IJE TRANSACTIONS A: Basics Vol. 35 No. 10, (October 2022) 1803-1819

International Journal of Engineering

Journal Homepage: www.ije.ir

Bi-level Scenario-based Location-allocation-inventory Models for Post-crisis Conditions and Solving with Electromagnetic and Genetic Algorithms

Z. Sahraei, P. Samouei*

Department of Industrial Engineering, Faculty of Engineering, Bu-Ali Sina University, Hamedan, Iran

PAPER INFO

Paper history:
Received 16 December 2020
Received in revised form 02 May 2022
Accepted 14 May 2021

Keywords:
Crisis
Location
Allocation
Inventory
Mixed-integer Linear Programming
Meta-heuristic Algorithms

ABSTRACT

Incidents that occur suddenly due to natural and human functions and impose hardships on society are called crises. As the Earth's climate changes have increased the number of natural crises, including earthquakes, floods, hurricanes, etc., in recent years, human beings have felt the need for crisis management and the necessary planning in critical situations more than ever. This research aims to model and solve the problem of location, allocation, and inventory in post-crisis conditions. To meet this purpose, first, we have conducted a review of the previous papers. Then, we have identified the research gaps in management and planning in critical situations. In this study, uncertain budgets and demands and bi-level programming decision-making are the innovations. As a result, we have developed mixed-integer linear mathematical models to cover the research gaps. Finally, several problems have been solved in small dimensions by GAMS software and large-sized problems by genetic and electromagnetic meta-heuristic algorithms. Then, we analyzed the algorithms' performance which indicates the genetic algorithm is better than the electromagnetic algorithm in this issue.

doi: *10.5829/ije.2022.35.10a.01*

1. INTRODUCTION

A disaster or crisis is a set of events that disrupt human beings' environmental relations with their surroundings. Due to the accidental and unpredictable nature of natural crises, comprehensive plans are necessary to reduce and mitigate the risks and consequences of the crisis and deal with it. Demand for logistic items and services increases with the emergence of critical situations and the reduced capabilities due to the damage to infrastructures. In recent years, Earth's climate changes are increasing the number of natural disasters, including earthquakes, floods, hurricanes, etc., and their corresponding losses. According to the related latest statistics, approximately, 70000 people die, and 200 million people are annually injured due to natural disasters [1]. Despite the governmental and non-governmental organizations' efforts to respond promptly to disasters and use resources effectively, numerous studies indicate a relatively low level of crisis preparedness [2]. In addition, there was not any research that considered the problem as discussed in this paper. As a result, the above reasons motivated us to do this research.

The first step that we required to take in the case of a crisis is building local warehouses to transport medicine, food, and other necessities of the victims and allocate the warehouses to the disaster areas. In this research, the proposed mathematical model determines local warehouses' optimal location among the potential points intending to minimize construction costs and the optimal allocation of constructed warehouses to the damaged sites to minimize allocation costs. After constructing local warehouses and simultaneous with their optimal allocation, we need to take necessary measures to purchase emergency items such as food, medicine, clothing and blankets, and transfer them to the warehouses. Since there is a possibility of an aftershock, and it will be almost time-consuming to respond to a catastrophe, it is also essential to plan, manage, and inventory control in each period after preparing the items.

*Corresponding Author Institutional Email: p.samouei@basu.ac.ir (P. Samouei)

Please cite this article as: Z. Sahraei, P. Samouei, Bi-level Scenario-based Location-allocation-inventory Models for Post-crisis Conditions and Solving with Electromagnetic and Genetic Algorithms, ***International Journal of Engineering, Transactions A: Basics***, Vol. 35 No. 10, (2022), 1803-1819

The mathematical model in this research considers this issue by using the periodic preparation and distribution of items to minimize inventory costs [3-6]. Ferreira et al. [7] have addressed the issue of the distribution of relief items with the assumption of the items' normalcy. Failure to pay attention to the expiration date of some items, such as medicine and food, can cause further damage to the victims because the slightest negligence can endanger the lives of the people who survived the disaster or prevent the timely supply and distribution of essential items. For instance, in Bam earthquake in Iran in 2007, about 30% of the antibiotics stored in the warehouses expired. The relief network faced the problem of preparing and responding quickly to the crisis [8]. Therefore, it is necessary to adopt the most appropriate policy to recover perishable products to preclude this problem. In this research, we assumed that in our periodic ordering policy, some necessary items are perishable, and we need to check the expiry date of the products and take out the obsolete items.

In the real world, we can state uncertainty in all factors. In critical situations, indeterminacy can also occur at the time and place of the accident, the severity of the incident, the likelihood of a strike, infrastructure disruption, the amount of damage, access to communication routes to the affected areas, supply and demand of relief items, and the specific budget allocated to cover the existing costs. Such uncertainties may happen because of insufficient information about the degree of personal injuries or financial damages, so they should be regarded when making more accurate and realistic planning decisions. Since few surveys have considered the assumption of uncertainty in demand (54%) and budget (0.02%) in their model, the present study covered the premise of demand and budget uncertainty by considering the scenarios on the magnitude of the earthquake.

Bi-level programming is a powerful tool for modeling and solving decentralized planning problems, but it has enormous computational complexity. In the real world, various systems have different subsystems that make it a hierarchical structure, and decision-making has its characteristics. In this type of planning, decisions are at different levels, and each identifies only some decision variables. Because of the computational complexity of planning, few articles in recent years have included this assumption in their research. In the present study, we turn the issue into bi-level programming, in which the leading decision-maker determines the variable of the optimal location of warehouses. Consequently, the decision-maker at the lower level determines the optimal amount of the items' allocation and inventory control according to the parameters and functional criteria.

The remaining structure of the paper is as follows:

Literature review of the related papers is presented in section 2. Problem description, assumptions, and mathematical model are given in section 3. Using solving methods consisting of the electromagnetic and genetic algorithms are in section 4. Section 5 is related to the computational results and discussions for different problems. Finally, in the last section, conclusion and future research directions are presented.

2. LITERATURE REVIEW

Cozzolino et al. [9] define disaster cycle management as the four main stages of mitigation, preparedness, response, and recovery. In our research, we have performed part of the measures related to the response phase. Naji Azimi et al. [10] proposed a location model. The points are selected from some potential points as satellite distribution centers, and people come to these locations to receive relief items. Their purpose was to minimize the distance that the vehicles traveled. Hu and Sheu [11] examined the reverse supply chain issue in waste management after a disaster. Their multi-objective linear programming model minimizes reverse logistic costs, the corresponding environmental and operational risks and the psychological harm to residents. Bozorgi Amiri et al. [12] proposed a mixed-integer linear programming model for natural disaster relief logistics under uncertain conditions. They used the particle swarm optimization approach to solve their proposed mathematical model. Finally, they presented computational results for several cases of this problem to demonstrate the feasibility and effectiveness of their proposed model and algorithm. A location-allocation model in uncertain crisis conditions for post-disaster debris management was presented by Habib and Sarkar [4]. It selected the temporary disaster debris management site and allocated waste from the affected areas to selected areas in two phases. Yu [13] proposed a multi-objective optimization model to maximize minimum access guarantee and minimize operating costs for pre-determining the location of emergency facilities. For this purpose, he used the concepts of the maximum flow and the shortest path in the network, respectively. He also showed the effect of the minimum access guarantee in the model by solving an example and comparing the number of inaccessible points in different random scenarios and proved that the proposed model could effectively determine the appropriate location of emergency facilities. Oksuz and Satoglu [14] presented a two-staged random model to determine the location and number of temporary medical centers in the event of a disaster, intending to minimize the total cost of construction and transportation. They tried to find an optimal solution for locating temporary medical centers by considering the location of the existing hospitals, the types of casualties, demand, the possibility of damage to roads and hospitals, and the distance between the disaster area and the medical center. Boonmee et al. [15] examined an integrated mathematical optimization model and the fuzzy hierarchical analysis process for shelter location and evacuation planning. They tested their proposed model with a real case study in Banta Municipality, Chiang Rai Province, Thailand. Finally, they proposed a suitable and realistic plan as an alternative for the decision-maker, whether an organization or the government in Banta Municipality. One year later, Boonmee et al. [3] examined post-crisis waste management issue to optimize the location and allocate resources. Chakravarty [16] offered a stochastic two-stage mathematical model for determining response time and post-accident relief values to minimize order, maintenance, and transportation costs as well as the expected response time. Hong et al. [17] proffered a two-stage stochastic programming model that determined the number and location of facilities with a limited capacity and the number of relief supplies available at each center. They efficiently calculated the proposed model using a method based on hybrid patterns. Mohammadi et al. [18] proposed a multi-objective stochastic programming model to develop earthquake response planning that integrated pre-and post-disaster decisions. They aimed to locate distribution centers, determine their inventory levels, and the relief items' flow to distribute essential items immediately in affected areas. Tofighi et al. [19] developed a two-stage stochastic programming problem consisting of multiple central warehouses and local distribution centers. They have implemented their relief network in Tehran city in the probable pre-and post-earthquake stages. One year later, Hu et al. [20] proposed a two-stage stochastic programming model to integrate decisions in critical situations. The model determines the location and number of suppliers and the pre-disaster inventory level in the first phase. In the second phase, this model makes decisions about logistic quantifying, transportation fleet, and selection of post-disaster procurement quantities. Their purpose is to minimize transportation, logistics, and construction costs and set penalties for customer dissatisfaction. Some researchers have added inventory management to facility location, resource allocation, and other types of disaster management to improve their work in recent years. Shen et al. [21] proposed a modified economic manufacturing quantity model for perishable inventory with a minimum volume limit for drug management for the National Strategic Plan. They indicated in their article that minimizing such a system's maintenance cost can be formulated as an optimization issue without non-uniform convex constraints. They showed the performance of their proposed model by analyzing sensitivities for various parameters. Manopiniwes et al. [22] offered a mixed-integer programming model to locate distribution centers and their inventory level according to capacity and time constraints with minimum total logistic costs. Roni et al. [23] proffered a mixed-integer programming model, including regular and irregular demand modes. They solved their model using the forbidden search algorithm for a hypothetical example to minimize the total costs of ordering, maintenance, and scarcity, showing the proposed model's efficiency. Tavana et al. [24] scrutinized the location-inventory-routing problem in the humanitarian supply chain, assuming pre-and post-disaster management. Their model determines the location of central warehouses and the amount of purchase and transfer of items from suppliers to central warehouses based on the prediction of product demands before the disaster. In the second phase and after the disaster, it determines the location of local warehouses, allocation of demand points to the local warehouses, and the local warehouses inventory. To solve this Mixed-integer linear programming problem, they proposed an Epsilon-constraint method, a Nondominated Sorting Genetic Algorithm (NSGA-II), and the Reference-Point-Based Nondominated Sorting Genetic Algorithm-II. Ferreira et al. [7] presented a decision-making model for the inventory management of perishable items for long-term relief operations (continuous assistance) using the Markov decision-making process. They sought to determine the optimal quantity of perishable items to minimize inventory costs (maintenance and corruption). Resource allocation models allot resources or tasks without considering the flow of items in each direction. Researchers often model resource allocation in addition to facility location. Celik et al. [25] presented a two-stage stochastic location-allocation model to determine the number and the location of relief distribution centers in the pre-disaster phase and to allocate the demand points to the relief distribution centers in the post-disaster phase. Loree et al. [26] developed a mathematical model for determining the location of different distribution centers and allocating them to the demand points in post-crisis conditions. They modeled their problem to minimize the costs of construction, procurement, and deprivation (such as some points of demand's lack of access to vital resources). Cavdur et al. [27] provided a spreadsheet-based decision support tool for allocating temporary disaster relief facilities to distribute relief resources. Their tool allowed the user (i.e., decision-makers) to provide the necessary facilities for the transient response to various disasters by considering the possible uncertainties after the disaster (i.e., different rates of the affected population, planning periods, etc.). Baharmand et al. [28] offered a multi-objective multi-layered model to locate and allocate facilities for sudden disasters, assuming limitations in the facilities and fleets' number and capacity. They selected the 2015 Nepal earthquake as a case study to solve the model. Recently, Liu et al. [29] proposed an integrated model of location-inventory-routing for perishable products, considering the factors of carbon emissions and product freshness. They developed a multi-objective mathematical model to minimize cost and carbon emissions and maximize product freshness. They used the YALMIP toolbox to solve the model. Mahtab et al. [30] proposed a multi-objective robust-stochastic humanitarian logistics model for relief goods distribution. They determined the location of temporary facilities, and the number of commodites to be pre-positioned and provided a detailed schedule for the distribution of commodities and the dispatch of vehicles.

