International Journal of Engineering

Journal Homepage: www.ije.ir

A Bi-level Programming Approach for Pre-positioning Emergency Warehouses

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PAPER INFO

Paper history:
Received 20 March 2020
Received in revised form 02 September 2020
Accepted 03 September 2020

Keywords:
Relief Supply Chain
Bi-level Programming
Evolutionary Algorithm
National Emergency Warehouse
Location-allocation Problem

ABSTRACT

In some countries, regional authorities may attempt to rebalance the allocation of national facilities in benefit of their own region which, in turn, may cause disturbances in the central government's decision-making proces. Regarding the hierarchical nature of these types of decisions, classical optimization models are not effective in decision-making and the use of multi-level programming can increase the efficiency of planning. Our paper aims to address the issue of a bi-level programming model to conduct the location analysis of emergency warehouses. A three-echelon relief supply chain is considered in which the relief network involves national and regional warehouses and demand cities. The upper-level model decides on the location of national warehouses, allocating them to regional warehouses. The lower-level model determines the location of regional warehouses and allocates them to demand points. The structure of both levels is based on the median location-allocation problem. Three solution approaches are presented based on the full enumeration and two types of nested evolutionary methods (genetic and heuristic local search algorithms). For the model to be used in Iran, the efficiency of algorithms is analyzed for two sizes of problems. The obtained results show the proper functioning of the solution approaches.

***doi**: 10.5829/ije.2021.34.01a.15*

1. INTRODUCTION

Although many advances in science and technology have contributed to the increased immunity of human beings against natural disasters, numerous crises have caused various socioeconomic damages annually. As evidenced in 2015, natural disasters affected more than 90 million people with 23000 people losing their lives in 113 countries. Added to this, the damage caused by these disasters is estimated to be $ 66.5 billion [1]. Owing to both human and financial losses, interests and efforts are devoted to the development of disaster management strategies. It consists of four sequential stages: mitigation, preparedness, response, and recovery. At the preparedness stage, the aim is to decrease the operation time in the response phase [2]. Pre-positioning of emergency warehouses is one of the main tasks concerning the preparedness stage. Positioning relief supplies near the expected location of disaster is called pre-positioning [3]. These relief supplies include food, potable water, medicine, vaccines, medical equipment, tents and generators [4]. Pre-positioning is one of the appropriate strategies employed to reduce human casualties and damages to the logistics infrastructure. This strategy may develop several benefits, including an improved response time and better purchase price of supplies for relief organizations [5].

Management of the emergency warehouses network is considered the responsibility of the central government in most countries, and the design of this network is usually centralized at the upper-level of governance. Facility positioning is one of the key issues in designing a network of emergency warehouses for pre-positioning relief items. In some countries, the central government's decisions on the positioning of national resources have been ignored by regional decision-makers. Accordingly, provincial managers and parliamentarians use national facilities for their representative area regardless of

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Please cite this article as: E. Saghehei, A. Memariani, A. Bozorgi-Amiri, A Bi-level Programming Approach for Pre-positioning Emergency Warehouses, International Journal of Engineering, Transactions A: Basics Vol. 34, No. 01, (2021) 128-139

planning prospects, influencing the central government's optimal decisions. Clearly, in field studies of facility positioning for managing logistics at times of disaster, the modeling approach of most previous studies was based on classical optimization techniques. The use of single-level programming to model the problem of positioning emergency warehouses in these countries is not highly efficient. Therefore, to encourage the greater participation of lower-level decision-makers in the planning process, the bi-level programming approach can be used to model the problem of pre-positioning emergency warehouses. In this paper, a bi-level optimization model is designed to apply location-allocation to national and regional warehouses. Owing to the bi-level optimization model complexity, in this paper, three innovative solution approaches are presented by full enumeration and the nested evolutionary sequential approach. The main contributions of this research can be summarized as follows:

- Introduction of a bi-level programming structure for the use of national and regional decision-makers in the field of emergency warehouse positioning
- Development of a bi-level model to locate and allocate national and regional warehouses for relief supply pre-positioning
- Design of nested evolutionary approaches and an exact method based on full enumeration to solve binary bi-level location-allocation models
- Comparison of nested genetic and heuristic algorithms with different allocation modes to solve a model with a large number of variables

The remaining of this article is organized as follows. Section 2 and 3 are dedicated to review of the literature on pre-positioning problems and the application of single-level and bi-level programming in disaster logistics. Section 4 presents the bi-level model for location-allocation. Section 5 is related to the approaches to solve the model. Section 6 is devoted to the results of solving the optimization model. The final section presents conclusions and suggestions.

2. LITERATURE REVIEW

2. 1. Single-level Emergency Warehouses Location

Many review articles are found on the application of optimization in disaster management, of which [6-8] have especially addressed the pre-positioning problem. Balcik, Bozkir and Kundakcioglu [9] reviewed and categorized the pre-positioning based on problem characteristics and the structure of optimization models. Rawls and Turnquist [10] modeled the pre-positioning problem to determine the location of the distribution center, level of relief items and assignment of distribution centers to demand points, using the stochastic mix-integer model and the Lagrangian L-shaped method (LLSM). In their next study, they developed the previous model considering the service quality constraint [11]. Bozorgi-Amiri, Jabalameli, Alinaghian and Heydari [12] presented a multi-objective optimization model for the pre-positioning problem. They used a robust optimization approach to model uncertainty. Verma and Gaukler [4] designed two models for facility positioning in the United States' Strategic National Stockpile, one being deterministic and the other stochastic. The amount of damage inflicted upon response facilities and population centers was considered a probabilistic function of distance-damage. The results indicated that the costs of facility locationing in the stochastic model were less than those in the deterministic model. Rezaei-Malek, Tavakkoli-Moghaddam, Zahiri and Bozorgi-Amiri [13] developed a stochastic model to analyze the location of warehouses and design a distribution plan. The objective functions were considered to be the response time post-disaster and operation costs at the pre-disaster phase. Mohammadi, Ghomi and Jolai [14] presented a stochastic multi-objective model for the relief supply pre-positioning problem in which the demand covering and total cost and satisfaction ratio were considered objectives. Javadian, Modares and Bozorgi-Amiri [15] formulated the relief supply chain to locate local distribution centers and central warehouses. They proposed two multi-objective evolutionary algorithms and compared them with e-constraint method based real data in Iran case study. Aslan and Çelik [16] proposed two-stage stochastic programming in which the first stage includes the emergency warehouse location and relief supply transportation planning in the second stage. Their optimization model's innovation was taking into account the probabilistic cost of repairing damaged roads.

2. 2. Bi-level Location in Disaster Logistic

Decentralized decision-making problems are typically modeled under the Stackelberg game [17]. These problems can be modeled in the form of bi-level programming. In other words, an optimization problem as the leader (upper-level) is limited by another optimization problem as the follower (lower-level) [18]. In bi-level programming, the leader sets his/her decision first, and then the follower decides to optimize his/her goals while being aware of the decision taken by the follower. Not until does it reach the equilibrium point, this process continues [19]. The general form of the bi-level programming model is formulated as follows:

$$
\begin{aligned}
&\min_{x\in X,\, y\in Y} F(x,y)\\
&st\\
&y \in argmin\{f(x,y): g(x,y) \le 0, y \ge 0\} \qquad (1)\\
&y \in Y\\
&G(x,y) \le 0\\
&x \ge 0
\end{aligned}
$$

where $G(x, y)$ and $g(x, y)$ denote the upper and lower level constraints, respectively.

