

Designing a humanitarian logistics network for location-routing equipped with drone-enabled delivery systems under uncertainty conditions

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Abstract

This study aims to design a humanitarian logistics network for location-routing equipped with drone-enabled delivery systems under uncertainty conditions. Here, we divided the model into two phases including pre- and post-disaster. There is an important question in pre-disaster phase: Where the central warehouses better perform to minimize the cost and time? To this end, the logistics problem represented by the transportation of relief products was modeled as a Multi Echelon Multiple Depot Vehicle Routing Problem (MEMDVRP). For solving this mathematical problem, the presented model was initially solved using meta-heuristic algorithm of Non-dominated Sorting Genetic Algorithm III (NSGAIII) in large dimensions and sensitivity analysis was performed on its effective parameters via MATLAB software. Due to the scenario nature of the problem, 4 scenarios were considered in the model and then were compared separately for each goal. Given the results, scenario 4 showed the best situation in terms of benefits maximization. Regarding the cost, scenario 4 shows the worst status and the scenarios 1 and 2 revealed the best status. It should be noted that due to the nature of cost minimization objective, the lower this value, the better the result, indicating the best cost situation for Scenarios 1 and 2 and the worst for Scenario 4. In terms of time, Scenario 4 indicated the worst condition likewise the cost. Interestingly, regarding the benefits, the Scenario 4 leads to the most benefits, so it can be said that in this scenario, as the benefits increase, the cost and time also increase, suggesting a conflict in objectives.

Keywords: logistics network, humanitarian location-routing, goods transportation, drones

1- Introduction

The crisis is a sudden and catastrophic event that seriously disrupts the society's functioning and causes human, financial, material and environmental losses, making the society unable to use its resources. Crisis management includes four phases: prevention, preparation, response and reconstruction. Meanwhile, planning in the phases of prevention and preparation are of double importance, because they minimize surprise and distractions (Pourghader Chobar et al. 2022). Besides, humanitarian logistics consists of various processes that cover continuous relief and support activities (Zandbiglari et al. 2021 and 2023).

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 The natural and unnatural crises are predicted to increase in the future, therefore the need for relief is increasing, as well. In this regard, humanitarian aid is considered as a global and important industry. Accordingly, the current study aims at designing a humanitarian logistics network for location-routing under uncertainty conditions (Jahangiri et al. 2021; Babaeinesami et al. 2022).

 Humanitarian Supply Chain (HSC) is a branch of logistics that pays special attention to the organization of delivery and storage of resources to affected people during natural disasters. However, this definition only focuses on the physical flow of goods to the final destination, and in reality, HSC is far more complex and includes resource forecasting and optimization, inventory management, and information exchange (Asgharizadeh et al. 2022). Therefore, a broader definition of humanitarian logistics includes a process that plans, implements and controls the relief flow and focuses on efficient and cost-effective storage of goods and materials and also considers exchange of related information from the point of origin to the point of destination (consumption) for purposes such as reducing people's pain and suffering, and minimizing costs and time (Thomas, 2005; Chobar et al. 2022; Hosseini et al. 2022; Eshghali et al. 2023).

 In this research, we divided the model into two pre- and post-disaster phases. In the former, it is tried to decide on the location of the central warehouse, transporting resources from the suppliers to the central warehouses, and determining the optimal order policy to adjust the inventory of relief goods. During the latter, rescue teams must deliver relief items such as food, water and medical kits to hospitals and affected areas. In order to minimize the operation time and cost, the logistics problem represented by the transportation of relief products was modeled as a Multi Echelon Multiple Depot Vehicle Routing Problem (MEMDVRP). The important question in pre-disaster phase is that where do the central warehouses perform better to minimize the cost? After answering this question, the central warehouses should be filled with the desired goods. The problem uses two types of goods for relief. Type 1 goods are among essential and perishable goods, including medical kits, water and light food. Type 2 includes the goods (e.g., travel tent and blanket) delivered by helicopters and drones to people who are far away and caught in a disaster and it may take some time for people to be evacuated and brought to shelter.

 Since the goods have an expiration date, not using them causes them to spoil, which involves costs, and we need a separate and double cost to refill the warehouse. Therefore, we use the inventory control policy and sell the perishable products in the warehouse before they approach the expiration date. With this, the cost of replenishing the warehouse is compensated. Ali Cock et al., (2019) proposed an integer programming model that specifies a policy for refilling goods in containers. They thereby established a trade-off between routing costs and inventory refilling. In their study, using the proposal model, the refilling date of each item in each container is determined and the optimal route is provided for each vehicle in the planning horizon. The proposed integer programming model is solved for a small sample in Lingo. With the help of this study and with a little change, we would proceed the inventory control. Considering the duration of the expiration date of perishable goods, we sell them before this date ends and through the profit obtained, we try to reduce the costs of this time, which include the costs of location and purchasing goods.

 In fact, we have to answer the question, where should the local and central warehouses be placed to minimize our cost and time at such situations? Bahramand et al., (2019) focused on finding a distribution center for the affected people after a sudden disaster. To find a solution to this problem, they divided the topography of the affected areas into several layers, considering the limited number and capacity of facilities and fleet. They examined decision makers' trade-offs between response time and logistics costs using the 2015 Nepal earthquake. Their proposed method leads to a significant reduction in logistics costs. In this paper, a location-allocating model in multi-commodity periods is proposed to specify temporary distribution centers during sudden disasters.