Having reviewed the previous research (from 2008 until now), we realized that the increasing number of natural disasters had increased the papers on crisis and its management, demonstrating the importance of research in this field. More than 75% (30 out of 39) of the articles have dealt with determining the optimal location of emergency facilities. Table 1 clearly shows this information. As a result, we can state that the issue of locating emergency facilities like the optimal location of local warehouses is one of the essential topics in the research on crisis management. However, there were gaps in the reviewed articles we covered in this study. Table 1 shows the most related reviewed papers' comparison in terms of subject matter, planning horizon, solution method, proposed mathematical model and used algorithms, optimization levels, facility capacity, type of relief items, and definite or indefinite demand budget.

TABLE 1. Review of the latest studies in disaster

Literature	Subject			Planning horizon		Solution Method			Algorithm	Modeling Method	Level of optimization		Facility capacity		Kind of items		Demand		Budget	
	Inventory	Location	Allocation	Pre-Disaster	Post-Disaster	Heuristic	Meta-Heuristic	Exact			MILP model	Bi-level	Limited	Unlimite	Normal	perishab	Certain	uncertain	Certain	uncertai
[3]		•	•		•		•		PSO/DE	MILP	•		•		•		•			
[15]		•	•		•			•		MILP	•		•		•		•			
[31]		•	•		•			•		MINLP	•		•		•		•			
[4]		•	•		•			•		MILP	•		•		•			•	•	
[11]		•	•		•			•		LP	•		•		•		•			
[32]		•	•		•		•		Shortest path problem	LP	•			•	•		•			
[5]		•	•		•			•		MILP	•		•		•		•			
[33]		•	•		•		•		NSGA-ll	MILP	•			•	•		•			
[34]		•	•		•		•		Tabu Search	MILP	•		•		•		•			
[35]			•		•		•	•	Warshall Floyd	MILP	•		•		•		•			
[6]		•		•		•			Evolutionary Optimization Algorithm	LP	•		•		•			•	•	
[10]		•			•	•			Modified local search	MILP	•		•		•			•		
[36]	•	•		•	•			•		MILP	•		•		•			•	•	
[12]	•	•	•	•				•		MILP	•		•		•			•		
[16]	•			•	•			•		stochastic programming	•		•		•			•		•
[37]	•			•		•			Sample average approximation	MILP	•		•		•			•		
[17]	•	•		•				•		MILP		•	•		•			•		
[22]	•	•		•				•		MILP	•		•		•		•			

[18]	●	●		●	●		●		MOPSO	stochastic programming	●		●		●			●	●	
[38]	●	●		●	●			●		LP	●		●			●		●		
[39]	●	●	●	●				●		MILP	●		●		●		●			
[19]	●	●		●	●		●		Tailored Differential Evolution	LP		●	●		●			●		
[7]	●				●	●			VI	MDP	●			●		●		●		
[20]	●	●		●	●			●		MILP	●		●		●			●		
[40]	●	●	●		●			●		MILP		●	●		●			●		
[23]	●				●		●		Tabu Search	MILP	●			●	●			●		
[21]	●				●			●		EMQ	●			●	●		●			
[26]		●	●		●			●		MINLP	●		●		●		●			
[41]		●	●		●			●		MILP	●		●		●			●		
[12]		●	●	●	●		●		PSO	MILP	●			●	●			●		
[24]	●	●	●	●	●		●		An epsilon-constraint/ NSGA-II	MILP	●		●			●		●		
[25]		●	●	●	●		●		Genetic	MILP	●		●		●			●		
[1]	●	●	●	●	●	●				MILP	●		●			●		●		
[27]	●		●		●			●		IP	●		●		●		●			
[28]		●	●		●	●			Augmented epsilon-constraint method version 2 (AUGMECON2)	MILP	●		●		●		●			
[13]		●		●				●		MILP	●			●	●		●		●	
[14]		●			●			●		MILP	●		●							
This Study	●	●	●		●		●		Electromagnetic and Genetic Algorithms	MILP		●	●			●		●		●

In this research, an attempt has been made to examine recent articles in crisis management in terms of uncertainty in budget and demand parameters. Most papers do not address the budget in their research and often assume sufficient and available financial resources. But in reality, this may not be the case because the problem of examining budget deficits and surpluses is one of the most challenging issues facing organizations. According to Table 1, out of only six articles that have applied the budget in their model, one of them has considered the uncertain budget. Uncertainty in demand is also one of the gaps studied in this research that more than half of the articles have ignored. Humanitarian relief operations management involves many actors, who differ in culture, goals, interests, commitments, capacity, and, most importantly, expertise. Therefore, each actor has a different role and task in crisis management. In many of the articles reviewed in this study (about 87%), only one decision-maker makes decisions about facility location, inventory control, or resource allocation. But in the real world, there are different organizations involved in crisis management that have various tasks. It is necessary to establish the required coordination to exchange information and establish coordinated communication in decisions. In recent years, this issue has been considered a research gap and needs more research than we have covered in this study.

3. MODELING

Defining and expressing an issue necessitates the statement, analysis, and resolution of the problem. In this research, we developed two mixed-integer linear programming models. These models determine the optimal location of local warehouses among the existing points, allocation of disaster-affected areas to the warehouses, purchase, inventory control, and the distribution of relief items. Figure 1 indicates an overview of the proposed supply chain network. In these models, we assume the unlimited supply capacity of perishable and ordinary relief items. Perishable items have an expiration date, before which we take them out of local warehouses at a cost to preclude the storage and distribution of spoiled items. Demand for items and the budget for the construction of local warehouses are considered uncertain. Decisions to determine the optimal location of warehouses, optimal allocation, and control of the inventory of items are modeled as mixed-integer and bi-level mathematical models. Then, they are compared with each other. A quadratic constraint has caused the model to deviate from the linear mode. For linearization and improvement of the model, we use a series of changes. At the first, we propose a nonlinear model, and then introduce its linear form.

The proposed mathematical model includes the following assumptions:

1) The problem is a three-level supply chain network with a central warehouse (supplier), several local warehouses (distributors), and several demand points (disaster-affected areas).

2) Relief items include two categories of ordinary and perishable items.

3) Crisis management is related to the post-disaster phase.

4) The central warehouse location and the demand points are known, and the location of the local warehouses is unknown.

5) The inventory policy is considered by the method of [1]. In this way, perishable items have an expiration date that we should pay attention to their date. Also, to reduce the risk of the items remaining in the warehouses and their decay, we should not purchase items with longer expiration dates. Moreover, since the deterioration items, such as canned food, can endanger human lives and even contaminate the warehouse environment, we will remove them from the warehouse at a cost before the expiration date.