The application of bi-level location in disaster logistics is concerned with evacuation, relief distribution, facility location, and pre-positioning. Each of these problems can be divided into two phases (pre and post-disaster). As Table 1 shows, most studies have focused on evacuation, and fewer researches have investigated the effect of pre-positioning emergency warehouses. Kongsomsaksakul, Yang and Chen [20] provided a bi-level optimization model for an evacuation plan, based on a problem presented by the Stackelberg game. Planning authority and evacuees were considered to be the leader and the follower, respectively. The leader determined the number and locations of shelters, and the follower selected the target shelter and route. Hua-li, Xun-qing and Yao-feng [21] developed a location-routing problem in the urban emergency system as bi-level programming in which the objective of the upper-level was to maximize the total time satisfaction served and the lower-level was to minimize the total cost. Li, Nozick, Xu and Davidson [22] in their study developed a scenario-based bi-level model for evacuation planning. The facility planner and network user were considered as upper and lower decision-makers, respectively. The upper-level was a two-stage stochastic programming model for location and allocation. The lower-level model was concerned with the network decision-maker regarding route selection. Camacho-Vallejo, González-Rodríguez, Almaguer and González-Ramírez [23] proposed a bi-level programming model to optimize the location of distribution centers in humanitarian logistics. The government of the affected country and non-profit international organizations were considered to be the upper-level and the lower-level, respectively. The objective functions of the upper and lower level model were known to be the minimization response time and the minimization cost of sending relief items to the storage center. Gutjahr and Dzubur [24] developed a multi-

TABLE 1. A review of recent researches on bi-level location in disaster logistic

Author's	Problem	Disaster	Upper-level		Lower-level		Solving	Uncerainty
			Decision	Objective function	Decision	Objective function		
Kongsomsaksakul, Yang and Chen [20]	Evacuation	General	Shelter location	Evacuation time(↓)	Route choice	Travel Time(↓)	Nested evolutionary	-
Ng, Park and Waller [27]	Evacuation	Manmade	Shelter location	Evacuation time(↓)	Route choice	Travel Time(↓)	Nested evolutionary	-
Apivatanagul, Davidson and Nozick [28]	Evacuation	Hurricane	location-Allocation	Risk, travel time(↓)	Route choice	Travel Time(↓)	Heuristic algorithm	+
Li, Nozick, Xu and Davidson [22]	Evacuation	Hurricane	location-Allocation	Cost(↓)	Route choice	Travel Time(↓)	Heuristic algorithm	+
Hua-li, Xun-qing and Yao-feng [21]	Facility location	General	Location	Cost(↓)	Route choice	Time satisfaction(↑)	Genetic algorithm	-
Camacho-Vallejo, González-Rodríguez, Almaguer and González-Ramírez [23]	Distribution	Earthquake	Allocation	Response time(↓)	Allocation	Shipping cost(↓)	Heuristic algorithm	-
Gutjahr and Dzubur [24]	Distribution	General	Location	Costs(↓), Uncovered demand(↓)	Allocation	Wardrop equilibrium(↓)	Exact method	-
Xu, Wang, Zhang and Tu [25]	Distribution	Earthquake	Location	Weighted distance(↓)	Route choice	Transportation times(↓)	Genetic algorithm	+
Chen, Tadikamalla, Shang and Song [29]	Pre-positioning	Earthquake	location-Allocation	Response time(↓)	Allocation	Allocation fairness(↓)	Nested differential evolution	-
Safaei, Farsad and Paydar [26]	Pre-positioning	Flood	Location-Allocation	Cost(↓)	Allocation	Supply risk(↓)	Exact method	+
Haeri, Motlagh, Samani and Rezaei [30]	Pre-positioning	Earthquake	Location-Inventory	Unsatisfied demand(↓) Cost(↓)	Allocation	Transportation costs(↓)	Fuzzy goal programming	+

