems: vehicle routing (VRP) and the scheduling of relief distribution at demand points considering three objective functions: The first objective function minimizes operational costs, including fixed and variable costs of using a heterogeneous fleet based on the designated route.

A scenario-based, multi-period, multi-objective location and allocation model for supplying relief products to demand points under uncertainty. The proposed nonlinear model is initially linearized and then solved using the epsilon constraint technique. Due to the model's NP-hard property, an NSGA-II and a hybrid algorithm are also presented to solve larger instances [22]. Each of these studies approaches humanitarian aid distribution from different perspectives, optimizing resource use and improving disaster response.

The algorithms used in the solutions found vary widely. This systematic review identified two main families of algorithms used most frequently:

1) Bio-inspired Algorithms: Several analyzed studies use genetic algorithms (pure, hybrid, NSGA-II) ([11], [23], [17], [6], [24],[29],[30]). One publication mentions the use of simulated annealing (SA) and bee colony (BC) algorithms for large-scale problems. Results showed that SA and BC provided similar responses, but SA achieved results in less time than BC [25]. Additionally, particle swarm optimization (PSO) and ant colony optimization are also good options, as they allow data population evaluation from different perspectives.

2) Metaheuristic Algorithms: Some solutions use metaheuristic algorithms primarily for comparison. For example, one case used a developed algorithm alongside three well-known metaheuristic algorithms for comparison [26]. Another interesting option observed in the research is a study that developed a Lagrangian relaxation algorithm to solve large-scale problems [27].

This literature review provided a clearer perspective on methods and studies related to humanitarian aid distribution in natural disasters. The most frequently considered factors in proposed solutions include time, cost, and route planning. However, several solutions also consider resource demand levels, prioritization, and equity. Based on these factors, the solution for this work was developed. Additionally, it was identified that many solutions use genetic algorithms, and recently, bee colony algorithms have gained traction due to their ability to produce good results in less time. Thus, it is expected that a bio-inspired algorithm based on the behavior of a *bee colony* will generate effective results in a short time, which is crucial for decision-making in such cases.

IV. Proposed Algorithm

Authors' proposition can be seen on Figure 2.

```
BeeColonyAlgorithm (N, Cmax, Limit):
population = InitializePopulation (N)
bestSolution = None
For c from 1 to Cmax do:
   newEmployedSolutions = GenerateNewEmployedSolutions (po-
      pulation, network, resources)
   EvaluateAptitude (newEmployedSolutions)
   bestSolution = GetBestSolution (bestSolution, newEmployed-
      Solutions)
   observerSolutions = SelectObserverSolutions (population)
   newObserverSolutions = GenerateNewObserverSolutions (ob-
      serverSolutions, network, resources)
   EvaluateAptitude (newObserverSolutions)
   bestSolution = GetBestSolution (bestSolution, newObserver-
      Solutions)
   population = ReplaceAbandonedSources (population, Limit)
End For
Return bestSolution
```

Fig. 2 Proposed BCA Algorithm

BeeColonyAlgorithm function is the core of the algorithm, responsible for finding optimal solutions. It receives three parameters: N (population size or number of candidate solutions), Cmax (maximum number of cycles), and Limit (number of cycles without improvement before stopping). The procedure begins with the generation of a random population of solutions through *InitializePopulation* function, representing different ways to distribute resources across the network of distribution points. Then, a main loop of Cmax iterations is executed, where several optimization stages are developed:

1) Generation of new solutions for employed bees: New solutions are generated by exploring local neighborhoods of existing solutions. This process aims to find close neighbors and improve the current solutions.

2) Evaluation of employed bee solutions: Each newly generated solution is evaluated to determine its quality based on the objectives set in the optimization functions.

3) Selection of solutions for observer bees: Solutions are selected from the population for exploration by observer bees, considering quality and diversity.

4) Generation of new solutions for observer bees: Ob server bees generate new solutions by exploring neighborhoods close to the selected solutions. This process further improves the existing solutions and diversifies the search.

5) Evaluation of observer bee solutions: Newly generated solutions by observer bees are evaluated for quality and compared with existing solutions in the population.

6) Verification and replacement of abandoned sources: It is checked whether some solutions have not improved for several cycles defined by the Limit parameter. If this condition is met, these solutions are replaced by new randomly generated solutions to maintain diversity and explore the search space.

The loop repeats for *Cmax* iterations or until the best solution does not improve for *Limit* consecutive iterations. Finally, the function returns the best solution obtained throughout the process, representing the optimal distribution of resources for planning aid delivery in natural disaster scenarios in Peru.

V. Numerical Experimentation

To compare the results obtained from the implementations of the bee colony algorithm and the genetic algorithm, a numerical experiment was conducted. The data collection was based on the best-calibrated parameter results for each algorithm. The results were then summarized by grouping the number of resources distributed from warehouses to destination points to facilitate organized analysis.

Figures 3 and 4 show graphical representations of the results generated by both algorithms.

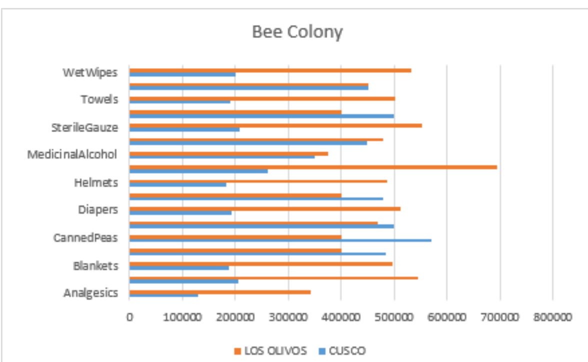

Fig. 3. Results graph for BCA in statistical tests

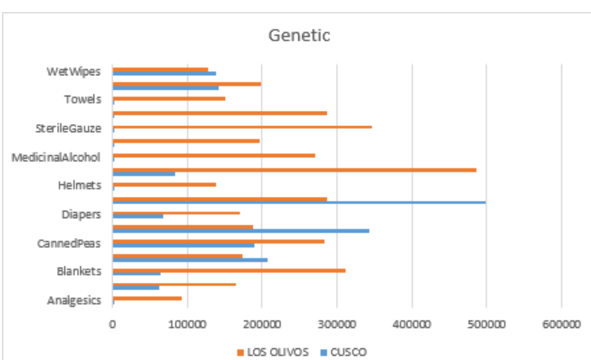

Fig. 4. Results graph for the genetic algorithm in statistical tests.