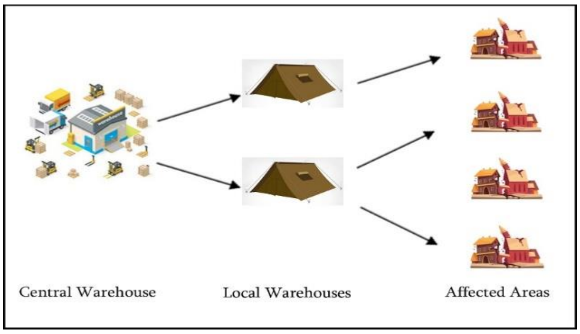

Figure 1. Overview of the relief supply chain

6) Demand and budget are considered uncertain. Therefore, the budget and demand will be different in various scenarios.

7) In this research, a bi-level decision-making process is considered. In this way, one organization is responsible for locating warehouses, and another makes decisions about inventory control and allocation. These two organizations make the optimal decision by contributing and swapping information. How one decision-maker makes all the decisions is also considered and compared to the multi-decision mode.

8) Some parameters are considered according to various scenarios.

Indices

i: index of local warehouse *i=1,…, I*

j: index of demand point *j=1,…, J*

k: index of relief items *k=1,…, K*

s: index of possible scenarios *s=1,…,S*

t: index of periods *t=1,…,T*

h_k: index of the remaining lifetime of product k h_k=1,…, H_k

Deterministic parameters

CH_k: additional unit holding penalty of item type *k*

SP_k: penalty cost of unit shortage of item type *k*

CP_k: purchase cost for each item type *k*

CM_{ki} : cost of unit item type *k* movement to warehouse i

α_k: allowable remaining lifetime (period) for item type *k* for purchasing

Δ_{pq}: acceptable difference of the equity level between two demand points *p* and *q* (*p≠q*)

CE_k: removal cost for each item type *k*

U_{ik}: The capacity of warehouse i to store item k

β_k: allowable remaining lifetime (period) for item type *k* for removing from warehouses

CT_{kijtsh_k}: The cost of transporting item k with the lifetime of h_k from warehouse *i* to point *j* in period *t* under scenario *s*

Uncertain parameters

f_{is}:The fixed cost of building warehouse i under scenario s

p_s: Probability of scenario s' occurrence

d_{jkst}: The amount of point j's demand for item k under scenario s in period t

τ_{jkst} : The cost of the shortage of item k at point *j* under scenario s in period t

ψ_{jks}: The ratio of item k's deficiency at point j under scenario s

B_s: The available budget for the construction of warehouses under scenario s

variables:

Scenario dependent

X_{ijksth_k}: The amount of the type-k item transferred from warehouse i to point j in period t under scenario s

W_{jkst}: The amount of the shortage of item k at point j under scenario s in period t

Q_{kitsh_k}: The quantity of the item k purchased for warehouse i in period t under scenario s with a lifetime ofh_k

I_{kitsh_k}: The Inventory level of item k with the lifetime of$h_k$in warehouse i kept in period t under scenario s

b_{kitsh_k}: The amount of item k with the lifespan of h_k taken out from warehouse i under scenario s in period t to prevent decay

Scenario independent

E_{kit}: The mathematical expectation of the shortage of item k in warehouse i in period t

φ_{jt}: The amount of deficiency at point j in period t

y_i: The binary variable whose value is one if warehouse i is constructed; otherwise, its value is zero

g_{ij}: The binary variable whose value is one if point j is allocated to warehouse i; otherwise, it is zero.

3. 1. Mixed Integer Linear Programming Model Mathematical Model

$$Min \quad z = \sum_{i=1}^{I}\sum_{1=1}^{S} f_{1s} y_i \; p_s + \sum_{k=1}^{K}\Big(\sum_{t=1}^{T}\Big(\sum_{j=1}^{J}\sum_{s=1}^{S}\tau_{jkst}W_{jkst}p_s + \sum_{i=1}^{I}\Big(SP_k\, E_{kit} + \sum_{s=1}^{S}\Big(\sum_{h_k=\alpha_k}^{H_k} Q_{kitsh_k}(\,CM_{ki} + CP_k)\, p_s + \sum_{h_k=1}^{\beta_k} CE_k\, b_{kitsh_k}\, p_s + \sum_{h_k=1}^{H_k}(\,CH_k\, I_{k1tsh_k}\, p_s + \sum_{j=1}^{J} CT_{kijtsh_k}X_{ijksth_k}\, p_s)\Big)\Big)\Big)\Big) \quad (1)$$

$$I_{kitsh_k} = 0 \qquad \forall k.i.s.\ h_k.t = 0 \quad (2)$$

$$X_{ijksth_k} = 0 \qquad \forall i.j.k.s.\ h_k.t = 0 \quad (3)$$

$$I_{kitsh_k} = I_{kit-1sh_k+1} + Q_{kitsh_k} - b_{kitsh_k} - \sum_{j=1}^{J} X_{ijksth_k} * p_s \qquad \forall k.i.s.h_k.t \in \{1.\dots.T\}. \quad (4)$$

$$b_{kitsh_k} = 0 \qquad \forall k.i.s.h_k \in \{\beta_k + 1.\dots.\ H_k\}.t \in \{1.\dots.T\} \quad (5)$$

$$Q_{kitsh_k} = 0 \quad \forall k.i.s.h_k.t. \in \{1.\dots.\alpha_k\} \quad (6)$$

$$b_{kitsh_k} \le I_{kitsh_k} \qquad \forall k.i.s.t \in \{1.\dots.T\}.\ h_k \in \{1.\dots.\ \beta_k\} \quad (7)$$

$$\sum_{h_k=\alpha_k}^{H_k} Q_{kitsh_k} \le U_{ik}\, y_i \qquad \forall k.s.i.t \quad (8)$$

$$X_{ijksth_k} \le g_{ij}\, I_{kitsh_k} \quad \forall i.j.k.h_k.s.t \in \{1.\dots.T\} \quad (9)$$

$$W_{jkst} + \sum_{i=1}^{I}\sum_{h_k}^{H_k} X_{ijksth_k} = d_{jkst} \qquad \forall j.k.s.t \in \{1.\dots.T\} \quad (10)$$

$$W_{jkst} \le \psi_{jks}\, d_{jkst} \qquad \forall j.k.s.t \in \{1.\dots.T\} \quad (11)$$

$$\sum_{i=1}^{I} f_{is} y_i \le B_s \qquad \forall s \quad (12)$$

$$g_{ij} \le y_i \qquad \forall i.j \quad (13)$$

$$-\Delta_{pq} \le \varphi_{pt} - \varphi_{qt} \le \Delta_{pq} \quad \forall p.q \in \{1.\dots.J\}.t \qquad p \ne q \quad (14)$$

$$\varphi_{jt} = \sum_{k=1}^{K}\sum_{s=1}^{S} W_{jkst} * p_s \quad \forall j.t \in \{1.\dots.T\} \quad (15)$$

$$E_{kit} = \sum_{j=1}^{J}\sum_{s=1}^{S} d_{jkst}\ g_{ij} * p_s - \sum_{s=1}^{S}\sum_{h_k=1}^{H_k} I_{kitsh_k} * p_s \qquad \forall k.i.t \in \{1.\dots.T\} \quad (16)$$

$$X_{ijksth_k}.W_{jkst}.E_{kit}.Q_{kitsh_k}.I_{kitsh_k}.b_{kitsh_k}.\varphi_{jt} \ge 0 \quad \forall i.j.k.s.t.\ h_k \quad (17)$$

$$y_i.\ g_{ij} \in \{0.1\} \qquad \forall i.j \quad (18)$$

Relation (1) represents the objective function of the problem which minimizes total cost. Its first part is the cost of the warehouse construction. Total shortage cost in demand points is in the second part of this relation. Total shortage cost in warehouses is shown in the third part, and the fourth part is the costs of purchasing and transporting items from the central warehouse to local warehouses. Part five to seven, respectively, demonstrate the costs of transporting items out of the warehouse to prevent decay and their maintenance and transportation from local warehouses to demand points. In this model, we assume the disaster occurred at t = 0. Constraints (2) to (4) show the number of items in the warehouses and their purchase and transfers at t = 0 are zero. The Constraint sets (5) and (6) show the inventory balance the constraint set's difference is between the lifetimes of the purchased and transferred items. The Constraint set (7) indicates the number of items transported out of the warehouse to prevent decay should be less than the inventory of items in that period. The Constraint set (8) guarantees that the total purchased items for that warehouse shall not exceed its capacity if a warehouse is constructed. The Constraint set (9) ensures that if a warehouse is allocated to a demand point, the quantity of the items sent from that warehouse to that point shall not exceed that warehouse's inventory. Constraints (10) and (11) prove that the shortage at one point is equal to the difference between the demand of that point and the quantity of the items transferred to the point, and it should not be more than the allowed limit. The Constraint set (12) ensures the construction of warehouses does not cost more than the available budget. The Constraint set (13) proves if there is no warehouse, no demand point will be allocated. The Constraint set (15) calculates the weight deficit of a point in various periods. The Constraint set (14) indicates the difference in the weight deficiency of two points in a period should not exceed a particular value. This limitation assures us that the weight deficiency of the points is close to each other. The Constraint set (16) shows deficiencies in each warehouse, and Constraints (17) and (18) indicate the types of decision variables. The Constraint set (9) has taken the mathematical model out of the linear form. To solve this problem, we convert it to the following two constraints:

$$X_{ijksth_k} \leq g_{ij} U_{ik} \qquad \forall i.j.k.s.h_k.t \tag{19}$$

$$X_{ijksth_k} \leq I_{kitsh_k} \qquad \forall i.j.k.s.h_k.t \tag{20}$$

Which show that the number of transferred items will not exceed the warehouse's capacity and inventory.