objective bi-level optimization model to locate distribution centers in a relief supply chain. The aid-providing organization was regarded as the leader and the beneficiaries as followers. The objectives of the leader were to minimize the total opening cost for distribution centers and total uncovered demand, and the followers' objective was to provide user equilibrium related to the leader. Xu, Wang, Zhang and Tu [25] proposed a multi-objective bi-level programming for the location-routing problem in the post-earthquake phase. The leader (Rescue Control Center) decided on the location of distribution centers, and the follower (Logistics Company) selected an optimal route to collect relief supplies from distribution centers. Road conditions were considered a source of uncertainty in this optimization model. Safaei, Farsad and Paydar [26] utilized a bi-level programming model to locate distribution centers and select suppliers. The leader's objective function was to minimize operational costs and uncoated demands, and the lower-level aimed to minimize the risk of the supplier's choice.

3. PROBLEM DESCRIPTION

In this paper, the disaster emergency network was assumed to comprise three stages (see, Figure 1). The first stage includes a set of national warehouses, the second contains regional warehouses, and the last is comprised of demand cities. Regional warehouses receive their relief supplies from national warehouses. Demand cities are serviced only from regional warehouses, and the direct shipment of goods from national warehouses to demand cities is prohibited.

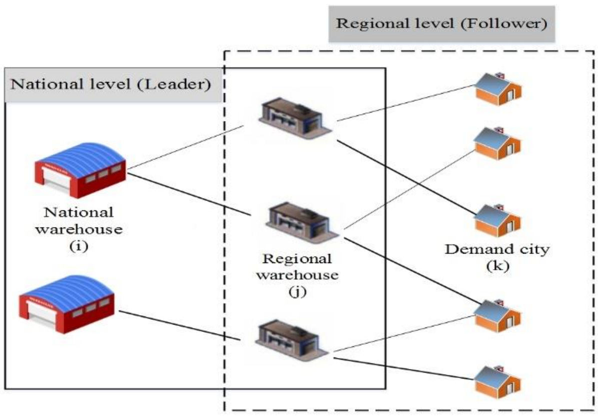

Figure 1. Bi-Level Emergency Warehouse Location-Allocation Problem (BL-EW-LAP)

