

Analysis of optimized response time in a new disaster management model by applying metaheuristic and exact methods

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Abstract

Purpose – The purpose of this paper is to maximize the total demand covered by the established additive manufacturing and distribution centers and maximize the total literal weight assigned to the drones.

Design/methodology/approach – Disaster management or humanitarian supply chains (HSCs) differ from commercial supply chains in the fact that the aim of HSCs is to minimize the response time to a disaster as compared to the profit maximization goal of commercial supply chains. In this paper, the authors develop a relief chain structure that accommodates emerging technologies in humanitarian logistics into the two phases of disaster management – the preparedness stage and the response stage.

Findings – Solving the model by the genetic and the cuckoo optimization algorithm (COA) and comparing the results with the ones obtained by The General Algebraic Modeling System (GAMS) clear that genetic algorithm overcomes other options as it has led to objective functions that are 1.6% and 24.1% better comparing to GAMS and COA, respectively.



Originality/value – Finally, the presented model has been solved with three methods including one exact method and two metaheuristic methods. Results of implementation show that Non-dominated sorting genetic algorithm II (NSGA-II) has better performance in finding the optimal solutions.

Keywords Humanitarian logistics, Drones delivery, Operation research in disaster relief, Additive manufacturing, Cuckoo optimization algorithm, Genetic algorithm

Paper type Research paper

1. Introduction

Any occurrence that causes damage, destruction, ecological disruption, loss of human life, human suffering or the deterioration of health and health services on a scale sufficient to warrant an extraordinary response from outside the affected community or area is called disaster. Such situations may include natural disasters such as drought, earthquakes, floods or storms, epidemics or man-made disruptions such as nuclear or chemical explosions (Duran *et al.*, 2011).

Since the 1950s, both the number and magnitude of disasters have been continuously increasing, with the number of affected people increasing in proportion (about 235 million people per annum on average since the 1990s (Balcik and Beamon, 2008). In 2016, 342 disasters triggered by natural hazards were registered, with estimated economic damages of US\$154bn (Boonmee *et al.*, 2017). According to the International Disaster Database, China and the USA are most frequently hit by natural disasters. In 2016, with 34 natural disasters reported, China experienced its fifth-highest number of natural disasters of the last decade, 15.3% above its 2006–2015 annual average of 29.5. The number of natural disasters in the USA (26) was the fourth-highest since 2006, 22.5% above its decadal annual average (21.5) (Boonmee *et al.*, 2017).

In recent years, a global trend can be seen among countries, which shows their extensive attention to crisis management processes. Their goal is to reduce the global number of deaths, which has been affected by these crises. In fact, their main approach to accomplish this goal is laid in helping at-risk persons to avoid or recover from the effects of a disaster. In this order, timely access to first-hand and accurate information on the location of the accident, its severity and extent is very important (Balcik *et al.*, 2010). In addition, their other goal is minimizing the financial losses significantly, which is measured in world-wide gross domestic goods. These losses are mainly caused by catastrophes, such as detrimental effects to high-priority infrastructure and spoiling the basic services. What can contribute greatly to these goals are new technologies if they are extensively introduced and applied in the field of crisis management, for example, unmanned aerial vehicles (UAV), robots, additive manufacturing (AM), software and satellites. It can be seen this process is highly important, specifically in the high amount of investment realized by individual nations and international firms. The EU, as an example, has spent huge budgets on research and development projects on novel solutions. Numerous human beings are directly or indirectly affected by the devastating impact of disasters, whether losing their lives or suffering damage to their property and the natural environment as well.

As a result, the decisions made by disaster managers have an important role in diminishing their impact. The success and efficacy of such decisions depend on the quality of support systems or solutions which are applied as a part of regular operating approaches. Consequently, to guarantee that the managers are supported adequately by novel technologies for making their vital decisions, it is necessary to research and test the solutions, ideally under authentic conditions, before applying them in disaster response (Zwęgliński, 2020). This is especially important for health-care services. The operational volume of relief activities must have a high standard to be able to address the affected areas as shortly as possible. Having a firmly established preparedness plan for issues that deals with human health, validity and accuracy of data is vital for maintaining an efficient response in case of emergencies in rescue systems. (Goniewicz and Goniewicz, 2020).

According to the reasons mentioned above, the use of new technologies such as UAV or AM has become the focus of researchers today. These superior approaches can be successful both in providing accurate and timely information in response activities and in crisis relief activities, as well as by eliminating manual and time-consuming activities in each of the relief circles, avoiding unavoidable delays in a humanitarian supply chain (HSC). Among related studies, it is rare for both issues to be considered simultaneously in an HSC, in most cases being used alone or focusing on the diverse goals of locating models.

1.1 Additive manufacturing methods

The idea of AM, a rapidly growing technique, can be incorporated to ensure a robust and resilient supply chain network.

AM is a production technology that speeds up supply chain processes and is a technology that finalizes and manufactures its designs using 3D models, eliminating many of the extra loops in the supply chain (Muthukumarasamy *et al.*, 2018). This technology aims to be able to meet the greater demand of its customers and have a production commensurate with just-in-time production. Because this technology is speed based and accelerates the process, it reduces overhead time in the entire supply chain, which is the key to achieving customer excellence. This technology is very important in covering crisis management processes and therefore enhances the efficiency of the HSC (Tasé Velázquez *et al.*, 2020). According to Corsini *et al.* (2020), the HSC is unpredictable and its resources are much more limited. As the risk of sudden demand is much higher, the impact of AM technology performance on HSC effectiveness will be greater.

However, for the model, facility location models are used, which involve the location and selection of distribution centers, warehouses, shelters, medical centers, etc. The purpose of this paper is to maximize the total demand covered by the established AM and distribution centers.