 We used the future suggestions in their paper and we used three transport models for different layers. Here, in the post-disaster phase, after determining the local warehouses, we divided the topology of the region into layers. In the first layer, relief equipment is usually sent to the places that are accessible through highways or main roads via high-capacity vehicles. The second layer includes the places that are relatively less accessible and the roads that can be used by special cars. For example, trailers and trucks cannot move on these roads. The third layer cannot be accessed through remote places or ground transportation and thus are high-risk positions. In these places, we can use air transportation such as helicopters and drones. In this

way, we will make a planning for the use of vehicles, which will reduce the cost and time required. In the first layer, on the way out, we have type 1 goods, and on the way back, people are transferred to shelters or medical aid centers (in this section, people are evacuated). In the second layer, two types of special cars and helicopters can be used on the ways out and back. A place for the helicopter to land must be determined through the limitation it has for landing. Therefore, locating the helicopter is another objective that we must consider in mathematical modeling. In the third layer, which includes the most difficult places, essential relief items can be sent through drones, which requires more time to evacuate people and rebuild the roads due to bad topology. As mentioned, type 2 goods include tents and blankets, which are sent by air transportation at this phase.

 This study is organized in five sections as follows: the introduction and statement of the main challenge of the study are explained in the first section, and by reviewing the recent studies conducted in the field of the subject raised in the present study, the research gap of this study is presented in the second section. Next, in the third section, the proposed model is presented, and after introducing the indices and parameters, the objective functions are presented, and finally, the assumptions and limitations of the model will be stated in section 4. In the last section, the numerical results obtained from solving the model using the metaheuristic algorithm of the Non-Dominated Sorting Genetic Algorithm (NSGAIII) are presented.

2- Literature review

 Among the new studies in the field of HSCM, Hashemi Petrudi et al. (2020) examined the challenges of HSCM facing the Iranian Red Crescent population. Fuzzy Delphi method (FDM) and Fuzzy Interpretive Structural Modeling (FISM) were used to identify these challenges. In their study, the cause-and-effect relationships between these challenges were investigated. Finally, the general framework of the HSCM challenges and the FISM hierarchical model were statistically validated using the Partial Least Squares (PLS).

 Timperio et al., (2020) suggested integrating multi-criteria decision making, network optimization and discrete event simulation to address inventory defaults to improve the efficiency, effectiveness and agility of supply chains. They argue that while humanitarian logistics has traditionally relied solely on the practical experience of practitioners. Their paper presents a case for a paradigm shift as it proposes an interdisciplinary approach that integrates this practical experience with analytical and dynamic modeling widely applied in commercial supply chains. A real case study of Indonesia, one of the countries with the highest exposure to disaster risk on a global scale, was investigated using the Logistic software. The findings of this work showed the ideal network configuration along with the transport and inventory policies for the case at hand.

 Aghajani et al., (2020) developed a two-stage scenario-based stochastic probabilistic hybrid programming model to deal with various uncertainties. First-stage decisions include supplier selection and capacity reservation level per supplier/period and inventory addition level. Also, in the second stage, the decisions related to the time and amount are made. The applicability of the model was confirmed through a real case study. Finally, several sensitivity analyzes were conducted to investigate the influence of important parameters on the solutions to obtain useful management insights. The weighted ε-constraint sum method was used to find Pareto optimal solutions in the resulting bi-objective model. Also, a case study was presented to demonstrate the performance and application of the proposed models in practice. In addition, numerical experiments and several sensitivity analyzes were performed to understand the effects of agreement conditions and some key parameters on the final decisions.

 Agarwal et al. (2020) investigated the Humanitarian Supply Chain Management Barriers (HSCMBs) and evaluated solutions to overcome these barriers to improve the implementation of Humanitarian Supply Chain Management (HSCM). Their study aimed to evaluate solutions to overcome HSCMBs using a hybrid framework that includes Step-wise Weight Assessment Ratio Analysis (SWARA) and Fuzzy Weighted Aggregated Sum Product Assessment (WASPAS). They identified 29 HSCMBs and 20 solutions to overcome these HSCMBs through literature review and brainstorming meetings conducted among experts. Fuzzy SWARA was used to calculate the weight of HSCMBs and evaluate the relative importance of each HSCMB. Additionally, Fuzzy WASPAS was employed to rank solutions in order to overcome HSCMBs for efficient and effective implementation of HSCM. Their results indicate that "long-term strategic planning for humanitarian operations" is the highest ranked and most urgent solution, followed by "collaboration, cooperation and coordination among humanitarian supply chain actors" to overcome HSCMBs.

 García-Alviz et al., (2021) discussed a road network reconstruction planning and relief distribution under heterogeneous road disturbances. In this regard, a mathematical model for the timing and routing of relief vehicles and machines was presented. This approach seeks for a reconstruction plan dedicated to providing support to relief operations. This requires the prioritization of road reconstruction, taking into account their impact on the efficiency of relief operations. In addition, a heuristic algorithm was presented to solve large instances of the problem. This approach was applied to a realistic case study based on a flood that occurred in the Mojana region of Northern Colombia in 2010-2011.

 In Fatemi et al. (2021), a multi-purpose three-objective mathematical model is presented for pharmaceutical supply chain, considering the congestion of medicines in the factories. A Pharmaceutical Supply Chain (PSC) was developed with three objective functions, which aim to simultaneously minimize total costs, decrease unmet demands, and reduce waiting time at the factory entrance. In their study, the literature review in PSC modeling and problem solving were discussed. Then, the nonlinear programming model was proposed in line with the previous research to solve the existing deficiencies. Also, multiobjective decision making methods were used to concurrently match the conflicting objectives of the model. Next, the software GAMS was used to solve the problem of different sizes. Finally, extensive sensitivity analysis and evaluation results were discussed and suggestions for future development were presented. In this regard, two major challenges including perishable goods and queuing theory, which have not been considered in the existing literature, were paid into attention. In addition, objective functions and constraints were considered to solve the deficit of other models to reduce the queue time outside the manufacturer's input related to the products and materials obtained from the supplier according to specific conditions for their transportation and storage period. Two approaches (i.e., Genetic Algorithm and LP_metric) were used to solve the three-objective mathematical model. Several test problems of different sizes were solved to test effectiveness of the considered approaches and only small and medium problems were solved due to the nonlinearity of the mathematical model and the high complexity of the proposed PSC model.