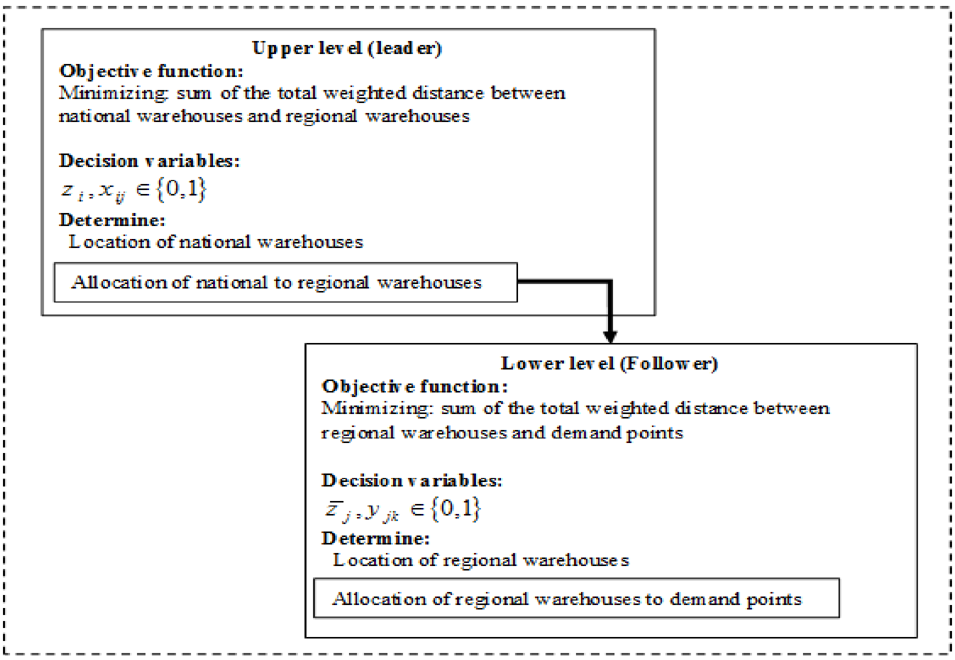

Figure 2. Framework of model for bi-level location-allocation problem

According to Figure 2. the problem has a bi-level structure for which the national top-level decision-maker is regarded as the leader and regional decision-maker as the follower. The aim of both decision-makers is to locate warehouses that completely cover all demands. The leader makes the decision on the location of national warehouses, and their assignment to regional warehouses. The case holds the same for the follower deciding on the location of regional warehouses and their assignment to demand cities. The following assumptions are considered for modeling:

- This model considers a single relief item
- The capacity of each emergency warehouse at both levels is based on the proportion of demand covered by candidate cities.
- Each demand city cannot be served by more than one regional warehouse.
- Each regional warehouse cannot be served by more than one national warehouse.
- The total capacity of all located regional warehouses must be more than the total weight of demand cities.
- The total capacity of all located national warehouses must be greater than the capacity of all regional warehouses.

There is no shipping between the same warehouses in each stage.

Indices

I set of candidate cities for national warehouses
J set of candidate cities for regional warehouses
K set of demand cities

Parameters:

urd_{ij} Road distance of national warehouse i from regional warehouse j
lrd_{jk} Road distance of regional warehouse j from demand cities k
ldw_k Demand weight associated to demand cities k
$ucap_i$ Capacity of national warehouse i
$lcap_j$ Capacity of regional warehouse j
$umax$ Number of national warehouses to establish
$lmax$ Number of regional warehouses to establish

Decision variable:

$Z_i = 1$ if a national warehouse is established at candidate city i, and 0 otherwise.
$X_{ij} = 1$ if regional warehouse j is allocated to national warehouse i, and 0 otherwise.
$\bar{Z}_j = 1$ if a regional warehouse is established at candidate city j, and 0 otherwise.
$Y_{jk} = 1$ if demand point k is allocated to regional warehouse j and 0 otherwise.
udw_j Demand weight associated to each regional warehouse j
$\left(udw_j = \sum_{k=1}^{k} ldw_k * Y_{jk}\right)$

BL-EW-LAP Model:

Upper-level model (ULM)

$$min \quad \sum_{i=1}^{n} \sum_{j=1}^{m} udw_j urd_{ij} X_{ij} \tag{2}$$

$$Subject\ to: \quad \sum_{i=1}^{n} Z_i = umax \tag{3}$$

$$\sum_{i=1}^{n} X_{ij} = 1 \qquad \forall j \tag{4}$$

$$\sum_{j=1}^{m} udw_j X_{ij} \le ucap_i Z_i \qquad \forall i \tag{5}$$

$$\sum_{k=1}^{k} ldw_k Y_{jk} = \sum_{i=1}^{n} udw_j X_{ij} \quad \forall j \tag{6}$$

$$Z_i \ , X_{ij} \in \{0,1\} \tag{7}$$

Lower-level model (LLM)

$$Min \quad \sum_{j=1}^{m} \sum_{k=1}^{k} ldw_k lrd_{jk} Y_{jk} \tag{8}$$

$$Subject\ to: \quad \sum_{j=1}^{m} \bar{Z}_j = lmax \tag{9}$$

$$\sum_{j=1}^{m} Y_{jk} = 1 \quad \forall k \tag{10}$$

$$\sum_{k=1}^{k} ldw_k Y_{jk} \le lcap_i \bar{Z}_j \qquad \forall j \tag{11}$$

$$\sum_{k=1}^{k} ldw_k Y_{jk} = \left(\sum_{i=1}^{n} udw_j X_{ij}\right) \bar{Z}_j \qquad \forall j \tag{12}$$