From a visual inspection, the bee colony algorithm shows better performance as it distributes a larger number of resources. This observation was validated through the following statistical tests.

First, the Shapiro-Wilk test was used to verify whether the data followed a normal distribution. This test is necessary because normality is a prerequisite for the Z-test.

For each algorithm, the Shapiro-Wilk test was applied separately. The hypotheses are:

1) H_0: The sample follows a normal distribution.

2) H_1: The sample does not follow a normal distribution.

Shapiro-Wilk's test for BCA proposed can visualize in follow Figure 5:

```
> shapiro_test_plan <- shapiro.test(bee_plan)
> print(shapiro_test_plan)

        Shapiro-Wilk normality test

data:  bee_plan
W = 0.93234, p-value = 0.2381
```

Fig. 5. Shapiro-Wilk's Test for BC Algorithm.

The p-value is 0.2381, greater than 0.05, so we do not reject the null hypothesis. Therefore, there is no evidence to say the data does not follow a normal distribution.

In other hand, for competitor Genetic Algorithm, Shapiro-Wilk's test can visualize in Figure 6:

```
> genetic_plan<-as.numeric(distribution_genetic_plan_summary$LOSOLIVOS)
> shapiro_test_genetic_plan <- shapiro.test(genetic_plan)
> print(shapiro_test_genetic_plan)

        Shapiro-Wilk normality test

data:  genetic_plan
W = 0.91261, p-value = 0.1107
```

Fig. 6. Shapiro-Wilk test for the genetic algorithm.

The p-value is 0.1107, also greater than 0.05, confirming the data follows a normal distribution.

Next, the F-test (Fisher's test) was used to check the homogeneity of variances:

1) H_0: The variances are homogeneous.

2) H_1: The variances are different.

F test is showing in Figure 7:

```
> fisher_test <- var.test(bee_plan, genetic_plan)
> print(fisher_test)

        F test to compare two variances

data:  bee_plan and genetic_plan
F = 0.73644, num df = 16, denom df = 16, p-value = 0.5477
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 0.266693 2.033562
sample estimates:
ratio of variances
          0.736435
```

Fig. 7. F-test for both algorithms.

The p-value of 0.5477, greater than 0.05, indicates there is not enough evidence to reject H0. Thus, we conclude that the variances between both samples are homogeneous.

Once normality and variance homogeneity were confirmed, a Z-test was performed to compare the means. The hypotheses are:

1) H_0: The mean of BCA is equal to the mean of GA.

2) H_1: The mean of BCA is different to the mean of GA.

```
> n_bee_plan <- length(bee_plan)
> n_genetic_plan <- length(genetic_plan)
> se_diff <- sqrt((sd_bee_plan^2 / n_bee_plan) + (sd_genetic_plan^2 / n_genetic_plan))
> z <- (mean_bee_plan - mean_genetic_plan) / se_diff
> p_value <- 2 * (1 - pnorm(abs(z)))
> cat("Test Z\n")
Test Z
> cat("Valor Z:", z, "\n")
Valor Z: 7.77343
> cat("p-valor:", p_value, "\n")
p-valor: 7.549517e-15
> cat("mean_bee_plan: ",mean_bee_plan, "\n")
mean_bee_plan:  472876.3
> cat("mean_genetic_plan: ",mean_genetic_plan, "\n")
mean_genetic_plan:  227570.1
```

Fig. 8. Z-test for both algorithms.

The very small p-value (7.549517e-15) indicates a very low probability that the observed difference in means is due to chance. Therefore, we reject H0 and accept H1, concluding that the bee colony algorithm achieves a significantly better mean performance.

Hence, the results indicate that the bee colony algorithm is an effective and optimal tool for disaster relief distribution, fulfilling the objectives set and outperforming the genetic algorithm.

VI. Conclusions

After conducting the necessary research and implementing proposed BCA to solve the problem of resource distribution in natural disasters, the following conclusions were made:

A. Variable and Constraint Definition

Key variables and constraints were determined based on previous studies and interviews with humanitarian logistics specialists.

B. Adaptation and Implementation Bee Colony Algorithm

The algorithm was successfully adapted and coded, including the necessary data structures and auxiliary functions.

C. Software Development

A graphical interface was de- signed to allow users to input problem data, configure algorithm parameters, and visualize results.

D. Algorithm Comparison

BCA was compared against a genetic algorithm using statistical tests such as Shapiro-Wilk and the Z-test, confirming its superior efficiency.

E. Validation of Results

Empirical tests confirmed the bee colony algorithm as an effective tool for optimizing humanitarian aid distribution in disaster scenarios.

In summary, it is concluded that implementation of the BCA for the humanitarian aid distribution problem is feasible and provides an optimal and practicable solution in real-life scenarios. Furthermore, this work con- tributes to the field of humanitarian logistics by introducing an algorithm that has not been previously applied in this context. This innovative approach not only increases the efficiency and effectiveness of resource distribution during emergencies but also establishes a solid foundation for future research and development in the field of resource optimization

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