AM centers along with distribution centers can address the challenges in the structure, capacity and management of an HSC (Corsini *et al.*, 2020). In fact, they accelerate the rapid response and cover more relief activities in the affected areas.

On the other hand, as second object, the total literal weight assigned to the drones is maximized. The use of drones to improve the HSC efficiency is remarkably grown and is one of the distinguishing aspects of our model with other models available. According to The United States Agency for International Development, one of the benefits of drones is their use in environments that are unsafe for humans and also difficult and time consuming to access (USAID, 2017).

1.2 Unmanned aerial vehicles

Use of UAV provides safety, protection and relief from disasters. Natural and man-made disasters destroy environments, often making conditions so difficult that relief workers are unable to access areas and provide assistance. Drones have the ability to take on roles where relief workers and manned vehicles fall short.

They also reduce the potential financial and human risks in the relief process. In addition, in the use of drones, the focus and accuracy of the machine replace human error and ultimately lead to increased quality and speed of response in some areas of relief operations (Soesilo *et al.*, 2016). These reasons make the importance of using drones, especially in an HSC, more and more apparent. The various ways in which these drones can assist emergency services in an HSC and rescue operations can be described as follows.

In flood disaster: In gathering data such as assess the direction in which the flood is heading, drone can be more helpful, even to predict which buildings might be at risk.

In earthquake: In the aftermath of an earthquake, rescue teams can use UAVS to identify routes that were destroyed due to caved-in tunnels or bridges that had given way. They can also use drones to identify population-dense buildings that had collapsed.

Search and rescue: Missing persons must be found as soon as possible to maximize their chance of survival.

To deliver emergency supplies: Drones can be used to deliver essential items such as food, water or life-saving medical supplies after a disaster, especially in a situation when traditional lines of communication and delivery are disabled while the air is nearly always accessible.

Disaster recovery: Drones can assist in the safe inspection of infrastructure for rebuilding areas where the disaster occurred, and it can be made more quickly than if they were done using traditional methods.

Situational awareness: It involves in evaluating the scale and impact of a disaster, managing traffic flow after a road traffic collision or monitoring an ongoing fire emergency (Adams *et al.*, 2016).

Examining the advantages and strengths mentioned in all previous research shows how much their application can affect the performance of an HSC. Most studies show on which aspect of an HSC improvement occurs, while in a small number of them, the simultaneous effect of two factors has been addressed. Taking into account this shortcoming, this research develops a model that considers the optimization of AM distribution centers at the same time as the allocation of drones, and its focus is on how to optimize the model using both technologies.

In fact, we develop a relief chain structure that accommodates emerging technologies in humanitarian logistics into the all four phases of disaster management – mitigation, preparedness response and recovery stages. As Tufekci and Wallace suggest, an effective emergency response plan should combine all of these stages while its objective is considered simultaneously (Altay and Green, 2006).

Further, the presented pre-disaster model is considered as facility location problem (FLP) model with two objectives and categorized as linear program (LP) problems. This type of models is usually stochastic due to the uncertainty of the disaster impact level. Two-stage stochastic programming (Lin *et al.*, 2011) and stochastic scenario analysis approaches (Balcik and Beamon, 2008), (Chang *et al.*, 2007) are frequently used to solve these models.

These solutions are applied to overcome emergency humanitarian logistics challenges, (Boonmee *et al.*, 2017). Based on Boonmee, two approaches can be used:

- (1) a heuristic algorithm; and
- (2) an exact algorithm.

Normally, the emergency humanitarian logistics' facility location problems are non-deterministic polynomial-time hardness (NP-hard), and most research studies have usually addressed this by using a heuristic algorithm because it requires less time to use and can solve complicated problems, but the results of this approach are of poor quality when compared with the exact algorithm. Although the first approach can overcome the second approach, the second approach is necessary because it can be used to check the heuristic algorithm. Moreover, in some real cases, an exact algorithm can also be used to solve the problem. Hence, the use of an exact algorithm is important and unavoidable. In this paper, it has been solved with three methods including one exact method and two metaheuristic methods – cuckoo and genetic algorithm (GA) – to find the best solution among them.

This article is structured in the following steps: In the first stage, after examining the importance of crisis management, the efficient implementation strategies of an HSC in

emergencies are discussed and the relevant studies are reviewed. In the second stage, data are collected, and problem-solving methods are evaluated. Considering the success of AM and UAV technologies in relief activities, a model is presented that considers the simultaneous nature of both of them in one HSC. Then, to verify the model, the designed problem is solved using two metaheuristic algorithms and a precise method, and the obtained results are compared. Finally, the analysis shows the extent to which the application of both technologies is effective in reducing the complexity and shortening of HSC loops. Recommendations for future research are also provided.

2. Literature review

In recent years, various articles have been published on the supply chain of humanitarian relief and humanitarian relief logistics, such as [Balcik and Beamon \(2008\)](#), [Overstreet et al. \(2011\)](#), [Wisetjindawat et al. \(2014\)](#), [Gutjahr and Nolz \(2016\)](#), [Daud et al. \(2016\)](#), [Boonmee et al. \(2017\)](#) and [Amideo et al. \(2019\)](#). The main focus of these studies has been decision-making in emergency situations and activities, and this shows the importance of the HSC. One of our most important innovations in this paper has been the simultaneous use of AM technology and drones to respond to crisis situations. For this reason, some articles have used the AM model for performing relief-building activities in crisis management, such as [Westphal et al. \(2020\)](#) and [Wang et al. \(2016\)](#). In a recent article, [Maximilian and Christian \(2020\)](#) discussed the application of AM in rapid response and its remarkable performance in emergency response to COVID-19 pandemic. Accordingly, AM provided relief to the strained health-care systems and manufacturing environments by offering an alternative way to rapidly produce desired products. This study sheds light on how AM was used globally in response to the COVID-19 pandemic.