 Kyriakakis et al., (2022) consider the humanitarian problem of vehicle routing with time windows and solve it by a new approach with a predetermined number of available vehicles and with the meta-heuristic Tabu hybrid search algorithm. Their study presented a metaheuristic Hybrid Tabu Search-Variable Neighborhood Descent (HTS-VND) algorithm for the Cumulative Capacitated Vehicle Routing Problem with Time Windows (CCVRPTW). This algorithm was also used to solve the unconstrained Cumulative Capacity Vehicle Routing Problem (CCVRP) whose effectiveness was tested against benchmark examples known from the literature and the results were compared with the results of other advanced approaches. The proposed meta-heuristic algorithm was able to find the best new known solutions in two examples of CCVRP. For CCVRPTW, two additional algorithms, a Tabu search algorithm and a variable neighborhood descent algorithm, were implemented to present benchmark values for the results obtained with HTS-VND.

 Escribano Macias et al., (2020) defined a framework for modeling drone-based humanitarian logistics missions. They presented a mixed integer programming formulation for the problem and proposed an effective large neighborhood search approach to solve this problem. In their study, the algorithm optimizes routes, warehouse location and battery allocation. To address these issues, they presented a novel two-stage operational planning approach that includes a route optimization algorithm (which considers multiple flight phases), and a hub routing selection algorithm that includes a novel battery management heuristic which was presented in the problem for a hypothetical response mission in Taiwan after the 1999 Chi-Chi earthquake, considering the duration of the mission and fair distribution. Their analysis showed that a fleet of drones can be used to provide rapid relief to a population of 20,000 people in less than 24 hours. Furthermore, the proposed method achieved a significant reduction in mission duration and battery storage requirements given the conservative energy estimates and other heuristics.

 Therefore, the research gap that we intend to fill is that by considering both the time before and after the disaster and having the prediction and planning of location and routing for both phases, it makes the problem closer to reality. As we know, the main task of relief is to help and save people with less risk and higher efficiency. In this study, considering the operation of evacuating people and transferring the injured patients to relief centers can help these goals. It is also tried to reduce costs as much as possible by selling stored materials for use in emergency situations. Adjusting and controlling inventory can take a lot of effort to reduce costs, which is one of the main goals. Through this study, it is tried to consider mountainous areas or those that are in difficult conditions in terms of geographical conditions. Here, we emphasize more on the impact of the transportation of relief-related vehicles. The use of drones in air transportation is another innovation of this study. Also, the charging station for the drone and the landing for the helicopter are of the first items considered in the mathematical model of this research.

For this research, we consider three objective functions: 1) Maximizing the benefits(Pre-disaster phase), 2) Minimizing the cost of location-routing (post-disaster phase), and 3) Minimizing the total time (postdisaster phase).

3- Methodology

 This study aims to design a humanitarian logistics network for location-routing by drone-enabled delivery systems under uncertainty conditions. We divided our model into two pre- and post-disaster phases. In the former, it is tried to decide on the location of the central warehouse, transporting resources from the suppliers to the central warehouses, and determining the optimal order policy to adjust the inventory of relief goods. During the latter, rescue teams must deliver relief items such as food, water and medical kits to hospitals and affected areas. In order to minimize the operation time and cost, the logistics problem represented by the transportation of relief products was modeled as a Multi Echelon Multiple Depot Vehicle Routing Problem (MEMDVRP). The important question in pre-disaster phase is that where the central warehouses do better to minimize the cost? After answering this question, the central warehouses should be filled with the desired goods. The problem uses two types of goods for relief. Type 1 goods, which are among essential goods and considered perishable ones, including medical kits, water and light food. Type 2 includes the goods (e.g., travel tent and blanket) delivered by helicopters and drones to people who are far away and caught in a disaster and it may take some time for people to be evacuated and brought to shelter.

 Since the goods have an expiration date, not using them causes them to spoil, which involves costs, and we need a separate and double cost to refill the warehouse. Therefore, we use the inventory control policy and sell the perishable products in the warehouse before they approach the expiration date. With this, the cost of replenishing the warehouse is compensated. Considering the duration of the expiration date of perishable goods before this date ends, we sell them and through the profit obtained, we try to reduce the costs of this time, which include the costs of location and the cost of purchasing goods. In fact, we have to answer the question, where should the local and central warehouses be placed that will minimize our cost and time at such situations? Here, in the post-disaster phase, after determining the local warehouses, we divided the topology of the region into layers. In the first layer, relief equipment is usually sent to the places that are accessible through highways or main roads by high-capacity vehicles. The second layer includes the places that are relatively less accessible and the roads that can be used by special cars. For example, trailers and trucks cannot move on these roads. The third layer cannot be accessed through remote places or ground transportation and have a high risk. In these places, we can use air transportation such as helicopters and drones. In this way, we will make a planning for the use of vehicles, which will reduce the cost and time required. In the first layer, on the way out, we have type 1 goods, and on the way back, people are transferred to shelters or medical aid centers (in this section, people are evacuated). In the second layer, two types of special cars and helicopters can be used on the ways out and back. A place for the helicopter to land must be determined through the limitation it has for landing. Therefore, locating the helicopter is another goal that we must consider in mathematical modeling. In the third layer, which includes the most difficult places, essential relief items can be sent through drones, which requires more time to evacuate people and rebuild the roads due to bad topology. As mentioned, type 2 goods include tents and blankets, which are sent by air transportation at this phase.