3. 2. Scenarios According to Rezaei-Malek et al. [1], the magnitude of an earthquake is considered in three ranges: less than 6 Richter, between 6 and 8 Richter, and more than 8 Richter, which their probabilities are 0.3, 0.5, and 0.2, respectively. In this study, we divide the day's hours into two categories, rest and working hours. These categories occupy eight and sixteen hours of the day, respectively. Since planning is related to the post-crisis phase, we considered the scenarios for the aftershocks. The importance of this classification lies in considering the difference in human beings' reaction speed to earthquakes during sleep and wakefulness; different reaction speeds affect the extent of the possible damage. Accordingly, we regarded six different scenarios with different probabilities and calculated them. Table 2 summarized the calculation results. For example, statement 21 is the calculated probability of the first scenario related to an earthquake with less than 6 Richter during sleep or rest.

$$p_1 = \left(\frac{8}{24}\right) \times 0.3 = 0.1 \tag{21}$$

Since the question is related to the post-crisis phase, we have considered the scenarios for the possible aftershocks.

3. 3. Bi-level Programming Bi-level programming is an effective tool for modeling and solving decentralized planning problems, but it has too many computational complexities. In the real world, numerous existing systems have different subsystems that make them a hierarchical structure, and decision-making in this structure has its characteristics. For instance, consider a company includes several factories. The board of directors is at the forefront of decision-making. Given its responsibilities and information, this board makes more critical decisions to develop and optimize the objective functions of the company. Managers of the subsidiary factories must make such decisions because they have higher ranks; however, factory managers can make decisions based on their authority to optimize their performance criteria. Different parts of factories have the same attitude towards managers.

On the other hand, these decisions can affect the company's goal and the decision-making space of the board and force them to change their decisions. These types of decisions are called bi-level programming. In this structure, decisions are at different levels, and each identifies only a few decision variables. In this study, we also turned the problem into bi-level programming, and while the leader determines the optimal location of warehouses, the follower determines the optimal amount of the items' allocation and inventory according to their parameters and criteria.

Relations 22 to 42 specify the bi-level programming model. In this model, at the first, the optimal location of warehouses is determined, then, the optimal allocation and control of the inventory of the items are planned.

$$Min \quad z = \sum_{i=1}^{I} \sum_{s=1}^{S} f_{is} y_i \tag{22}$$

$$s.t{:}\ \sum_{i=1}^{I} f_{is} y_i \leq B_s \qquad \forall s \tag{23}$$

$$g_{ij} \leq y_i \qquad \forall i.j \tag{24}$$

$$y_i.\ g_{ij} \in \{0.1\} \qquad \forall i.j \tag{25}$$

$$Min \quad zz = \sum_{k=1}^{K} \left(\sum_{t=1}^{T} \left(\sum_{j=1}^{J} \sum_{s=1}^{S} \tau_{jkst} W_{jkst} p_s + \sum_{i=1}^{I} \left(SP_k E_{kit} + \sum_{s=1}^{S} \left(\sum_{h_k=\alpha_k}^{H_k} Q_{kitsh_k} (CM_{ki} + CP_k) + \sum_{h_k=1}^{\beta_k} CE_k\, b_{kitsh_k} + \sum_{h_k=1}^{H_k} (CH_k\, I_{kitsh_k} + \sum_{j=1}^{J} CT_{kijtsh_k} X_{ijksth_k}\, p_s) \right) \right) \right) \right) \tag{26}$$

$$s.t{:} \quad I_{kitsh_k} = 0 \qquad \forall k.i.\ h_k.t = 0 \tag{27}$$

$$X_{ijksth_k} = 0 \qquad \forall i.j.k.s.\ h_k.t = 0 \tag{28}$$

$$I_{kitsh_k} = I_{kit-1sh_{k+1}} + Q_{kitsh_k} - b_{kith_k} - \sum_{j=1}^{J} \sum_{s=1}^{S} X_{ijksth_k} * p_s \qquad \forall k.i.s.h_k.t \notin \{0\} \tag{29}$$

$$b_{kitsh_k} = 0 \qquad \forall k.i.s.h_k \in \{ \beta_k + 1. \dots . H_k\}.t \in \{1. \dots . T\} \tag{30}$$

$$Q_{kitsh_k} = 0 \qquad \forall k.i.s.h_k.t. \in \{1. \dots . \alpha_k\} \tag{31}$$

$$b_{kitsh_k} \leq I_{kitsh_k} \qquad \forall k.i.s.t \in \{1. \dots . T\}.\ h_k \in \{1. \dots . \beta_k\} \tag{32}$$

TABLE 2. Probability of the occurrence of scenarios

Scenario	Magnitude≤6 (Richter)		6≤Magnitude≤8		Magnitude≥8 (Richter)	
	W	N	W	N	W	N
Scenario Number	1	2	3	4	5	6
Probability	0.1	0.2	0.17	0.33	0.07	0.13

Note: N, Non-Working; W, Working

$$\sum_{h_k=\alpha_k}^{H_k} Q_{kitsh_k} \leq U_{ik}\, y_i \qquad \forall k.s.i.t \tag{33}$$

$$X_{ijksth_k} \leq g_{ij}\, U_{ik} \qquad \forall i.j.k.s.h_k.t \in \{1.\dots.T\} \tag{34}$$

$$X_{ijksth_k} \leq \sum_{h_k=1}^{H_k} I_{kith_k}\, \rho_{iks} \qquad \forall i.j.k.s.h_k.t \in \{1.\dots.T\} \tag{35}$$

$$W_{jkst} + \sum_{i=1}^{I} X_{ijksth_k} = d_{jkst} \qquad \forall j.k.s.h_k.t \in \{1.\dots.T\} \tag{36}$$

$$W_{jkst} \leq \psi_{jks}\, d_{jkst} \qquad \forall j.k.s.t \in \{1.\dots.T\} \tag{37}$$

$$-\Delta_{pq} \leq \varphi_{pt} - \varphi_{qt} \leq \Delta_{pq} \qquad \forall p.q \in \{1.\dots.J\}.t \qquad p \neq q \tag{38}$$

$$\varphi_{jt} = \sum_{k=1}^{K}\sum_{s=1}^{S} W_{jkst} * p_s \qquad \forall j.t \in \{1.\dots.T\} \tag{39}$$

$$E_{kit} = \sum_{j=1}^{J}\sum_{s=1}^{S} d_{jks}\, g_{ij} * p_s - \sum_{s=1}^{S}\sum_{h_k=1}^{H_k} I_{kitsh_k} * p_s \qquad \forall k.i.t \in \{1.\dots.T\} \tag{40}$$

$$X_{ijksth_k}.W_{jkst}.E_{kit}.Q_{kitsh_k}.I_{kitsh_k}.b_{kitsh_k}.\varphi_{jt} \geq 0 \qquad \forall i.j.k.s.t.\ h_k \tag{41}$$

$$g_{ij} \in \{0.1\} \qquad \forall i.j \tag{42}$$

4. SOLVING METHODS

4. 1. The Electromagnetic Algorithm Electromagnetism is a branch of physics that considers electrical and magnetic phenomena and their relationship. In electromagnetic theory, forces are described by an electromagnetic field. In fact, electromagnetism states that the force exerted on a point by other points is inversely related to the distance between the points and is directly related to these points' charge. This algorithm is a population-based method and like the genetic algorithm, we equate an answer with a chromosome. Each solution is announced as a charged particle. Each point is assumed to be a charged particle in space, and its amount of charge also changes based on the value of its objective function. As a result, the fitness function in this algorithm is the particle charge. In each iteration, after changing the charge of each point, we determine the result of the forces acting on the points and their movement. Like electromagnetic forces, the force exerted on each point is obtained by summing all the forces exerted on it. Hence, after getting the initial population, calculating the total forces on each particle and moving the particle using the resultant force exerted are necessary.

• **Steps of electromagnetic algorithm**

This algorithm consists of four main phases:

1. Setting up or producing an initial population
2. Local search (using local search in neighborhoods to find the optimal local)
3. Calculation of the force exerted on each particle (calculation of the total force exerted on each particle)
4. Moving in the direction of the exerted force

4. 2. Genetic Algorithm A genetic algorithm is a search technique in computer science to find approximate solutions to optimize models, mathematics, and search problems. It is a type of evolutionary algorithm that utilizes biological processes like inheritance, biology mutation, and Darwin's selection principles to find the optimal solution. Genetic algorithms are often item choices for regression-based prediction techniques. The problem to be solved has inputs converted into solutions during a modeled process of genetic evolution. Then, the solutions are investigated by the evaluation function, and if the stopping rule has been satisfied, the algorithm terminates. In general, it is an iteration-based algorithm whose parts are selected through random processes; these algorithms consist of parts of the fitness function, display, selection, and modification.

• **Steps of the genetic algorithm**

1. Creating an initial population and evaluating it,
2. Selecting parents and combining them to create a crossover population
3. Selecting population members to cause mutations and create mutation populations (mutation)
4. Integrating the initial population and crossover and mutation populations, as well as developing a new main population and evaluating it
5. Checking the termination condition (If the condition is met, the algorithm is terminated; otherwise, we go to step two).

In this algorithm, the way the problem's answer is displayed is called a chromosome. Since this algorithm is population-based, we first generate a set of chromosomes randomly or based on an innovative method as the initial population selection. After examining the fitness function's value, we select some of these chromosomes as parents for neighborhood production. Then we create neighborhoods using crossover and mutation concepts. The crossover operator directs the answers to the optimal solution, and the mutation operator prevents falling into the optimal local trap. We perform this procedure until the stop condition occurs.

4. 3. How To Display the Answers The first step in applying and implementing any metaheuristic algorithm is to display its coding.