The findings of the research well demonstrate the effective use of AM capacities in responding to social crises and managing potential disasters. Other studies by [Tönissen and Schlicher \(2020\)](#) and [Tatham et al. \(2015\)](#) examined the potential of AM technology to support preparedness and rapid response to a natural disaster or complex emergency and showed how AM potential improves the efficiency and effectiveness of humanitarian logistics operations. In other studies, [Corsini et al. \(2020\)](#), [Rodríguez-Espindola et al. \(2020\)](#) and [Wankmüller and Reiner \(2020\)](#) examined the effects of AM in helping to manage humanitarian crises. Some studies have considered the use of drones to be effective in the optimal coverage of disaster management and crises, and many articles have been published in this field, some of which are discussed below. [Pathak et al. \(2019\)](#) examined the humanitarian effects of using drones in crisis management, community health and past uses of these widely used devices to date, which clearly demonstrates their importance. One of the most widely used tools in operational and research projects for large military and operational organizations around the world today, especially in the USA, is drones. Another practical article on the use of drones examines the conditions of pre-flight processes to minimize the risk of using manned flights. As a result of this research and the laws and regulations based on it, the use of these processes in research projects has become mandatory for all US Navy organizations, and the importance of the issue in these circumstances is very clear ([Millar, 2015](#)). Another paper discusses the use of drones in the optimization approaches and planning operations and describes the applications of air drones ([Otto et al., 2018](#)). Application of different drones in humanitarian crisis management by the type of events and their impact on timely coverage and response to these events have been addressed in other articles such as [Woo\(2018\)](#), [Rabta et al. \(2018\)](#), [Van Wynsberghe and Comes\(2020\)](#), [Schlag \(2012\)](#) and [Chowdhury et al. \(2017\)](#). To the best of the authors' knowledge, no article has been published so far on the simultaneous use of AM and drones

in Humanitarian Relief Logistics and Supply Chain Management and in this respect; this research is unique in terms of addressing these issues together and integrating them to cover human crises.

The heuristic, metaheuristic and even precise methods to solve logistics and crisis management models have frequently been used by researchers. As such, [Stanley *et al.* \(2012\)](#) in an article entitled “Metaheuristics in Logistics and Supply Chain Management” examined various metaheuristic techniques, including ant colony optimization, GA, simulated annealing and taboo search metaheuristics. Because of the importance of rapid decision-making in disaster management, [Kim *et al.* \(2019\)](#) developed an innovative algorithm using Benders analysis to generate high quality and efficient solutions. Computational experiments showed the superiority of the developed algorithm, and sensitivity analysis was performed to gain additional insight.

Also, in another paper, [Zhang *et al.* \(2012\)](#) formulated the emergency resource allocation problem with constraints of multiple resources and possible secondary disasters, and a heuristic algorithm was designed to efficiently solve it based on linear programming and network optimization. The algorithm modifies the solutions of the linear programming by setting a priority of preference for each location where the secondary disasters will take place with certain possibilities.

Finally, in this article, we used metaheuristic methods such as GAs and cuckoo optimization as well as an accurate computational method called GAMS to show the application and high accuracy of the model. The details and results of each of the methods can be understood by the case comparison mentioned below.

3. Model

3.1 Mathematical model

Based on the above scenarios, the new model is constructed by a multi-objective integer programming formulation. This section first summarizes sets, parameters and define decision variables, followed by a presentation of a mathematical formulation for the model.

The model assumption:

- There are several s-scenarios. Each scenario is selected by the decision-maker based on factors such as the type of geographical area, the size of the affected area, the depth and extent of the disaster and the relief infrastructure available in the area.
- Demand is defined in terms of being able to be 100% successful in covering k items from the aid package if any of the predicted s scenarios occur.
- None of the objective functions takes precedence over the other, and they are ultimately given the same weights for optimization.
- The capacity of AM centers was considered equal to the capacity of distribution centers.
- The model was written in such a way that the capacity of distribution centers alone cannot meet the existing demand in the crisis area.
- The demand level for the affected area and the locations related to the demands are uncertain and depend on various factors including the disaster scenario and the impact of the disaster. Also, the uncertainty for the supplies and the cost parameters are considered through discrete scenarios from a set S of possible disaster situations are used.
- Multiple rescue commodities are delivered, and each commodity comes with different volume and logistic costs.

Sets

S = set of scenarios, $s \in S$;
 N = set of AM centers, $r \in N$;
 D = set of distribution centers, $j \in D$;
 K = set of item types, $k \in K$;
 I = set of drone, $i \in I$; and
 L = set of item assigned to the drone, $l \in L$.

Parameters

p_s = probability of occurrence of scenario s ;
 d_{sk} = expected demand in scenario s for item type k (units);
 Cap_j = the capacity of distribution center j (volume);
 Cap_r = the capacity of AM center r (volume);
 y_k = unit volume of item type k ;
 B_1 = emergency relief funds allocated for post-disaster distribution (post-disaster budget);
 w_k = criticality weight for item type k ;
 a_k = coverage for item type k over the q -mile radius;
 g'_{ik} = literal weight of item k assigned to drone i ;
 g_i = the weight capacity of drone i (volume);
 w'_{ik} = criticality weight of item k assigned to drone i ;
 c_{sjk} = the unit cost of shipping item type k from distribution center j to the disaster location of scenario s (\$/unit); and
 c_{srk} = the unit cost of shipping item type k from AM center r to the disaster location of scenario s (\$/unit).