Indices and parameters

In the objective functions, the following indices were used:

j central warehouse; *k* local distribution centers; *l* affected areas; *m* rescue centers; *n* shelter; *v* ground vehicle; p drone; h helicopter; w potential locations; c essential goods; d unnecessary goods and r route.

Also, the following parameters were taken into account:

Besides, decision variables have been defined as follows:

 Three objectives are considered for this research. The first objective function, which includes the predisaster phase and as mentioned, is responsible for maximizing the benefits. The second objective function includes minimizing the cost of routing and location, and the third objective function includes minimizing the total time. However, the second and third objective functions are related to the post-disaster stage. The first objective function of the problem seeks to maximize the benefits for the supply chain, which minimizes the gap between the profit from selling perishable goods and locating and inventory costs.

 For this study, the model's hypotheses are as follows. 1) Three layers are considered for the level of service provision. 2) The second and third objective functions are considered in non-deterministic state.

3) Locating is done for central warehouses, local distribution centers and helicopter landing sites. 4) Routing is done from local warehouses to affected, from affected to rescue centers and from rescue centers to shelters. 5) The first objective function seeks to determine the best locations. 6) The second objective function seeks to minimize the cost. 7) The third objective function seeks to minimize construction time. 8) The question of charging the drone's battery does not matter in the current model. 9) Perishable inventory is considered in the current model. 10) The perishable inventory that still exists until the expiry date is sellable and is therefore considered a revenue component for the chain. 11) Refilling the inventory in central warehouses is subject to a fee. 12) Drones and helicopters are used in the third layer. The first objective function seeks for maximizing the benefits (constraint 1).

$$
\max z1 = \left[\sum_{j} \sum_{w} FCjw_{jw} . XCjw_{jw} + \sum_{k} \sum_{w} FCkw_{kw} . XCkw_{kw} + \sum_{h} \sum_{w} FChw_{hw} . XChw_{hw} \right]
$$

+
$$
\left[\sum_{c} \sum_{j} RC_{cj} . XRC_{cj} + SCC_{cj} . XSCC_{cj} + \sum_{a} \sum_{j} SCD_{aj} . XSCD_{aj} \right]
$$

-
$$
\left[\sum_{c} \sum_{j} R_{cj} . XR_{c} \right]
$$
 (1)

The second objective function of the problem seeks to minimize the routing cost (constraint 2)

$$
\min z2 = \sum_{r} \sum_{v} \sum_{k} \sum_{l} VCRKL_{rvkl} . XCRKL_{rvkl} + \sum_{r} \sum_{v} \sum_{m} \sum_{l} VCRlm_{rvlm} . XCRlm_{rvlm} \n+ \sum_{r} \sum_{v} \sum_{n} \sum_{l} VCRln_{rvln} . XCRln_{rvln} \n+ \sum_{r} \sum_{v} \sum_{k} \sum_{l} SVRRL_{rvkl} . XSCRKL_{rvkl} \n+ \sum_{r} \sum_{v} \sum_{m} \sum_{l} SVERlm_{rvlm} . XSCRlm_{rvlm} \n+ \sum_{r} \sum_{v} \sum_{n} \sum_{l} SVERln_{rvlm} . XSCRlm_{rvlm} \n+ \sum_{r} \sum_{v} \sum_{n} \sum_{l} SVERln_{rvln} . XSCRln_{rvln} + \sum_{r} \sum_{p} \sum_{k} \sum_{l} PCRkl_{rpkl} . XPCRkl_{rpkl} \n+ \sum_{r} \sum_{p} \sum_{m} \sum_{l} PCRlm_{rplm} . XPCRlm_{rvlm} + \sum_{r} \sum_{p} \sum_{n} \sum_{l} PCRln_{rpln} . XPCRln_{rvkl} \n+ \sum_{r} \sum_{h} \sum_{k} \sum_{l} HCRKL_{hrkl} . XHCRKL_{hrkl} \n+ \sum_{r} \sum_{h} \sum_{m} \sum_{l} HCRLM_{hrlm} . XHCRLm_{hrlm} \n+ + \sum_{r} \sum_{h} \sum_{n} \sum_{l} HCRLm_{hrlm} . XHCRLn_{hrln}
$$

The third objective function of the problem seeks to minimize the routing time (constraint 3).