4. 3. 1. How to Display the Answer in the Ga This section displays the answer or the chromosome associated with the problem using Figure 2. The answer is represented by a matrix in which the number of rows equals the number of items. The number of columns represents the sum of the number of local warehouses and demand points. In each row, the cells have integer values between one and the sum of the number of local warehouses and the number of demand points. These values indicate the importance of the warehouses for distributing the desired items or the importance of receiving the items by the demand points; the larger the numbers, the higher the priority.

An example of solution representation is displayed in Figure 2 which the first row represents the product distribution priorities. In this row, considering the largest number, i.e., number 5, is located in the second cell, and this cell belongs to the second warehouse, the priority is distributing items from the second warehouse. According to the distribution cost, out of the four demand points, the point to which sending items from this warehouse costs the lowest obtains the license to receive the items, and the items have transferred to that point. Based on the warehouse's capacity, the quantity of the transferred items is equal to or less than the demand at that point. In this way, items are distributed based on the priority of each warehouse or point. In this problem, if there is no warehouse within the potential points, the cell value of that warehouse and the number of dispatched items from there will be zero, and the cost of delivering items will be infinite.

4. 3. 2. Operators Genetic operators imitate the process of inherited gene transfer to create new offspring in each generation. An essential part of the genetic algorithm is the creation of new chromosomes called parents. This critical process is carried out by mutation and crossover operators. But in practice, operators are defined by the type of problem and are utterly dependent on the analyst’s ability, and are empirical. The efficiency of these operators in achieving optimal solutions varies in different problems. Some operators work on just one chromosome and others on a few chromosomes or even all the chromosomes in the previous population. The role of genetic operators in the performance algorithm is very significant. Genetic operators are divided into mutation operators and crossover operators.

• Crossover operators

Operators select one or more points from two or more answers and exchange their values. These operators consider a solution and swap their places with other solutions to generate new solutions. The fewer the responses that participate in this operation, the closer the responses will be to the previous population. These operators are themselves divided into one, two, or multiple cutting points.

In this study, the crossover operator is defined is as follows. First, a pair of current-generation chromosomes are selected. Since the chromosome in question is a matrix chromosome, we cut both selected chromosomes longitudinally and transversely. Thus, we divide each chromosome into four parts. These two parent chromosomes produce two children; the upper-left- and

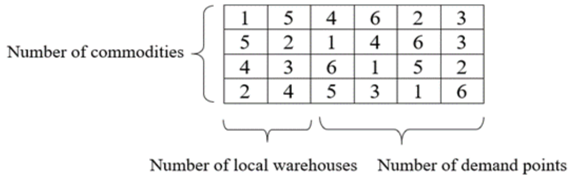

Figure 2. An example of a solution representation in the GA

lower-right-corner genes of the first parent make the values of the first child’s upper-left and lower-right corner genes, and the second parent genes produce the second child. The remaining values of the genes are examined cell by cell from the other parent chromosome and if repeated, removed from the parent cell's same values. In this way, two children are produced with different amounts of genes. Figure 3 shows an example of producing offspring with this crossover method.

• Mutation operators

Mutation operators are operators with random change characteristics. One or more locations of a string of characters with a certain length are considered in them, and the values of the characters in those locations are varied. Important items in this type of operator are:

- The number of locations to be changed
- How to select locations
- How the change operation is performed

In this study, for mutation, we select two genes in each row randomly and exchange their values. Figure 4 indicates an example of producing a new chromosome by this method.

4. 3. 3. How to Display the Answer in the Electromagnetic Algorithm Figure 5 displays the answer for the electromagnetic algorithm in the present research. In this case, we computed the charged particle’s length by multiplying the number of items by the total number of local warehouses and demand points.

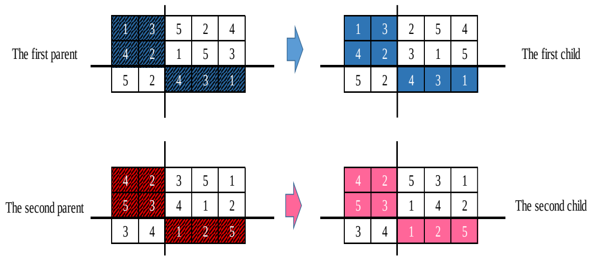

Figure 3. An example of child production employing the crossover method

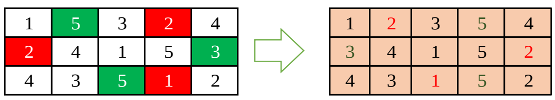

Figure 4. An example of producing a new chromosome using a mutation operator

There are also upper and lower limits for the cell values. Each cell, in the initial population takes a random value between -10 and 10. Subsequent generations are produced based on the structure of the algorithm. We consider the discrete problem-solving space and use the electromagnetic algorithm structurally for continuous problems. Therefore, to convert the discrete solution after creating the initial population, we reshape the charged particle to the number of items and the total number of warehouses and demand points and convert it to a matrix. Then, we arrange the numbers in each row to produce a matrix containing integers. At this stage, the display mode turns into the display mode in the genetic algorithm. Then we calculate the fitness function and continue the algorithm until the procedure stops.

Figure 5 shows an example of how the coding of the answer in the electromagnetic algorithm is prepared for a problem with three types of items, two demand points, and two local warehouses. Figure 6 indicates the conversion of an array to a matrix. Figure 5 transforms into Figure 6 because the array is converted to a matrix with the number of rows equal to the number of items and the number of columns equal to the total number of warehouses and demand points. MATLAB software uses the reshape function for this purpose. Figure 7 also shows the sorted mode of the matrix indicated in Figure 6.

4. 3. 4. Stop Condition of the Algorithm We continue repeating algorithms and producing a new generation until the stop condition is met. The stop condition in algorithms can be one way to reach an acceptable minimum of response (objective function), the number of iterations, time, convergence, and getting a certain number of responses in the solution space. In this research, both algorithms' stop condition is the number of repetitions of the new generation production.

5. COMPUTATIONAL RESULTS

5. 1. Small-Sized Problems To show the proposed model's efficiency and compare the solution methods, we have first solved several small-sized problems with GAMS software version 24.1.3 by a core i5 computer with 4GB of memory. Table 3 presents the information about the problem's size, the objective function's value, solution time, and the number of constructed warehouses. Table 4 shows the number of items allocated to the demand points from local warehouses for the first problem. The dash in the column corresponding to each demand point means that point is unassigned to the warehouse associated with its row. Since the problem is a Np-hard and cannot be solved in large-scale in polynomial time, we have solved several small-sized problems with GAMS which their results have shown the results in Tables 3 and 4.

We have considered two scenarios with probabilities of 0.25 and 0.75 to solve small-sized problems. Figure 8 shows the sensitivity of the objective function to these parameters by changing the cost parameters from 0.75% to 200%. As it is known, the total cost varies more with the change in purchase cost and shows the sensitivity of the total cost to this parameter. As a result, to reduce costs, managers should look for cheaper suppliers than trying to reduce other parameters. Also, Figure 9 shows increasing the number of warehouses reduces the total cost, even though it incurs construction costs because having several different warehouses with different shipping costs reduces the total costs. However, since we have a budget constraint for the construction of warehouses, it is impossible to build the desired number of local warehouses. If the relevant organizations can get more funding from the government, the total cost can be reduced.

5. 2. Problem-solving by the Bi-level Method In this study, we considered a bi-level programming approach for only small-sized problems. Out of the problems solved in Table 3, we selected three problems and solved them by Gams software with EPM solver. we turned the issue into a bi-level programming in which the leader decision-maker determines the optimal location of the warehouses, and the follower determines the optimal allocation and inventory planning.

0.25	2.15	5.24	-2.5	4.95	-7.59	-8.14	7.65	5.78	3.69	-4.87	3.78

Figure 5. An example of an answer displaying in the electromagnetic algorithm

0.25	2.15	5.24	2.5-
4.95	7.59-	8.14-	7.65
5.78	3.69	4.87-	3.78

Figure 6. Figure 5's converted array into a matrix

2	3	4	1
3	2	1	4
4	2	1	3

Figure 7. The sorted mode of Figure 6

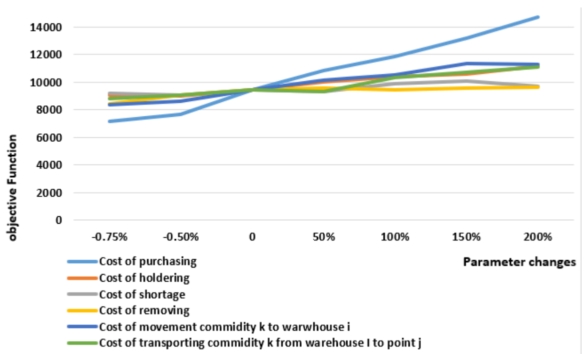

Figure 8. Impact of changing parameters on the objective function

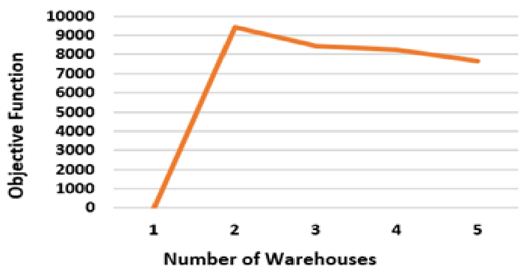

Figure 9. Impact of changing the number of warehouses on the value of the objective function

As indicated in Figure 10, the total cost of the bi-level programming increases compared to the mixed-integer linear programming. This type of planning has complexities that can be optimally addressed and answered at a cost. In critical situations, unsuitable planning, such as buying fewer items to reduce costs, can have irreparable consequences; thus, spending a little more if the budget is responsive will benefit the decisive bi-level programming decision-making.