Decision variables

f_{sjk} = the proportion of item type k demand satisfied by distribution center j in scenario s ;
 f_{srk} = the proportion of item type k demand satisfied by AM center r in scenario s ;
 Q_{jk} = units of item type k stored at distribution center j ;
 Q_{rk} = units of item type k stored at AM center r ;
 y_j = 1 if distribution center j is located, 0 otherwise;
 y_r = 1 if manufacturing additive center r is located, 0 otherwise; and
 x_{il} = 1 if part l is assigned to drone i , 0 otherwise.

3.1.1 Demand covering. We take off the constraint on emergency relief funds allocated for pre-positioning supplies.

The amount of funds allocated to the AM centers is limited by the capacity of the AM center and constraint for units of item type k stored at the center. Using the above notation, we formulate the model as follows:

$$Z_1 = \text{Max} \sum_{s \in S} \sum_{r \in N} \sum_{k \in K} p_s d_{sk} w_k a_k f_{srk} + \sum_{s \in S} \sum_{j \in N} \sum_{k \in K} p_s d_{sk} w_k a_k f_{sjk} \quad (1)$$

subject to

$$Q_{rk} \geq f_{srk} d_{sk} \quad \forall s \in S, r \in N, k \in K \quad (2) \quad \text{Analysis of}$$

$$Q_{jk} \geq f_{sjk} d_{sk} \quad \forall s \in S, j \in D, k \in K \quad (3) \quad \text{optimized}$$

$$Cap_r y_r \geq \sum_{k \in K} y_k Q_{rk} \quad \forall r \in N \quad (4)$$

$$Cap_j y_j \geq \sum_{k \in K} y_j Q_{jk} \quad \forall j \in D \quad (5)$$

$$\sum_{s \in S} \sum_{j \in D} \sum_{k \in K} d_{sk} c_{sjk} f_{sjk} + \sum_{s \in S} \sum_{r \in N} \sum_{k \in K} d_{sk} c_{srk} f_{srk} \leq B_1 \quad (6)$$

$$\sum_{j \in N} f_{sjk} + \sum_{r \in N} f_{srk} \leq 1 \quad \forall s \in S, k \in K \quad (7)$$

$$f_{sjk}, f_{srk} \geq 0, Q_{rk}, Q_{jk} \in \mathbb{Z}^+$$

$$\forall s \in S, r \in N, j \in D, k \in K \quad (8)$$

$$\sum_{k \in K} w_k = 1 \quad (9)$$

$$y_j, y_r \in \{0, 1\} \quad \forall r \in N, j \in D \quad (10)$$

Experiences from the speed of response approaches to previous disaster show that, regardless of the source of the disaster, the role of speed and logistical efficiency is very important (Pettit *et al.*, 2010), which can affect all activities of an HSC from planning to efficient control of item transfer flows. Humanitarian logistics is the application of processes and systems that use people, knowledge, skills and resources to help those affected (Tomasini *et al.*, 2009). In this model, in addition to distribution centers, AM centers were used as a new technology in crisis management because it can simultaneously lead to the eliminating duplicate steps from the production chain, maintaining inventory to cover existing demand and ultimately increasing the flexibility of the chain in quick reactions in times of crisis. In the first objective function, at each center (r), the probability of occurrence of each scenario (ps) measures the performance of that scenario in each crisis as the effectiveness of each AM center in crisis recovery and relief activities depends directly on the type of scenario selected. The “ d_{sk} ” determines the amount of demand coverage for commodity K in each scenario S that contributes to determining the amount of demand allocated to the AM center. The critical weights w_k indicate how effective the K item can be in covering the damage occurred. Factors such as the type of occurred crisis and the extent of damage weigh the importance or insignificance of a “ K ” item. Thus, the more K item, as a

factor of a_k , can cover the greater distance of the affected area by AM centers, the higher the efficiency of crisis relief activities. In other words, the greater the coverage, the faster each response and recovery step. All the above parameters were also considered for the distribution centers.

The objective function (1) maximizes the expected demand covered by the established AM and distribution centers. It must be noted that the sum of all weights over k must be equal to one. Constraint set (2) ensures that the inventory level at AM centers is no smaller than the maximum amount of demand that the AM centers will face from a single disaster scenario. Similarly, constraint set (2) ensures that the inventory level at the additive distribution center is no smaller than the maximum amount of demand that the additive distribution center will face from a single disaster scenario. Constraint set (4) guarantees that the inventory is held only at established AM centers, and the amount of inventory kept at any AM centers does not exceed its capacity. Similarly, constraint set (4) guarantees that the inventory is held only at a distribution center, and the amount of inventory kept at any distribution center does not exceed its capacity. Constraint (6) guarantees that the transportation costs incurred between AM centers and each disaster scenario are less than the expected post-disaster budget. Constraint set (7) ensures the number of supplies sent to satisfy the demand for a disaster scenario does not exceed the actual demand. Constraint set (8) is the non-negativity constraint on the proportion of demand satisfied. Constraint set (10) guarantees that the sum of all weights over k is equal to one, and finally, constraint set (10) defines the binary location variable.

For the response stage, there have been algorithms and models developed. We try to solve assigned items to drones at each additive distribution center. For this, we modify the generalized assignment problem. The generalized assignment problem maximizes profit.

3.1.2 Assigned weight. In this section, we consider $l = 1, \dots, L$ kinds of items and $i = 1, \dots, I$ kinds of drones where each drone is associated with a weight capacity g_i . For each drone, each item has a criticality weight w'_{il} and literal weight g'_{il} . For each drone, the total literal weight assigned is g_i . We need to assign the items to drones according to their criticality weight and literal weight to maximize criticality value.

$$Z_2 = \text{Max} \sum_{i=1}^I \sum_{l=1}^L w'_{il} x_{il} \quad (11)$$

subject to

$$\sum_{l=1}^L g'_{il} x_{il} \leq g_i \quad i = 1, \dots, I \quad (12)$$

$$x_{il} \in \{0,1\} \quad i = 1, \dots, I, l = 1, \dots, L \quad (13)$$

The objective function (11) maximizes the total critical weight assigned to the drones. Constraint (12) ensures the amount of literal weight assigned to the drone does not exceed the weight capacity of a drone. Constraint set (10) defines the binary drone assignment.