$$\bar{Z}_j \ , Y_{jk} \in \{0,1\} \tag{13}$$

Equations (2)-(7) refer to the upper-level model (ULM), whereas Equations (8)-(13) represent the lower-level model (LLM). Equations (7) and (13) set binary conditions for the decision variables of both levels. The objective function of the upper-level is to minimize the total weighed distance between national and regional warehouses. Equation (3) ensures that the maximum number of national warehouses that can be established on the candidate sites is equal to ($umax$). From equation (4), it is guaranteed that each regional warehouse j is likely to be allocated to national warehouse i. Equation (5) is to ensure that the regional warehouse allocated to the national warehouse will not exceed the capacity. Equation (6) is a balance constraint for each regional warehouse. In other words, the amount of demand weights of cities allocated to a regional warehouse should be equal to the value allocated from the national warehouse. Similar to that of the upper-level, the objective function of the lower-level model minimizes the total weighed distance between regional warehouses and demand cities (Equation (8)). The interpretation of Equations (9)-(12) is similar to that of Equations (3)-(6). In fact, in Equation (12), udw_j is equal to $\sum_k ldw_k * Y_{jk}$; therefore, udw_j becomes a decision variable. Consequently, the equation will be non-linear. To linearize Equation (12), we utilize A_{jk} as an auxiliary variable and introduce the following sub-situations:

$$\sum_{k=1}^{k} ldw_k Y_{jk} = \sum_{i=1}^{n} \sum_{k=1}^{k} ldw_k A_{jk} X_{ij} \quad \forall j \tag{14}$$

$$A_{jk} \le Y_{jk} \quad \forall j, k \tag{15}$$

$$A_{jk} \leq \bar{Z}_j \quad \forall j,k \tag{16}$$

$$A_{jk} \geq Y_{jk} + \bar{Z}_j - 1 \quad \forall j,k \tag{17}$$

$$A_{jk} \in \{0,1\} \tag{18}$$

4. SOLUTION ALGORITHMS

Several approaches have been proposed to classify algorithms for bi-level optimization problems that can be generally divided into two groups; classical and evolutionary approaches [31]. For bi-level programming to be a strong NP-hard problem [32], utilization of evolutionary algorithms for this type of problems is well-suited. Applications of evolutionary algorithms for bi-level programming can be divided into four groups: i) Single level transformation, ii) Nested, iii) Multi-objective, iv) Co-evolutionary [33]. Genetic algorithm is one of the most effective evolutionary algorithms frequently used for bi-level optimization problems. In [34-37], the genetic algorithm is utilized in the nested evolutionary sequential approach. Different types of evolutionary algorithms have also been used to solve facility location bi-level programming models. Huang and Liu [38] developed an interactive evolutionary framework for mixed integer bi-level programming in the location-allocation problem. They employed genetic algorithm for the lower-level model and enumeration vertex method for the upper-level model. Chen, Tadikamalla, Shang and Song [29] developed an improved differential evolution algorithm (IDE) to solve a binary bi-level model for the emergency warehouse location-allocation problem. The computational results of IDE were compared with the results of conventional differential evolution algorithms.

As Table 2 shows, there have been three approaches developed to tackle the BL-EW-LAP. The first approach, named Full Enumeration and Exact Algorithm (FE-EA), is based on explicit complete enumeration methods. The general structure of the second and third approaches is based on the Nested Evolutionary Approach (NEA). These approaches have been named Nested Genetic and Exact Solution (NG-ES) and Nested Heuristic Local Search and Exact Solution (NHLS-ES), for which the genetic algorithm and the heuristic local search algorithm have been proposed to solve ULM. In both approaches, the LLM has been solved by the exact algorithm. In this study, GAMS was used with branch-bound algorithm as an exact algorithm in the proposed approaches.