 $min z3 = \sum_{r} \sum_{v} \sum_{k} \sum_{l} VTRKL_{rvkl}$. $XCRKL_{rvkl} + \sum_{r} \sum_{v} \sum_{m} \sum_{l} VTRlm_{rvlm}$. $XCRlm_{rvlm}$ + $+ \sum_{r} \sum_{v} \sum_{l} VTRln_{rvln} . XCRln_{rvln} + \sum_{r} \sum_{v} \sum_{k} \sum_{l} SVTRKL_{rvkl} . XSCRKL_{rvkl} +$ $\sum_{r} \sum_{v} \sum_{m} \sum_{l} SVTRlm_{rvlm}$. $XSCRlm_{rvlm} + \sum_{r} \sum_{v} \sum_{n} \sum_{l} SVTRln_{rvln}$. $XSCRln_{rvln} +$ $\sum_{r} \sum_{p} \sum_{k} \sum_{l} PTRkl_{rpkl}$. $XPCRkl_{rpkl} + \sum_{r} \sum_{p} \sum_{m} \sum_{l} PTRlm_{rplm}$. $XPCRlm_{rplm}$ $\sum_{r} \sum_{p} \sum_{l}$ PTRIn_{rpln}. XPCRIn_{rpln} + $\sum_{r} \sum_{h} \sum_{k}$ HTRKL_{hrkl}. XHCRKL_{hrkl} + $\sum_{r} \sum_{h} \sum_{m} \sum_{l} HTRLm_{hrlm}$. XHCRL $m_{hrlm} + \sum_{r} \sum_{h} \sum_{n} HTRLn_{hrln}$. XHCRL n_{hrln} (3) $\sum_{i} XRC_{ci} \leq cap_i \ \forall j$ (4) Constraint (4) states that the amount of goods to be refilled cannot exceed the warehouse capacity. $\sum_{c} XSCC_{ci} \leq cap_i \quad \forall j$ (5) Constraint (5) states that the amount of essential goods cannot exceed the storage capacity. $\sum_{d} XSCD_{d,i} \leq cap_i \quad \forall j$ (6) Constraint (6) states that the amount of non-essential goods cannot exceed the storage capacity. $XSCC_{cj} + XSCD_{dj} \leq cap_j \,\forall j, c, d$ (7) Constraint (7) states that the total amount of essential and non-essential goods cannot exceed the storage capacity. $\sum_{c} X R_c \leq \text{cap}_1 \forall j$ (8) Constraint (8) states that the amount of sales of essential goods cannot exceed the capacity of the warehouse. $\sum_{c} X R_c \leq \text{cap}_1 \forall j$ (9) Constraint (9) states that the amount of sales of essential goods cannot exceed the total amount of essential goods in the warehouse. $XR_c \le XSCC_{ci}$ $\forall j, c$ (10) Constraint (10) states that each central warehouse can be located at one potential location. $\sum_{\mathbf{w}} X \mathbf{C} \mathbf{j} \mathbf{w}_{j\mathbf{w}} = 1 \; \forall j$ (11) Constraint (11) states that each local warehouse can be located at one potential location. $\sum_{\mathbf{w}}$ XCkw_{kw} = 1 \forall k (12) Constraint (12) states that there is one route for each vehicle from each local warehouse, and only to one affected center we can move from this route. $\sum_{\mathbf{r}} \sum_{\mathbf{l}} XCRKL_{\text{rvkl}} = 1 \,\forall v, k$ (13) Constraint (13) states that there is one route for each vehicle from each affected center, and only to one rescue center we can move from this route. $\sum_{r} \sum_{m} XCRlm_{rvlm} = 1 \forall v, l$ (14) Constraint (14) states that there is one route for each vehicle from each affected center, and only to one shelter we can move from this route.

$$
\sum_{\mathbf{r}} \sum_{\mathbf{n}} \text{XCRln}_{\text{rvln}} = 1 \,\forall \mathbf{v}, \mathbf{n} \tag{15}
$$

Constraint (15) states that there is one route for each vehicle in the second layer of each local warehouse, and to only one affected center we can move from this route.

$$
\sum_{\mathbf{r}} \sum_{\mathbf{l}} XCRkl_{\mathbf{rvkl}} = 1 \,\forall \mathbf{v}, \mathbf{k} \tag{16}
$$

Constraint (16) states that there is one route for each vehicle in the second layer of each affected center, and to only one rescue center we can move from this route.

$$
\sum_{\mathbf{r}} \sum_{\mathbf{l}} XCRkl_{\mathbf{r}vkl} = 1 \,\forall v, k \tag{17}
$$

Constraint (17) states that there is one route for each vehicle in the second layer of each affected center, and to only one shelter we can move from this route.

$$
\sum_{\mathbf{r}} \sum_{\mathbf{m}} XCRlm_{\text{rvlm}} = 1 \,\forall v, l \tag{18}
$$

Constraint (18) states that there is one route for each drone in the third layer from each local warehouse, and to only one affected center we can move from this route.

$$
\sum_{\mathbf{r}} \sum_{\mathbf{n}} XCRln_{\text{rvln}} = 1 \,\forall v, l \tag{19}
$$

Constraint (19) states that there is one route for each drone in the third layer from each affected center, and to only one rescue center we can move from this route.

$$
\sum_{\mathbf{r}} \sum_{\mathbf{l}} \text{XPCRKL}_{\text{prkl}} = 1 \, \forall \mathbf{p}, \mathbf{k} \tag{20}
$$

Constraint (20) states that there is one route for each drone in the third layer from each affected center, and to only one shelter we can move from this route.

$$
\sum_{\mathbf{r}} \sum_{\mathbf{m}} \text{XPCRlm}_{\text{pr1m}} = 1 \,\forall \mathbf{p}, \mathbf{l} \tag{21}
$$

Constraint (21) states that there is one route for each helicopter in the third layer from each local warehouse, and to only one affected center we can move from this route. $\sum_{r} \sum_{n} \text{XPCRIn}_{\text{nrIn}} = 1 \,\forall p, l$ (22)

Constraint (22) states that there is one route for each helicopter in the third layer from each affected center, and to only one rescue center we can move from this route.

$$
\sum_{\mathbf{r}} \sum_{\mathbf{l}} \mathbf{X} \mathbf{H} \mathbf{C} \mathbf{R} \mathbf{k} \mathbf{l}_{\mathbf{h} \mathbf{r} \mathbf{k} \mathbf{l}} = 1 \, \forall \mathbf{h}, \mathbf{k} \tag{23}
$$

Constraint (23) states that there is one route for each helicopter in the third layer from each affected center, and to only one shelter we can move from this route. $\sum_{r} \sum_{m} X HCRlm_{hrlm} = 1 \forall h, l$ (24)

Constraint (24) states that each helicopter can be placed in at most one potential location. $\sum_{r} \sum_{n}$ XHCRln_{hrln} = 1 \forall h, l (25)

Constraint (25) indicates that if a place for the warehouse is not determined, it is not possible to communicate with it through ground vehicles. $\sum_{w} XChw_{hw} = 1 \forall h$ (26)

Constraint (26) indicates that if a location for the central warehouse is not determined, it is not possible to communicate with it in the second layer through ground vehicles. $\text{XCRKL}_{\text{rvkl}} \leq \text{XCKw}_{\text{kw}} \,\forall r, v, k, l, w$ (27)

Constraint (27) indicates that if a location for the central warehouse is not determined, it is not possible to communicate with it through a drone in the third layer.