It is concluded by proving how emerging technologies like AM or 3 D printing and drones can be accommodated into existing models and their potential to reduce delivery time and optimize financial resources. We were able to successfully prove that this can be applied to the preparedness stage, the mitigation stage and the response stage of the disaster

relief chain. We were able to develop a structural model that clarifies the information and the goods flow including pre-stocking of supplies at various stages in the supply chain. Future research would include testing actual delivery times using drones and without using drones to compare factors that could affect drone delivery like weather and battery power.

4. Running of the model

4.1 Data

In many real cases of relief operations, the size of the problem is small. Hence, to make a fair comparison between optimization approaches, GAMS is used. The proposed model is solved by sample data generating from the direct conversion of discrete distribution simulation. These samples follow a normal distribution with certain means and variances. The given amount for each parameter (S, J, K, R) is determined based on the optimized amount of objective functions, and the stop point of the algorithm is defined according to the maximum iteration in which the objective function remains steady. The experiments are conducted on an Intel Core i5-2520M CPU 4GB RAM.

4.2 Solving methodologies

To define the ability and optimality of the model, two metaheuristic methods including the genetic and cuckoo optimization algorithm are used.

Although cuckoo algorithm is suitable for continuous and nonlinear problems, but it still works for discrete problems like layout designing problem, designing intelligent networks, as well as all the problems with many parameters to optimize. The algorithm main advantage is its operators like laying eggs and migration that consider several objectives simultaneously (Akhtaruzzaman *et al.*, 2016).

Cuckoo search can meet the thorough convergence of all solutions by the means of random step Lévy flight, and at first, cuckoo, the search is considered as the optimization method. To tackle this class of multi-objective models, the operators are corrected. On the other side, applying GA to similar models is a suitable criterion to evaluate the cuckoo optimization algorithm. It has been proved that among the non-exact methods for location problems GA is a good one in terms of reliability and flexibility (Liu *et al.*, 2019).

4.2.1 Genetic algorithm and NSGAI algorithm. Darwin's natural selection theory, GA, is a stochastic search technique. GA combines the individuals' good features to construct better individuals; (Barzinpour and Esmaeili, 2014). The following steps are taken to implement the algorithm:

- (1) Generating the initial population of N chromosome that equals the N solutions including distribution centers and potential AM centers that are generated randomly;
- (2) The acceptance degree of each solution is achieved by the alignment with the objective functions [1] and [11].
 - The current demand is met by the distribution and AM centers capacities.
 - The commodity relief is assigned to each drone randomly.
 - Scenarios 1 to 3 are assigned randomly to the centers.
 - The demands for the commodities 1 to 6 are specified according to the assigned scenarios.
- (3) At this stage, after fitting the objective functions with each solution, the next generation is selected by the method of fitness proportionate selection (Roulette wheel mechanism) and their probability of being optimal is calculated by

$p_i = \frac{f_i}{\sum_{i=1}^n f_j}$. In this approach, the fitness degree specifies if a chromosome can enter the next generation.

- (4) The crossover and mutation operators are used to generate the next generation children. The crossover method is used to improve the quality of a region of the solution space by checking the fitness of most of the solutions in the region. Uniform crossover is the suitable method for location problems (Zidi *et al.*, 2013). In this method, the parents are selected based on the two factors of demand coverage and assigned weight to each drone. The mutation operator with a specified rate is used to avoid local optimality.
- (5) Calculating the new generation fitness that due to being multi-objective, the optimality condition is considered based on the direct solution method or posterior articulation of preference. While the solution x_1 related to the objective Z_1 is superior to the solution x_2 related to the objective Z_2 if:
 - (6) x_1 is not worse than x_2 across all the objectives i.e. $f_i(x_1) \geq f_i(x_2)$ for all $i = 1, \dots, m$;
 - (7) x_1 is better than x_2 at least with one objective, i.e.; and
 - (8) $f_j(x_1) > f_j(x_2)$ for at least one $j = 1, \dots, m$.
- (9) The algorithm is repeated from stage 3, until the stopping criteria is met.

4.2.2 Cuckoo algorithm. The Cuckoo Search (CS) metaheuristic algorithm simulates the cuckoos' breeding in nature. It uses the location of the bird nest as a possible solution and improves the solution by updating the location of the bird nest. The improving method uses Lévy flight to simulate the movement pattern of birds in nature. The infrequent long-distance flight in Lévy flight can increase the search range to avoid any sort of local optimality. The algorithm steps are as follows:

- Generating the initial population or the hosts nests randomly. In an optimization problem with N_{var} variables, the hosts' nests matrix is of size $N_{pop} \times N_{var}$ where N_{pop} is the initial population size.
- A number of eggs, between VAR_{low} and VAR_{hi} as the lower and upper bounds respectively, are assigned to each cuckoo.
- Egg laying radius (ELR) is specified by the following formula:

$$ELR = \alpha \times \frac{\text{Number of current cuckoo's eggs}}{\text{Total number of eggs}} \times (Var_{hi} - Var_{low})$$

where α is the step-size factor, and is an integer, supposed to handle the maximum value of ELR, in this paper $\alpha = 1$ (Rajabioun, 2011).

- The cuckoos' eggs are randomly placed in the hosts' nests that are located inside their ELR.
- The eggs that are recognized by the hosts are destroyed with the probability of α . In fact, they are the solutions with lower fitness of the objective function compared to the others.
- The unrecognized cuckoos' eggs are raised.
- The new cuckoos' nests are analyzed.