TABLE 2. The solution approaches for BL-EW-LAP

Name of Algorithm	Type of approach	Upper-level solution	Lower-level solution
FE-EA	Full enumeration	Exact algorithm	Exact algorithm
NG-ES	Nested evolutionary	Genetic algorithm	Exact algorithm
NHLS-ES	nested evolutionary	Heuristic local search	Exact algorithm

4. 1. Full Enumeration and Exact Algorithm (FE-EA)

According to Figure 3, in the first step, the FE-EA algorithm identifies all the allocation modes of national warehouses to regional warehouses (X_{ij}). In the second and third steps, (X_{ij}) are sent to the LLM and the optimal solutions of the LLM $(\bar{Z}_j^{\ *}, Y_{jk}^{\ *})$ are calculated by the exact algorithm. In steps 4 and 5, $(Y_{jk}^{\ *})$ as a parameter are sent to the ULM and the optimal solutions of the ULM $(Z_i^{\ *}, X_{ij}^{\ *})$ are calculated for all cases through the exact algorithm. Finally, the best solution of the ULM is determined to be the optimal solution for the bi-level problem.

1: **Construct** all allocation modes of the ULM (X_{ij})
2: **Let** X_{ij} be as a parameters into the LLM
3: **Calculate** $\bar{Z}_j^*, Y_{jk}^*$ by an exact algorithm
4: **Let** Y_{jk}^* be as a parameters into the ULM
5: **Calculate** $Z_i^*, X_{ij}^*, OF_{ULM}^*$ for each Y_{jk}^* by an exact algorithm
6: **Find** Min$\{OF_{ULM}^*\}$

Figure 3. Pseudo-code of FE-EA algorithm

4. 2. NEA for the BL-EW-LAP Model

In this approach, in the first step, an initial solution $(Z_i, X_{ij}, \bar{Z}_j, Y_{jk})$ is generated for the bi-level model. In the next step, X_{ij} is sent as a parameter for LLM. In the sequel, through the exact algorithm, optimal solutions of the LLM $(\bar{Z}_j^*, Y_{jk}^*)$ are calculated. In the next step, the values $(\bar{Z}_j^*, Y_{jk}^*)$ are transferred to ULM and replaced with the previous solutions. Then, the evaluation phase is performed. In this framework, the genetic algorithm and the heuristic local search algorithm are proposed separately. In the initial solution phase, $(Z_i, \bar{Z}_j)$ are generated randomly, and (X_{ij}, Y_{jk}) are calculated through the two heuristic allocation algorithms (Demand algorithm or Average distance algorithm), presented in [39]. In both heuristic allocation algorithms, assignment of facilities is based on the nearest distances. The difference between heuristic methods is the sorting criteria of nodes and their priority determination in the assignment. In the demand algorithm (DE), regional warehouses and demand cities with higher demand weights (udw_j, ldw_k) are of higher priorities. In Average distance algorithm (AD), regional warehouses with the highest average distance to national warehouses and demand cities with the highest average distance to the regional warehouses are of higher priorities. Since allocation processes at upper and lower levels are performed through two allocation methods, in the NEA framework, four algorithms can be separately used to solve the model for each approach.

4. 3. Nested Genetic-Exact Solution (NG-ES)

Generally, this algorithm consists of two phases; the initial solution generation and the evaluation phase.

Figure 13 presents the Pseudo code of NG-ES. In the initial solution phase, an initial population (POP_0) is generated. As Figure 4 shows, the structure of the chromosome is composed of two parts, the first one assigned to locating the national warehouse and the second dedicated to locating the regional warehouse. The length of the array for both parts is equal to the maximum number of warehouses, which can be placed at national and regional levels$(umax, lmax)$. A solution is made by unique integers between 1 and m for part 1 and unique integers between 1 and n for part 2. In this phase, demand cities are allocated to regional warehouses, and (Y_{jk}) is calculated by one of the heuristic allocation algorithms. In the next step, the weight associated to each regional warehouse (udw_j) is calculated using equation $(\sum_k ldwY_{jk})$. Again, through the heuristic allocation algorithm, regional warehouses are allocated to the national warehouse, and (X_{ij}) is calculated. Next, (X_{ij}) is sent to LLM as the parameter. In the next step, LLM is solved using the exact algorithm. Afterward, the optimal solution of LLM (Y^*_{jk}) is sent for ULM. Regarding (Y^*_{jk}), (X_{ij}) is modified and replaced with the previous solution.