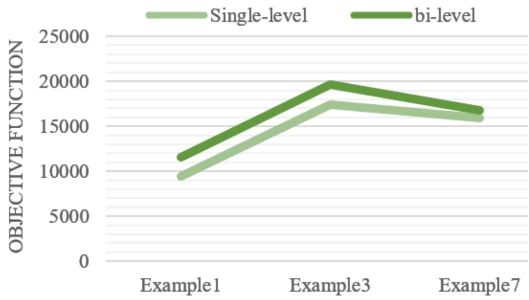

Figure 10. Comparing the mixed-integer linear programming model and bi-level programming

TABLE 3. Sample problems solved with a Mixed integer linear programming model method by GAMS software

Example	*I.J*	*T*	*S*	*K*	H_k	Objective Function (dollar)	Constructed Warehouse	Solving Time (s)
1	2.2	2	2	1	2	9434	1,2	1
2	2.3	2	2	1	2	8419	1,2	1000
3	3.3	2	2	1	2	17387	1,2,3	428
4	3.2	2	2	1	2	13640	1,2	30
5	4.2	2	2	1	3	19481	1,2	1995
6	4.3	2	2	1	3	15550	1,3	1872
7	2.2	5	2	1	2	15952	1,2	3
8	2.2	2	2	1	5	12272	1,2	13

TABLE 4. Distribution of items from warehouses to demand points

Example	Scenario	Period	Remainaing Lifetime	Warehouse	Demand Point	
					1	2
1	1	1	1	1	19	3
				2	-	0
			2	1	30	63
				2	-	30
		2	1	1	28	35
				2	-	19
			2	1	19	4
				2	-	0
	2	1	1	1	18	16
				2	-	0
			2	1	5	4
				2	-	30
		2	1	1	23	24
				2	-	7
			2	1	0	17
				2	-	0

5. 3. Large-Size Problems NP-hard class problems are the problems that no known definitive algorithm solves in polynomial time. In these cases, we use meta-heuristic algorithms to find solutions close to the optimal solution in a short time. This research solves and analyzes several relatively large problems in the mixed-integer programming model with genetic meta-heuristic and electromagnetic algorithms.

5. 3. 1. Parameter Setting The importance of any optimization algorithm parameters, especially meta-heuristic algorithms that have been designed to simplify the solution of optimization problems, is unquestionable. The optimal values of these parameters have a significant impact on the algorithms' performance and better searching of the answer space. Regarding this issue, we set the parameters of both algorithms to solve different problems by the Taguchi method in this research. The Taguchi method is a fractional factor scheme that selects the levels to be tested from orthogonal arrays. Each array is a specific set of parameter levels to be tested. An essential and critical factor in the Taguchi method is the reduction of variability. As indicated in Table 5, there are three different levels for setting the parameters. Because most articles graded them this way, we have considered an example of the experiment design answer in the same way. In Tables 5 and 6, Maxiter is the number of iterations, Npop is the number of the population, Pc and Pm are crossovers and mutation rates, respectively. Beta is the selection pressure by the roulette wheel method, and alpha is the movement radius. After designing the experiments and setting the parameter using the Taguchi method, we obtained the optimal levels of these parameters for each problem. Figures 11 and 12 show these results.

Higher rates of the SN demonstrate the algorithm's better performance. Table 7 shows the optimal value of both algorithms' parameters in this problem.

TABLE 5. Different levels of the genetic algorithm parameters

Level	Npop	Maxiter	Pc	Pm	Beta
1	50	100	0.7	0.1	5
2	100	150	0.8	0.2	10
3	150	200	0.9	0.3	15

TABLE 6. Different levels of ELA parameters

Level	Alpha	Npop	Maxiter
1	0.7	50	100
2	0.8	100	150
3	0.9	150	200

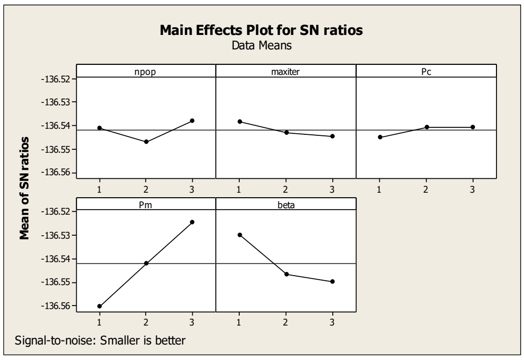

Figure 11. The SN rate in the genetic algorithm

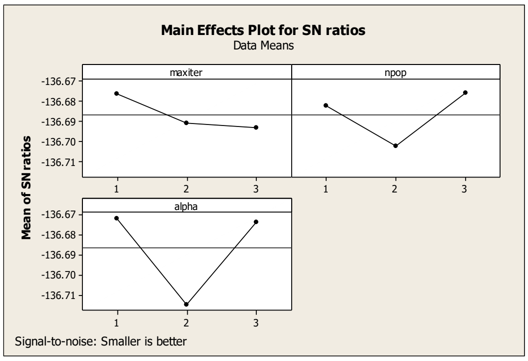

Figure 12. The SN rate in the electromagnetic algorithm

TABLE 7. The optimal value of the algorithms' parameters

Algorithm	Npop	Maxiter	Alpha	Beta	Pm	Pc
Genetic	150	100	-	5	0.3	0.9
Electromagnetic	150	100	0.7	-	-	-

After setting the algorithms' parameters, we solved ten problems in different sizes 25 times by GA and ELA which their results for maximum (the worth), minimum (the best), and the average objective function for each problem and their average solution time have presented in Table 8. Furthermore, for better comparison in terms of objective function and solution time have given in Table 8. According to this table, the genetic algorithm has better answers in most problems and less solution time than the electromagnetic algorithm. Also this table shows the standard deviation values for different problems for the both algorithms. Clearly, the standard deviation in the GA was less in most cases. In other words, the amount of variability is less, and this algorithm has achieved solutions closer to its mean than the electromagnetic algorithm.

To ensure the analysis and its generalization to the whole community, we initially test the normality of each index's data by Minitab software. After confirming the normality of the data, we perform the statistical

TABLE 8. Results of solving various problems with GA, ELA, and GAMS

Problem	Problem Size	The average objective functions in 25 run		The best objective functions in 25 run (the Minimum values)		The worst objective functions in 25 run (the maximum values)		The average solution time in 25 run		Standard deviation		GAMS	
	I,J,K,S,T,Hk	ELA	GA	ELA	GA	ELA	GA	ELA	GA	ELA	GA	Objective function	Time
1	3,2,3,2,3,3	1137430	1137430	1137430	1137430	1137430	1137430	49.88	36.114	0	0	Out of terminated time	2000
2	5,10,3,2,3,3	6826893.4	6708191.1	6771344	6701451	6864270	6721358	91.952	90.113	64.12	3.146	Out of terminated time	2000
3	10,10,3,2,3,3	7360067.4	7235276.3	7156690	7110647	7657959	7426157	117.831	113.889	34.52	15.17	Out of terminated time	2000
4	5,10,3,6,3,3	14490057.9	14194760.2	14331598	14181847	14572258	14257658	231.106	265.552	75.42	9.17	Out of terminated time	2000
5	10,10,3,6,3,3	22863938.4	21741634.5	21968322	20541369	23578461	23654123	328.024	318.311	85.45	52.37	Out of terminated time	2000
6	10,15,3,2,3,3	9362477.2	9326083.7	9351950	9321457	9369298	9331584	204.939	217.643	36.45	31.25	Out of terminated time	2000
7	15,15,3,2,3,3	12404516.8	23276003.1	12362354	12147362	12463952	122458763	229.376	223.776	47.98	3.71	Out of terminated time	2000
8	10,10,5,6,3,3	35103002.2	34226200.2	34125874	33457812	36312488	35124784	407.472	367.407	72.15	65.7	13640	30
9	2,3,1,2,2,2	13640	13640	13640	13640	13640	13640	2.384	2.16	0	0	15550	1872
10	3,4,1,2,2,2	15550	15550	15550	15550	15550	15550	26.023	24.756	0	0	Out of terminated time	2000

hypothesis test to prove our claim. Table 9 present the normality test results by the Kolmogorov-Smirnov method in Minitab software. Since the p-value is greater than 0.05 in all cases, all data have a normal distribution. Figure 13 shows an example of the normality test result performed on the electromagnetic algorithm's MID index data.

Having assured that the data are normal, we can now perform the t-test, a statistical hypothesis test, to compare the indicators more accurately. Table 10 indicates the test results conducted in the Minitab software with a 95% confidence level.

As indicated in Table 10, the p-values for both hypotheses are greater than 0.05, so there is no reason to reject the H0 hypothesis. Moreover, the genetic algorithm's convergence time to the answer is earlier than that of the electromagnetic algorithm. The genetic algorithm converges to its optimal solution in fewer

TABLE 9. The normality test result

Index	Algorithm	P-Value	Result
MID	GA	0.065	Normal
	ELA	0.118	Normal
MT	GA	0.15	Normal
	ELA	0. 32	Normal

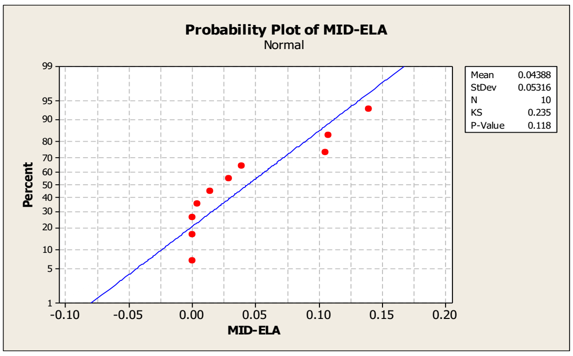

Figure 13. The result of the normality test on the MID index of the electromagnetic algorithm

TABLE 10. The results of the t-test

Null(H0) hypothesis	T-Test	P-Value	Result
The MID index in GA is lower than ELA.	2.25	0.35	H0 Hypothesis is not rejected
The MT index in GA is lower than ELA.	1.84	0.28	H0 Hypothesis is not rejected

iterations. We infer this result from Figure 14 obtained for Problem 2 in one iteration, and Table 11 presents the result. As observed from the table's values, the genetic algorithm gets to the answer in fewer iterations.