- The maximum number of cuckoos possible in each location are specified, and the ones belong to inappropriate locations are removed.
- The cuckoos are clustered based on the method of k-means, while the best group based on the objective function fitness is determined as the target nest.
- The new population of cuckoos approaches the target nest as much as $\% \lambda$ (a random number between 0 and 1), while the deviation is $\% \varnothing$ (a number between $-\frac{\pi}{6}$ and $\frac{\pi}{6}$).
- The algorithm is repeated from stage 7, until the stopping criteria is met.

5. Computational results

To illustrate characteristics explored in this study, a sample computational has been presented.

5.1 First stage

To maximize the expected demand covered by the established AM and distribution centers, we generate an $S = 3$ scenario for $k = 6$ item type. We considered the following:

$r = 3$ AM center and $j = 4$ distribution center.

a_k , The radius coverage of relief commodities in relief bases is about 4 km.

Capacity of distribution center and AM center are shown as below (Tables 1 and 2):

$Cap_j = [3120, 2760, 21, 20]$

$Cap_r = [1890, 1770, 1950]$

$f_j = [900, 450, 1980, 1110]$

$f_j = [2760, 1240, 1320]$.

5.1.1 COA algorithm parameters. Max Iteration = 150

P_a = Discovery rate of alien eggs/solutions (Kill Factor) = 0.2

N_{pop} = The number of initial population = 50

N_{Pareto} = Number of Pareto = 100

5.1.2 NSGA algorithm parameters. N_{Pareto} = Number of Pareto = 100

Max Iteration = 150

$P_c = 0.8$

$P_m = 0.2$

5.2 Second stage

For maximizing the total critical weight assigned to the drones, we considered $I = 20$ set of drone and $L = 15$ set of items assigned to the drone.

The following table shows the nominal weights and critical weights.

$g_i = \{166, 189, 128, 154, 255, 254, 172, 125, 241, 170\}$

5.3 Solution method

5.3.1 Analysis of cuckoo and genetic algorithms. In this study, based on the fitting condition of fitness functions, the model parameters are defined as follows, and the problem is then quantified. In the set parameter of the multi-objective cuckoo algorithm, the optimal value of p_a means the percentage of identification of cuckoo eggs in each step $p_a \in [0, 1]$. The increase in the p_a limits elitist elaboration limited, and many of the nests, which are likely to be optimal in the subsequent repetitions, are eliminated in the first repetition. Besides, the

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	K	w_k	s	C_{sjk}	C_{srk}	
1	1	0.24	1	[33,30,40,45]	[70,30,39]	
			2	[32,16,25,31]	[67,52,38]	
			3	[20,31,16,29]	[48,34,47]	
2	2	0.44	1	[39,37,22,23]	[38,33,44]	
			2	[30,15,25,11]	[70,28,43]	
			3	[34,28,13,21]	[20,32,33]	
3	3	0.85	1	[10,45,32,26]	[41,66,55]	
			2	[12,22,37,20]	[62,42,29]	
			3	[34,41,44,41]	[26,52,41]	
4	4	0.73	1	[39,44,26,15]	[63,60,59]	
			2	[22,14,17,33]	[30,65,54]	
			3	[24,17,17,42]	[39,69,49]	
5	5	0.86	1	[34,29,11,33]	[52,25,43]	
			2	[30,42,22,39]	[43,56,50]	
			3	[18,22,31,29]	[68,66,39]	
6	6	0.74	1	[14,40,12,36]	[32,46,55]	
			2	[14,22,22,40]	[36,53,20]	
			3	[17,20,30,15]	[48,31,25]	

Table 1.
Unit cost of shipping
and criticality weight
of item type k

		K_1	K_2	K_3	K_4	K_5	K_6
D_{sk} expected demand for item type k in scenario s (units)	S_1	360	400	210	170	390	350
	S_2	300	380	390	150	200	390
	S_3	330	310	170	250	360	230

decrease in it leads to falling into the local optimal trait, and early convergence occurs. On the other hand, increasing or decreasing the parameters λ and φ , in term (1–4) within the defined interval for φ can affect the diversity of scenarios and increase or reduce the accuracy of the previous scenarios in λ .

In the real world, based on the differences between hosts and attacking eggs, searches are made.

This operator is the same as the Markov chain function, which places or increases the amount of α in the ELR relationship based on the size of the problem of this study, assuming the fact that the AM center and distribution center are fixed, considers more number of possible locations space.

The diagrams below show the distribution of optimal solutions in the Pareto front. The convergence of solutions in two algorithms is close to each other and covers almost the entire space of the objective function. Each of the horns defined in Table 3 evaluates the performance of the algorithm. The index of “Diversity” indicates the accuracy of the algorithms to investigate all points in searching space and the higher the number is more desirable. While the “spacing” index shows. The range of answers obtained is wide and the less the number is more desirable for this metric and the mean ideal distance (MID) also shows the distance between the Pareto replies from the origin of the coordinates, the lower the number will be. According to the diversity index, the variation in the answer to the cuckoos is less than genetic, which suggests that convergence has occurred in several