Constraint (30) indicates that if a location for helicopters is not determined, it is not possible to transfer cargo from affected to rescue centers. $XHCRk_{hrkl} \leq XChw_{hw} \forall h, r, k, l, w$ (31)

Constraint (31) indicates that if a place for the placement of helicopters is not determined, it is not possible to transfer the cargo from the affected to the shelter.

4- Findings

4-1- Solving the model by the meta-heuristic algorithm

 In this section, at first, the presented model was solved using NSGAIII meta-heuristic algorithm in large dimensions and parametric sensitivity analysis was performed on its effective parameters. MATLAB software was used to implement meta-heuristic algorithms. The problem is represented in large dimensions as described in table 1.

Problem	Central Warehouse	Local Distribution	Affected areas	Rescue centers	Shelter	Ground vehicles	Drone	Helicopter	Potential places	Essential goods	Non- essential goods	Route
	3	15	10	20	12	25	10	3	10	5		10
◠	3	15	11	20	13	25	10	3	10			10
3	3	15	12	20	14	25	10	4	10	5		11
4		15	12	21	15	25	10	4	10	5		12
5	4	15	13	22	16	25	10	4	10	5		12
6	4	16	13	23	17	25	10	4	11	5		13
⇁		17	14	24	18	26	10	4	11	6	6	13
8		17	15	25	19	26	10		11	6	6	13
9	6	18	15	25	20	27	10			6	6	14
10	6	18	16	26	20	27	10		12	6	6	14

Table 1. The problem in large dimensions

 By introducing the problem in a large scale, the model can now be implemented, the result of which is the Pareto points produced by each algorithm (figure 1).

Fig 1. Pareto graph for NSGAIII

 By solving the NSGAIII algorithm, according to the presentation of Pareto points, it can be seen that the NSGAIII algorithm has succeeded in solving the designed model.

4-2- Examining scenarios

 Due to the scenario nature of the problem, 4 scenarios were considered in the model, and in this section, different scenarios are compared separately for each objective. The results of which are as follows.

Fig 2. Comparison of different scenarios in terms of the benefits maximization

 As it can be seen, the scenario 4 has the best situation in terms of benefits maximization. Therefore, the more benefits a scenario creates, the better conditions it will have. On the other hand, the worst conditions in terms of benefits belong to the scenario 1, and the scenarios 2 and 3 are in between these two scenarios.

Fig3. Comparison of different scenarios in terms of the cost minimization

 Regarding the cost minimization, it can be seen that the scenario 4 shows the worst conditions and scenarios 1 and 2 have the best conditions. It should be noted that due to the nature of minimizing the cost, the lower this value, the better the result. Therefore, the scenarios 1 and 2 indicate the best situation and the scenario 4 indicates the worst one regarding the cost minimization.

Fig 4. Comparison of different scenarios regarding the time minimization

 It can be seen in the above graph that although scenario 1 it shows the best situation regarding the cost minimization, it does not work in the same way when it comes to the time. The scenario 4 is the worst case in terms of time, just as the situation was similar in terms of cost. However, the interesting thing to note is that regarding the benefits maximization, the scenario 4 leads to the most benefits, so it can be said that in the scenario 4, as the benefits increase, the cost and time also increase, and this indicates a conflict in objectives.

4-3- Sensitivity analysis in large dimensions

 In this section, the sensitivity analysis of the problem was conducted in large dimensions and the results were examined and explained according to the benefits, cost and reaction time of the model according to different scenarios. The results of the sensitivity analysis of the cost of constructing a central warehouse are presented in tables 2 and 3.

			Benefits				Cost	Time				
Increase	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario
rate												
0%	29.467	29.614	29.810	29.929	37.713.502	37.730.833	37,748,586	37.762.577	6.031.371	6.048.706	6.060.181	6.077.897
10%	29.642	29,806	29.918	30.101	37.726.934	37,744,796	37.763.636	37,777,469	6.045.019	6.067.703	6.221.891	6.202.639
20%	29.748	29.943	30.097	30,232	37, 737, 743	37.756.011	37.781.447	37.793.936	6.055.323	6.083.034	6,371,395	6,396,712
30%	29.925	30,093	30,250	30,400	37.749.921	37,771,156	37.795.899	37.812.344	6.075.123	6.102.058	6.512.678	6.594.451
40%	30,056	30.262	30.393	30,600	37,763,982	37,781,588	37,810,282	37.822.961	6.090.505	6.115.610	6.655.616	6.761.918
50%	30.157	30.364	30.505	30.757	37,779,409	37,799,897	37,823,134	37,833,724	6.104.982	6,135,136	6.763.409	6.941.910

Table 2. Sensitivity analysis of central warehouse construction cost

Table 3. Changes resulted from the increased cost of constructing a central warehouse

Fig 5. Sensitivity analysis of the cost of constructing a central warehouse in terms of benefits maximization

As it can be seen in the above graph, the increased cost of constructing a central warehouse can cause a change in benefits, but this change is more visible in scenarios 2 and 4, and scenarios 3 and 1 show almost a poorer effect, so it can be said that an increased cost leads to a change in benefits among different scenarios.

Fig 6. Sensitivity analysis of the cost of constructing a central warehouse in terms of the cost minimization

 In the above graph, it can be seen that if the cost of constructing a central warehouse increases, the cost of the entire system will naturally increase, and this increase is downward in scenario 4 and it is upward in scenarios 2 and 1, while scenario 3 also indicates a neutral situation in terms of cost of constructing a central warehouse.