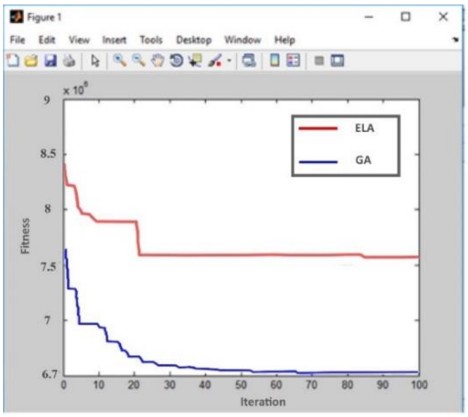

Figure 14. Comparing the convergence speed in genetic and electromagnetic algorithms

TABLE 11. The results of comparing the convergence in genetic and electromagnetic algorithms in problem 2

Algorithm	The iteration where convergence begins	Solution Time	Objective function
ELA	85	233.19	6809638
GA	66	210.65	6722158

Fallahpour et al. [42] developed an integrated model to consider the sustainability and Industry 4.0 criteria for the supplier selection management. They used the fuzzy best worst method and the two-stage fuzzy inference system to assess the selection of suppliers. Researchers can use their approach for extension of our paper. Fathollahi-Fard et al. [43] presented a bi-level programming for home health care supply chain considering outsourcing. Another direction for developing our paper is considering home health care with outsourcing in post-disaster phase. Another issue for developing our paper is related to Pasha et al. [44] research. They developed an integrated optimization model for liner shipping. Researchers can extend our paper with their approach.

6. CONCLUSION

Disaster or crisis is an event that occurs suddenly and sometimes increasingly and leads to a dangerous and unstable situation for an individual, a group, or society. A crisis creates a situation that needs fundamental and extraordinary action. The random and unpredictable nature of a crisis requires the presentation of comprehensive crisis plans to reduce and mitigate the crisis's risks and consequences. The improvement of the area of relief and support leads to significant results in such reductions. After reviewing the literature in recent years, we identified issues like the assumption of a budget for relief costs, the uncertainty of the budget and demand, bi-level programming in critical issues, and the negligence of assuming the items' decay in most reviewed articles as research gaps. The purpose of this study is to cover the identified research gaps. For this purpose, we developed an integer linear programming model that finds the optimal location of local warehouses from among the available points and determines the optimal allocation of demand points and the optimal number of items transferred to those points. Also, we designed the inventory policy to take the items out of the warehouse before the expiration date at a cost to prevent corruption. We solved several hypothetical problems in small sizes by GAMS software and in larger sizes by genetic and electromagnetic meta-heuristic algorithms to investigate the proposed model. After solving hypothetical problems with larger dimensions by electromagnetic and genetic algorithms and comparing the performance indices in these two algorithms, we found that genetics has a better performance than electromagnetism in this problem. This algorithm also converges to its optimal answer in fewer iterations than its competing algorithm, showing the high speed of genetics compared to electromagnetism. On the other hand, in most cases, the standard deviation of the objective function in genetics was less than electromagnetism, which indicates that genetic responses have fewer digressions, and they are close to the mean. As a result, genetics generally performed better than electromagnetism. This claim has also been substantiated in this study by a statistical hypothesis. Consequently, in the case of an earthquake, the relevant organizations can use this efficient model to decide on the optimal location of warehouses or field tents, the optimal number of purchased and stored items in local warehouses, and the optimal allocation of items to demand points in situations with uncertain budgets and demand.

Relief operations, like any other operations, need their costs. Moreover, the premise of demand uncertainty enhanced the issue's verisimilitude. In this study, we also covered the bi-level programming gap. After solving a problem in both mixed-integer linear programming model and bi-level programming models and recording the value of the problem's cost function, we found that this assumption increases the total cost to some extent. This increased cost is reasonable because we sometimes have to change the decision to make the necessary coordination for decision-making, and thus, the costs will increase. The organizations in charge are responsible for accepting the increased cost of the bi-level programming compared to the mode; it is up to them to pay the price to take advantage of the bi-level programming benefits. Unfortunately, one of the limitations of this study was the lack of access to real-world data, which we could not access despite our best efforts. Therefore, we had to use random data.

In this study, since the scenarios have been arranged based on the severity of the events, they can be generalized to other crises like floods and storms. Moreover, because of the high probability of ruining the infrastructure for relief during a crisis, we suggest adding routing and transportation of items through various communication routes such as land and air to the model to develop it. Another issue that one can augment is temporary hospitals with different equipment and conditions to treat the injured. Additionally, other objective functions, such as the satisfaction level of the victims and, most importantly, the response time to demand in the critical situation, can be inserted into the model.

7. REFERENCES

1. Rezaei-Malek, M., Tavakkoli-Moghaddam, R., Zahiri, B. and Bozorgi-Amiri, A., "An interactive approach for designing a robust disaster relief logistics network with perishable commodities", ***Computers & Industrial Engineering***, Vol. 94, (2016), 201-215, doi: 10.1016/j.cie.2016.01.014.
2. Kohn, S., Eaton, J. L., Feroz, S. and Bainbridge, A. A., Hoolachan, J., Barnett, D. J., "Personal disaster preparedness: an integrative review of the literature", ***Disaster medicine and Public Health Preparedness***, Vol. 6, No. 3, (2012), 217-231, doi: 10.1001/dmp.2012.47.
3. Boonmee, C., Arimura, M. and Asada, T., "Location and allocation optimization for integrated decisions on post-disaster waste supply chain management: On-site and off-site separation for recyclable materials", ***International Journal of Disaster Risk Reduction***, Vo. l31, (2018), 902-917, https://doi.org/10.1016/j.ijdrr.2018.07.003.
4. Habib, M. S. and Sarkar, B., "An integrated location-allocation model for temporary disaster debris management under an uncertain environment", ***Sustainability***, Vol. 9, (2017), 716, https://doi.org/10.3390/su9050716.
5. Lorca, Á., Çelik, M., Ergun, Ö. and Keskinocak, P., "An optimization-based decision-support tool for post-disaster debris operations", ***Production and Operations Management***, Vol. 26, No. 6, (2017), 1076-1091, doi: 10.1111/poms.12643.
6. Paul, J. A. and MacDonald, L., "Location and capacity allocations decisions to mitigate the impacts of unexpected disasters", ***European Journal of Operational Research***, Vol. 251, No. 1, (2016), 252-263, https://doi.org/10.1016/j.ejor.2015.10.028.
7. Ferreira, G. O., Arruda, E. F. and Marujo, L. G., "Inventory management of perishable items in long-term humanitarian operations using Markov decision processes", ***International Journal of Disaster Risk Reduction***, Vol. 31, (2018), 460-469, https://doi.org/10.1016/j.ijdrr.2018.05.010.
8. JICA, C. "The study on seismic microzoning of the Greater Tehran Area in the Islamic Republic of Iran.", Pacific Consultants International Report, OYO Cooperation, Japan, (2000), 291-390.
9. Cozzolino, A., Rossi, S. and Conforti, A., "Agile and lean principles in the humanitarian supply chain: The case of the United Nations World Food Programme", ***Journal of Humanitarian Logistics and Supply Chain Managemen***t, Vol. 2, No. 1, (2012), 16-33, https://doi.org/10.1108/20426741211225984.
10. Naji-Azimi, Z., Renaud, J., Ruiz, A. and Salari, M., "A covering tour approach to the location of satellite distribution centers to supply humanitarian aid", ***European Journal of Operational Research***, Vol. 222, No. 3, (2012), 596-605, doi: 10.1016/j.ejor.2012.05.001.
11. Hu, Z. H. and Sheu, J. B., "Post-disaster debris reverse logistics management under psychological cost minimization", ***Transportation Research Part B: Methodological,*** Vol. 55, (2013), 118-141, https://doi.org/10.1016/j.trb.2013.05.010.
12. Bozorgi-Amiri, A., Jabalameli, M. S., Alinaghian, M. and Heydari, M., "A modified particle swarm optimization for disaster relief logistics under uncertain environment", ***The International Journal of Advanced Manufacturing Technology***, Vol. 60, No. 1-4, (2012), 357-371, doi: 10.1007/s00170-011-3596-8.
13. Yu, W., "Reachability guarantee-based model for pre-positioning of emergency facilities under uncertain disaster damages", ***International Journal of Disaster Risk Reduction***, Vol. 42, (2020), 101335, https://doi.org/10.1016/j.ijdrr.2019.101335.
14. Oksuz M. K. and Satoglu, S. I., "A two-stage stochastic model for location planning of temporary medical centers for disaster response", ***International Journal of Disaster Risk Reduction***, Vol. 44, (2020), 101426, https://doi.org/10.1016/j.ijdrr.2019.101426.
15. Boonmee, C., Naotaka, I., Takumi, A. and Mikiharu, A., "Multi-model optimization for shelter-site selection: A case study in Banta municipality, Thailand", The 53rd Japan Society of Civil Engineers Conference, Hokkaido University, Japan, (2017), 2175-2181.
16. Chakravarty, A. K., "Humanitarian relief chain: Rapid response under uncertainty", ***International Journal of Production Economics***, Vol. 151, (2014), 146-157, https://doi.org/10.1016/j.ijpe.2013.10.007.
17. Hong, X., Lejeune, M. A. and Noyan, N., "Stochastic network design for disaster preparedness", ***IIE Transactions***, Vol. 47, No. 4, (2015), 329-357, https://doi.org/10.1080/0740817X.2014.919044.
18. Mohammadi, R., Ghomi, S. F. and Jolai, F., "Prepositioning emergency earthquake response supplies: A new multi-objective particle swarm optimization algorithm", ***Applied Mathematical Modelling***, Vol. 40, No. 9-10, (2016), 5183-5199, https://doi.org/10.1016/j.apm.2015.10.022.
19. Tofighi, S., Torabi, S. A. and Mansouri, S. A., "Humanitarian logistics network design under mixed uncertainty", ***European Journal of Operational Research***, Vol. 250, (2016), 239-250, https://doi.org/10.1016/j.ejor.2015.08.059.
20. Hu, S. L., Han, C. F. and Meng, L. P., "Stochastic optimization for joint decision making of inventory and procurement in humanitarian relief", ***Computers & Industrial Engineering***, Vol. 111, (2017), 39-49, https://doi.org/10.1016/j.cie.2017.06.029.
21. Shen, Z., Dessouky, M. and Ordóñez, F., "Perishable inventory management system with a minimum volume constraint", ***Journal of the Operational Research Society***, Vol. 62, No. 19, (2011), 2063-2082, https://doi.org/10.1057/jors.2010.181.
22. Manopiniwes, W., Nagasawa, K. and Irohara, T., "Humanitarian relief logistics with time restriction: Thai flooding case study", ***Industrial Engineering & Management Systems***, Vol. 13, No. 4, (2014), 398-407, https://doi.org/10.1057/jors.2010.181.
23. Roni, M. S., EksiogluJin, M. and Mamun, S., "A hybrid inventory policy with split delivery under regular and surge demand", ***International Journal of Production Economics***, Vol. 172, (2016), 126-136, doi: 10.1016/j.ijpe.2015.11.015.
24. Tavana, M., Abtahi, A. R., Di Caprio, D., Hashemi, R. and Yousefi-Zenouz, R., "An integrated location-inventory-routing humanitarian supply chain network with pre-and post-disaster management considerations", ***Socio-Economic Planning Sciences***, Vol. 64, (2018), 21-37.
25. Celik, E., Aydin, N. and Gumus, A. T., "A stochastic location and allocation model for critical items to response large-scale emergencies: A case of Turkey", ***An International Journal of Optimization and Control: Theories & Applications (IJOCTA)***, Vol. 7, No.1, (2016), 1-15, doi: 10.11121/ijocta.01.2017.00300.