g'_{ji}	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	38	34	29	27	30	37	23	28	34	23	35	32	28	23	33
2	26	26	37	22	29	20	21	40	40	37	25	20	26	40	40
3	25	25	35	32	26	25	32	31	32	27	38	37	32	22	40
4	21	33	28	31	24	34	21	22	30	30	37	34	34	33	29
5	35	39	25	40	29	28	36	34	34	32	21	31	26	38	27
6	30	29	30	32	23	31	40	29	22	21	23	34	22	40	33
7	33	33	25	20	26	32	21	29	39	34	36	24	35	26	40
8	23	26	33	37	34	26	30	25	39	28	32	25	24	32	35
9	31	29	21	30	34	32	38	37	21	32	29	32	31	37	32
10	26	31	21	24	39	34	25	40	22	26	31	28	31	24	2'
w'_{ij}	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	28	27	27	16	11	24	9	22	20	29	27	20	21	28	10
2	23	29	15	11	19	19	10	27	28	13	6	20	29	14	21
3	20	20	12	29	14	21	12	23	24	23	10	17	22	8	25
4	11	8	10	24	9	10	23	16	13	5	15	15	13	9	16
5	24	7	6	27	14	25	29	8	11	28	24	16	15	13	30
6	27	7	13	27	9	5	29	12	24	17	25	10	27	13	8
7	19	15	23	21	9	23	11	13	15	17	25	25	7	5	24
8	9	14	13	29	26	7	24	17	18	17	26	30	10	22	21
9	26	23	13	11	17	7	27	13	14	16	29	18	5	19	18
10	8	26	23	6	19	15	18	18	13	20	10	28	23	29	20

Table 3.
Nominal and critical weights

specific locations and has not searched all target areas. Based on the spacing and MID index, genetics is also superior. According to the concepts presented, the results show that the performance of the GA is better than cuckoo and is more efficient. A comparison of the numerical results of two genetic and cuckoo algorithms regarding the number of repetitive loops shows that in the cucumber in the iteration 123rd, an optimum answer has been obtained. While genetics has reached its optimum in iteration 59th.

The reason for this prominence is the coordinated action between the operators of the GA on binary issues. Proper choice of the values of these parameters will affect the duration of the problem-solving and the optimal amount. Reducing the rate of mutation increases the diversity and distance of the answers from their ideals and can lead to their more similarity to each other while increasing the number of replies that can be scattered and stay away from the optimal answer. Again, we show the superiority of the GA.

In the cuckoo algorithm, the stages of the implementation of the random process are based on the Levy distribution, which includes small steps, sometimes large ones, and long jumps that increase the efficiency of optimal search. However, this function increases the number of times the fitness of the objective function increases and the algorithm's execution time boosts. This indicates that the COA also has more time to reach the optimum level in the GA. Each of [Figures 1](#) and [2](#) compares the distribution and optimality of each of the target functions, although the two points obtained are very close to each other and follow almost the same search behavior ([Table 4](#)).

5.3.2 Simultaneous analysis of two objective functions in the first stage. In preparing the model, Each objective is optimized at the same level that the intersection points occurred [Figure 3](#) shows this Pareto level in the objective function space. In the obtained diagrams, each plot depicts an optimization approach that no one overweighs the other one. In both algorithms, the solution spaces are searched based on diversity and similarity of results, but the Pareto level comparing to the other algorithm is closer to origin coordinates, and the set of results has better fitness.

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The model is solved by mixed-integer nonlinear programming that first needs the variables to be defined. The model's data are as below:

- blocks of equation:2;
- blocks of variables:2;
- single equations: 11;
- single variables: 151;
- non-zero element: 301;
- non-linear N-Z: 0;
- derivative pool:10;
- constant pool:16; and
- discrete variables: 150.

The variable that the value of the first objective function is achieved.

compare best cost of two algorithm

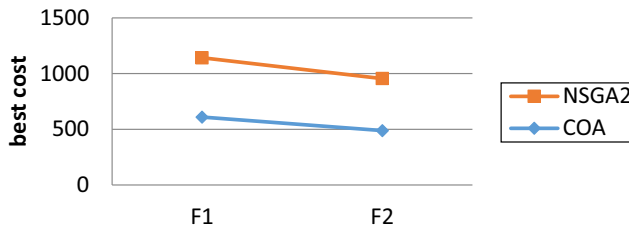
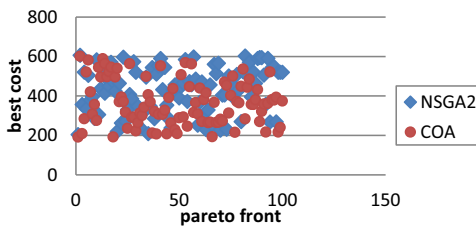


Figure 1. Comparison of the optimal functions of the two cuckoo algorithm and GA in the preparation stage

Comparative pareto front of two algorithm for second objective



Comparative pareto front of two algorithm for first objective

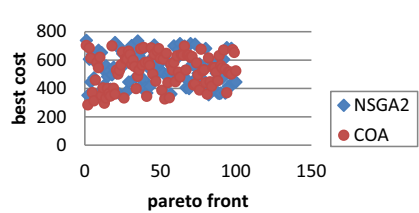


Figure 2. Comparison of the distribution of solutions in two cuckoo algorithm and GA

Table 4.

Comparison of diversity, order and distance of answers to the breakdown of target functions

Methodologies	Diversity	Spacing	MID	Best cost	
COA	645.43	0.665	134.58	F1	608.863
				F2	487.79
NSGA2	712.042	0.72	78.48	F1	532.476
				F2	467.23
GAMS	F				13634.27

After solving the model with the help of the above method, after the 208 repetitions in 0.031 s, the result of the first objective function is 13634.27. The other result is the response variables in the appendix.

5.3.3 *Cuckoo algorithm analysis and genetics (second model)*. At this stage, the goal is to achieve a model for helping the critical areas in the shortest possible time. The model of the response stage was implemented using two cuckoo algorithms and a GA in MATLAB software. Matching the objective function (3–2), the optimal allocation of the i items to the j drones is made considering the limitations of g_j . Therefore, the data and parameters of the problem and the algorithms are defined as follows:

COA Algorithm parameters:

Max Iteration = 150

Npop = The number of initial population = 50

P_a = Discovery rate of alien eggs/solutions (Kill Factor) = 0.25

GA Algorithm parameters:

Npop = 50

Maxit = 150

pc = percentage of crossover = 0.7

mu = percentage of mutation = 0.3

The best solution for every 150 repetitions of the COA algorithm according to Figure 4 shows that after iteration 55, no changes were made to improve the optimal problem and then the same process was followed (Table 5).