Fig 7. Sensitivity analysis of the cost of constructing a central warehouse in terms of time minimization

 The increased cost of constructing a central warehouse apparently cannot have much effect on the model, and this effect is slightly seen, scenario 4 shows the greatest impact, and scenarios 1 and 2 are in a neutral state. Meanwhile, scenario 3 also shows a downward effect. The results of sensitivity analysis of maintenance cost are presented in tables 4 and 5.

			Benefits				Cost	Time				
Increase	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario
rate												
0%												
10%	0.004547	0.003984	0.003499	0.003684	0.0004184	0.000383	0.000321	0.000493	0.002133	0.002066	0.002715	0.002961
20%	0.006317	0.003632	0.004459	0.004838	0.0004058	0.0005	0.000289	0.000297	0.003149	0.002668	0.003181	0.002116
30%	0.004398	0.003953	0.006041	0.006641	0.0002688	0.000341	0.000394	0.000347	0.003156	0.002273	0.002091	0.001725
40%	0.004011	0.005206	0.006602	0.004453	0.0002988	0.000327	0.000414	0.00039	0.002961	0.002575	0.002781	0.002364
50%	0.003529	0.004648	0.005867	0.00509	0.0004534	0.000509	0.000362	0.000431	0.002512	0.002636	0.001773	0.003244

Table 5. The changes resulted from increased maintenance cost

Fig 8. Sensitivity analysis of maintenance cost in terms of benefits maximization

 As it can be seen in the above graph, the increased maintenance cost leads to the increased profits, but apparently the nature of this increase is downward, that is, with a further increase in the cost of maintenance, the resulting profits in the supply chain will be descending.

Fig 9. Sensitivity analysis of maintenance cost in terms of cost minimization

In all the scenarios, we see an increase in the total cost due to the increase in the maintenance cost, only scenario 3 shows a relatively decreasing situation, but the other three ones show an increase in maintenance costs due to the increased costs. The highest amount of this increase is seen in the scenario 2, which indicates a serious and sharp increase.

Fig 10. Sensitivity analysis of maintenance cost in terms of time minimization

 In the above graph, it can be seen that the maintenance cost can increase the system time, but this increase is decreasing except for scenario 4, and it can be expected that with the increased maintenance cost in the long term, the total system time will decrease in all scenarios except scenario 4. The results of the sensitivity analysis of ground vehicles' relief costs are presented in tables 6 and 7.

Table 6. Sensitivity analysis of relief costs of ground vehicles

			Benefits				Cost		Time			
Increase	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario
rate												4
0%	29,467	29.621	29.724	29,859	37.713.502	37.713.625	37.729.943	37,747,436	6.031.371	6.049.274	6.061.265	6.080.898
10%	29.601	29.739	29.828	29,969	37.729.281	37,728,087	37,742,070	37.766,054	6.044.237	6.061.770	6.077.722	6,098,904
20%	29.788	29.847	29.961	30.114	37,744,592	37,746,969	37,752,980	37,777,265	6.063.271	6.077.940	6.097.058	6.111.811
30%	29.919	29.965	30.142	30.314	37,754,738	37.759.827	37, 767, 849	37.790.391	6.082,408	6.091.754	6.109.808	6.122.356
40%	30.039	30.121	30.341	30.449	37.766.020	37.772.157	37.783.498	37,805,133	6.100.417	6.107.440	6.126.801	6.136.827
50%	30.145	30,261	30,519	30,604	37,783,145	37,791,394	37,797,160	37,821,430	6,115,744	6,123,538	6.137.661	6,156,736

Table 7. The changes resulted from increased cost of ground vehicles

Fig 11. Sensitivity analysis of ground vehicle relief-related cost in terms of benefits maximization

 Given the above graph, it can be seen that the vehicles' relief-related costs lead to a decrease in benefits in scenarios 1 and 4, and in scenarios 2 and 3, despite a slight increase in benefits, a decrease in long term benefits will be yielded. Vehicles' relief-related costs can reduce benefits and leave a negative impact on benefits.

Fig 12. Sensitivity analysis of ground vehicles' relief-related costs in terms of cost minimization

 The results of the above graph show the increased cost of the system following the increased cost of reliefrelated cost of ground vehicles. This increase is completely upward in the three scenarios 1, 2 and 4, and apparently scenario 2 shows the worst situation, but in scenario 3, the general cost decreases, indicating different conditions compared to the other three scenarios.

Fig 13. Sensitivity analysis of ground vehicles' relief-related cost in terms of time minimization

 The results from the above graph show that the increased ground vehicles' relief-related cost can generally increase the system time, although this increase in scenarios 1 and 3 is downward in nature, but in scenarios 2 and 4, it is completely upward and increasing in nature, while the scenario 4 is the worst scenario in this regard. The results of the sensitivity analysis on the increased relief time of ground vehicles are presented in tables 8 and 9.