26. Loree, N. and Aros-Vera, F., “Points of distribution location and inventory management model for Post-Disaster Humanitarian Logistics”, ***Transportation Research Part E: Logistics and Transportation Review***, Vol. 116, (2018), 1-24, https://doi.org/10.1016/j.tre.2018.05.003.

27. Cavdur, F., Sebatli-Saglam, A. and Kose-Kucuk, M., “A spreadsheet-based decision support tool for temporary-disaster-response facilities allocation”, ***Safety Science***, Vol. 124, (2020), 104581, doi: 10.1016/j.ssci.2019.104581.

28. Baharmand, H., Comes, T. and Lauras, M., “Bi-objective multi-layer location–allocation model for the immediate aftermath of sudden-onset disasters”, ***Transportation Research Part E: Logistics and Transportation Review***, Vol. 127, (2019), 86-110, https://doi.org/10.1016/j.tre.2019.05.002.

29. Liu, A., Zhu, Q., Xu, L., Lu, Q. and Fan, Y., “Sustainable supply chain management for perishable products in emerging markets: An integrated location-inventory-routing model***”, Transportation Research Part E: Logistics and Transportation Review***, Vol. 150, (2021), 102319, doi: 10.1016/j.tre.2021.102319.

30. Mahtab, Z., Azeem, A., Ali, S. M., Paul, S. K. and Fathollahi-Fard, A. M. “Multi-objective robust-stochastic optimisation of relief goods distribution under uncertainty: a real-life case study”, ***International Journal of Systems Science: Operations & Logistics***, (2021), 1-22. https://doi.org/10.1080/23302674.2021.1879305.

31. Fetter, G. and Rakes, T., “Incorporating recycling into post-disaster debris disposal”, ***Socio-Economic Planning Sciences***, Vol. 46, No. 1, (2012), 14-22, https://doi.org/10.1016/j.seps.2011.10.001.

32. Kim, J., Deshmukh, A. and Hastak, M., “Selecting a temporary debris management site for effective debris removal”, 10th Annual Conference of the International Institute for Infrastructure Renewal and Reconstruction, (2014), 214-218, doi: 10.5703/1288284315362.

33. Onan, K., Ülengin, F. and Sennaroğlu, B., “An evolutionary multi-objective optimization approach to disaster waste management: A case study of Istanbul, Turkey”, ***Expert Systems with Applications,*** Vol. 42, No. 22, (2015), 8850-8857, https://doi.org/10.1016/j.eswa.2015.07.039.

34. Pramudita, A., Taniguchi, E. and Qureshi, A. G., “Location and routing problems of debris collection operation after disasters with realistic case study”, ***Procedia-Social and Behavioral Sciences***, Vol. 125, (2014), 445-458, https://doi.org/10.1016/j.sbspro.2014.01.1487.

35. Takeda, T., Mori, Y., Kubota, N. and Arai, Y., “A route planning for disaster waste disposal based on robot technology”, In 2014 IEEE Symposium on Robotic Intelligence in Informationally Structured Space (RiiSS), (2014), 1-6.

36. Balcik, B. and Beamon, B. M., “Facility location in humanitarian relief”, ***International Journal of Logistics***, Vol. 11, No. 2, (2008), 101-121, https://doi.org/10.1080/13675560701561789.

37. Garrido, R. A., Lamas, P. and Pino, F. J., “A stochastic programming approach for floods emergency logistics”, ***Transportation Research Part E: Logistics and Transportation Review,*** Vol. 75, (2015), 18-31, doi: 10.1016/j.tre.2014.12.002.

38. Rabbani, M., Manavizadeh, N., Samavati, M. and Jalali, M., “Proactive and reactive inventory policies in humanitarian operations”, ***Uncertain Supply Chain Management,*** Vol. 3, (2015), 253-272, doi: 10.5267/j.uscm.2015.3.004.

39. Renkli, Ç. and Duran, S., “Pre-positioning disaster response facilities and relief item”, ***Human and Ecological Risk Assessment: An International Journal***, Vol. 21, No. 5, (2015), 1169-1185, https://doi.org/10.1080/10807039.2014.957940.

40. Noyan, N., Balcik, B. and Atakan, S., “A stochastic optimization model for designing last mile relief networks”, ***Transportation Science,*** Vol. 50, (2015), 1092-1113, https://doi.org/10.1287/trsc.2015.0621.

41. Escudero, L. F., Garín, M. A., Monge J. F. and Unzueta, A., “On preparedness resource allocation planning for natural disaster relief under endogenous uncertainty with time-consistent risk-averse management”, ***Computers & Operations Research***, Vol. 98, (2018), 84-102, doi: 10.1016/j.cor.2018.05.010.

42. Fallahpour, A., Wong, K. Y., Rajoo, S., Fathollahi-Fard, A. M., Antucheviciene, J. and Nayeri, S., “An integrated approach for a sustainable supplier selection based on Industry 4.0 concept”, ***Environmental Science and Pollution Research***, (2021), 1-19. https://doi.org/10.1007/s11356-021-17445-y.

43. Fathollahi-Fard, A. M., Hajiaghaei-Keshteli, M., Tavakkoli-Moghaddam, R. and Smith, N. R. “Bi-level programming for home health care supply chain considering outsourcing***”, Journal of Industrial Information Integration***, Vol. 25, (2022), 100246. https://doi.org/10.1016/j.jii.2021.100246

44. Pasha, J., Dulebenets, M. A., Fathollahi-Fard, A. M., Tian, G., Lau, Y. Y., Singh, P. and Liang, B. “An integrated optimization method for tactical-level planning in liner shipping with heterogeneous ship fleet and environmental considerations”, ***Advanced Engineering Informatics***, Vol. 48, (2021), 101299. https://doi.org/10.1016/j.aei.2021.101299.

Persian Abstract

چکیده

حوادثی که بر اثر کارکردهای طبیعی و انسانی به طور ناگهانی رخ می دهد و سختی هایی را بر جامعه تحمیل می کند، بحران نامیده می شود. از آنجایی که تغییرات اقلیمی کره زمین در سال های اخیر بر تعداد بحران های طبیعی از جمله زلزله، سیل، طوفان و ... افزوده است، بشر نیاز به مدیریت بحران و برنامه ریزی های لازم را در شرایط بحرانی بیش از پیش احساس کرده است. هدف این تحقیق مدلسازی و حل مشکل مکان، تخصیص و موجودی در شرایط پس از بحران است. برای رسیدن به این هدف، ابتدا به بررسی مقالات قبلی پرداخته ایم. سپس خلأهای پژوهشی در مدیریت و برنامه ریزی در شرایط بحرانی را شناسایی کرده ایم. در این مطالعه، بودجه‌ها و خواسته‌های نامشخص و تصمیم‌گیری برنامه‌ریزی دوسطحی نوآوری‌ها هستند. در نتیجه، ما مدل‌های ریاضی خطی عدد صحیح مختلط را برای پوشش شکاف‌های تحقیق توسعه داده‌ایم. در نهایت چندین مسئله در ابعاد کوچک توسط نرم افزار GAMS و مسائل بزرگ توسط الگوریتم های فراابتکاری ژنتیک و الکترومغناطیسی حل شده است. سپس عملکرد الگوریتم‌ها را تحلیل کردیم که نشان می‌دهد الگوریتم ژنتیک در این شماره بهتر از الگوریتم الکترومغناطیسی است.