In the first best iteration the best cost is 110; in iteration 3 is 1,107; iteration 4 is 1,122; and in iteration 55 is 1,220, and the most possible optimized is achieved. In Table 5, the gained results and best scenario are achieved in the 150th iteration that is 1,515.

Comparison of cuckoo searches with a GA shows that despite the high convergence rate of the cuckoo algorithm and the process of searching the objective function space in each Levy flight, the GA has a better ability to obtain an optimal response. In Table 5, the allocation of items in the GA, there are more drones, indicating that the generated generation has extended the range of features of their parents' choices. In each of the operators, the chart below shows the reality of this. The reason for this is the discrete nature of the model. Research has shown that in discrete problems, discrete-type metaheuristic methods are better than algorithms that are continuous search and modified in conjunction with other discrete methods.

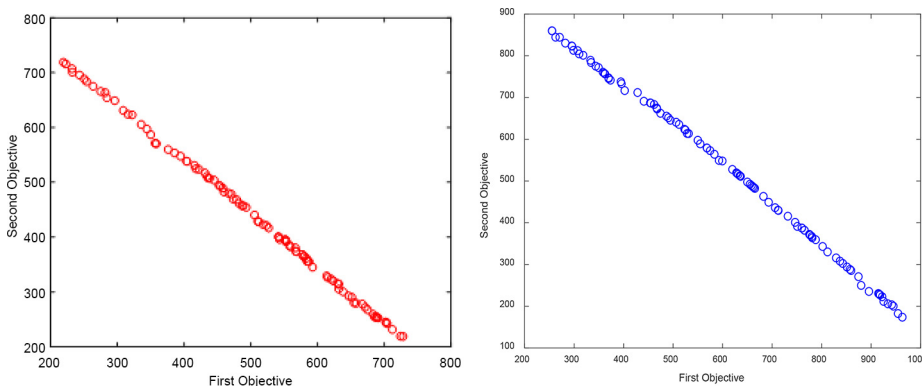


Figure 3.
Pareto front for two
objective functions in
the first level of mode
Pareto front diagram
for GA Pareto front
diagram for cuckoo
algorithm

6. Conclusion

This paper proves how emerging technologies like AM or 3D printing and drones can be accommodated into existing models and their potential to reduce delivery time and optimize financial resources. It was successfully proved that this can be applied to the preparedness stage, the mitigation stage and the response stage of the disaster relief chain. It was possible to develop a structural model by maximizing the total demand covered by the established AM and distribution centers and also maximizing the total literal weight assigned to the drones.

On the other hand, solving the model by GA and the cuckoo optimization algorithm and comparing the results with the ones obtained by GAMS clear that the GA overcomes other options as it has led to objective functions that are 1.6% and 24.1% better comparing to GAMS and COA, respectively. Although the cuckoo optimization algorithm is developed and turned to the discrete version, comparing to GA could not give a better result due to the specification of a GA operator and selecting fitted parameters in a binary model.

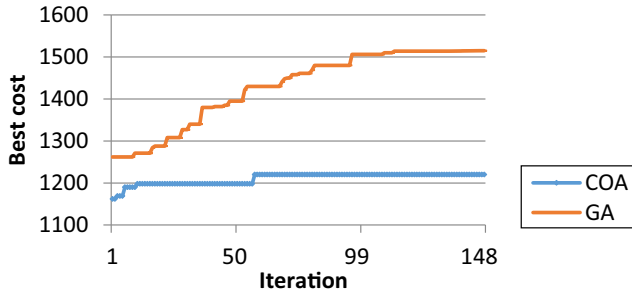


Figure 4.
Comparison of convergence of Pareto front solutions of GA vs COA

Item	COA			GA			Gams		
	Drones	Elapsed time	Best cost	Drones	Elapsed time	Best cost	Drones	Elapsed time	Best cost
1	(1,3,7,9,10)	17.84 s	1,220	(1,3,4,5,6,8,10)	1,405 s	1,515	(4,5,9,10)	0.08 s	1,492
2	(1,4,6,7,8)			(2,3,4)			(1,9,10)		
3	(3,6,10)			(2,3,5,7,8,9)			(1,2,6)		
4	(2,4,7,9,10)			(1,2,3,4,5,7,8,10)			(2,5,7,8,10)		
5	(4,5)			(5,6,10)			(5,6,7,8,9)		
6	(1,8,10)			(2,3,4,9)			(1,3,5,6,10)		
7	(1,2,3,4,8,9)			(5,7,8,10)			(2,3,4,6,9,10)		
8	(1,3,4,8)			(1,5,7,8,10)			(1,3,4,6)		
9	(2,6,8)			(2,5,6,7,8,9)			(4,5,6,8,9,10)		
10	(2,3,7,9)			(1,2,5,7,10)			(2,5,7)		
11	(4,5,9)			(4,6,8,10)			(2)		
12	(4,5,7)			(2,4,5,7,8,10)			(3,4,5,6,7,8)		
13	(1,2,4,6)			(1,2,3,6,7,8,10)			(1, 6,7,9,10)		
14	(1,2,7,10)			(1,2,7,9)			(1,2,9)		
15	(1,6,8)			(1,3,4,5,8,10)			(2,4,5,6,7,9)		

Table 5.
Comparison of optimal assignment, optimal amount and duration of problem-solving of GA vs COA and gams

Future research would include testing actual delivery times using drones and without using drones to compare factors that could affect drone delivery like weather and battery power.

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