	Benefits						Cost		Time			
Increase	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario
rate				4								4
0%	29.467	29.621	29.724	29.859	37.713.502	37.713.625	37.729.943	37,747,436	6.031.371	6.049.274	6.061.265	6.080.898
10%	29,601	29.739	29.828	29.969	37.729.281	37,728,087	37,742,070	37,766,054	6.044.237	6.061.770	6.077.722	6.098.904
20%	29.788	29,847	29.961	30.114	37.744.592	37,746,969	37.752.980	37,777,265	6,063,271	6.077.940	6.097.058	6.111.811
30%	29.919	29.965	30.142	30.314	37.754.738	37.759.827	37.767.849	37.790.391	6.082.408	6.091.754	6.109.808	6.122.356
40%	30,039	30,121	30,341	30,449	37.766.020	37,772,157	37,783,498	37,805,133	6.100.417	6,107,440	6.126.801	6,136,827
50%	30.145	30.261	30.519	30,604	37.783.145	37.791.394	37,797,160	37.821.430	6.115.744	6.123.538	6.137.661	6.156.736

Table 9. The changes resulted from the increased relief time of ground vehicles

Fig 14. Sensitivity analysis of the increased relief time of ground vehicles in terms of benefits maximization

 The increased relief time of ground vehicles can lead to a decrease in benefits. This decrease in benefits is quite tangible in scenario 1 and is also evident in the other three scenarios, however, scenarios 1 and 3 indicate the worst and the best conditions, respectively.

Fig 15. Sensitivity analysis of the increased relief time of ground vehicles in terms of cost minimization

 In the above graph, it can be seen that the increased relief time of vehicles leads to an upward increased cost in the three scenarios 1, 2 and 4, but the third scenario has a downward nature despite the increased cost, while the scenario 2 still shows the worst case and the scenario 3 seems to have a better situation compared to the other three scenarios.

Fig 16. Sensitivity analysis of the increased relief time of ground vehicles in terms of time minimization

 In the above graph, it can be seen that the increased relief time of the vehicles leads to an increase in the time, but this state is completely upward in scenarios 2 and 4 and completely downward in scenarios 3 and 1, so it can be said that the scenario 4 shows the worst situation. In total, the increased relief time of ground vehicles will lead to an increase in time.

5- Conclusion

 In this study, the designed humanitarian logistics network for location-routing equipped with droneenabled delivery systems under uncertainty was analyzed. According to the scenario nature of the problem, 4 scenarios are considered in the model, and in this section, different scenarios were compared separately in terms of each objective. The scenario 4 has the best situation for the benefits maximization, so the more benefits created by a scenario, the better conditions it has. On the other hand, the worst conditions belonged to the scenario 1, while the scenarios 2 and 3 were between these two scenarios.

 Regarding the cost minimization, it was seen that the scenario 4 showed the worst scenario and scenarios 1 and 2 had the best state. It should be noted that due to the nature of cost minimization objective, the lower this value is, the better the result is, so the scenarios 1 and 2 indicate the best situation regarding the cost and the scenario 4 indicates the worst one. Besides, in terms of time minimization, scenario 4 still showed the worst case. Nevertheless, the interesting thing to note is that regarding the benefits, the scenario 4 leads to the most benefits, so it can be said that in the scenario 4, as the benefits increase, the cost and time also increase, and this indicates a conflict in objectives.

 Sensitivity analysis was carried out in large dimensions, according to the benefits maximization, cost and response time of the model in different scenarios. The results showed that the increased cost of constructing a central warehouse can cause a change in the benefits, but this change is mostly observed in scenarios 2 and 4, and scenarios 3 and 1 show a poorer effect, so the increase cost leads to changes in benefits in different scenarios. If the cost of constructing a central warehouse increases, the cost of the whole system will naturally increase, and this amount will decrease in scenario 4 and increase in scenarios 2 and 1, while scenario 3 also indicates a neutral situation in this case. The increase in the cost of building a central warehouse apparently cannot have much effect on the model, and this effect is observed in a low level, while scenario 4 shows the greatest impact, and scenarios 1 and 2 are in a neutral state. Meanwhile, scenario 3 also shows a decreasing effect.

 The results showed that the increased maintenance cost leads to an increase in benefits, but apparently the nature of this increase is decreasing, that is, with a further increase in the cost of maintenance, the resulting benefits in the supply chain go down and decrease. Apparently, in all the scenarios we see an increase in the total cost due to the increased maintenance cost, only scenario 3 shows a relatively

decreasing situation, but the other three scenarios show increased maintenance costs due to the increased costs. The highest amount of such an increase was seen in the scenario 2 with a serious and sharp trend. The maintenance cost can increase the system time, but this increase is decreasing except for scenario 4, and it can be expected that with the increase in maintenance cost in the long term, the total system time will decrease in all scenarios except scenario 4.

 The results also showed that vehicles' relief-related costs lead to a decrease in benefits in scenarios 1 and 4, and in scenarios 2 and 3, despite a slight increase in benefits, it leads to a decrease in long term benefits. In sum, it can be said that vehicles' relief costs may reduce benefits and leave a negative impact on them. The increased system cost occurs at the time of the increased ground vehicles' relief-related costs. This increase is completely upward in the three scenarios 1, 2 and 4, and apparently the scenario 2 shows the worst situation, but in the scenario 3, we see a decrease in the total costs, indicating completely different conditions compared to other three scenarios. The increased vehicles' relief-related costs can increase the system time in general, although this increase in scenarios 1 and 3 has a downward nature, but in two scenarios 2 and 4, it completely shows the upward and increasing nature with the worst conditions for the scenario 4.

 Finally, the results showed that the increased relief time of land vehicles in total can lead to a decrease in benefits. This reduction of benefits is quite tangible in scenario 1 and is also evident in the other three scenarios, but apparently scenario 1 is the worst one and scenario 3 has the best situation compared to the other three scenarios. The increased vehicles' relief time leads to an upward increase in cost in three scenarios 1, 2 and 4, but the third scenario has a downward nature despite the increase in cost, while the second scenario still shows the worst situation and the third scenario has apparently a better situation compared to other three scenarios. The increased vehicles' relief time leads to an increase in time, but this state is completely upward in scenario 2 and 4 and completely downward in scenarios 3 and 1, so it can be said that the scenario 4 shows the worst conditions. In total, the increased ground vehicles' relief time will lead to increased time.

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