In the evaluation phase of the algorithm, crossover and mutation operators were applied to the existing solutions. A two-point crossover operator was designed according to Figure 4. In the crossover operation, one of the two parts of the chromosome is randomly selected with the same chance (probability of selection = 0.5), and the two-point crossover operator is applied to that part. If each chromosome part contains a duplicate index indicating an infeasible solution, it will be modified as observed in Figure 5. Similar to the crossover operator, the mutation operation selects one part of the chromosome randomly with the same chance. Afterward, one cell is randomly selected and replaced with an index not existing in the parent. Therefore, the mutation operator produces an offspring from one parent chromosome.

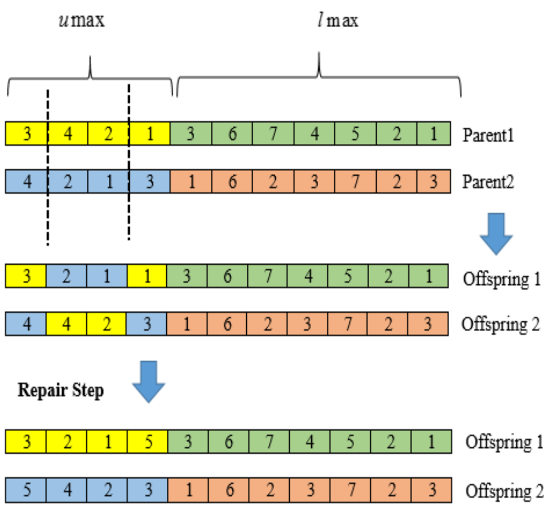

Figure 4. Two-point crossover operator

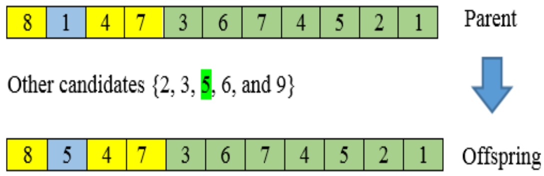

Figure 5. Mutation operator

4. 4. Nested Heuristic Local Search-Exact Solution (NHLS-ES)

The general structure of NHLS-ES is similar to that of NG-ES. Figure 12 presents the Pseudo code of the NHLS-ES algorithm. The initial solution generation is the same as the NG-ES algorithm. The evaluation phase uses the mutation operator to generate a neighborhood solution. Mutation operator selects one part of the chromosome randomly. The probability of the selection for the first and second parts of the chromosome is calculated based on formulas (19) and (20), respectively. Figure shows the neighbor search operator.

$$p_{first} = u\max/(u\max + l\max) \tag{19}$$

$$p_{second} = l\max/(u\max + l\max) \tag{20}$$

The mutation operator is sequentially three-point, two-point, and one-point. In each iteration of the mutation process, if it is better than the best solution, the objective value of a new solution is considered the best solution. At each stage of mutation, the Sub-Iter is specified as the number of internal repetitions. If in that number of repetitions, the objective value is not improved, the type of mutation is changed from three-point to two-point and eventually from two-point to one-point. Generally, unless the best answer improves the number of iterations $(MaxCon)$, the algorithm stops.

5. RESULTS

5. 1. Case Study

The model parameters were adjusted based on the Iran case study. Nine large cities and all centers of provinces in Iran (31 provinces) were selected as national and regional warehouses candidates, respectively. Furthermore, 118 cities with more than 150000 people were considered demand cities. According to formula (21), (udw_k) is calculated based on the earthquake risk (ER) and the population of the city (PO). Population statistic was extracted from the

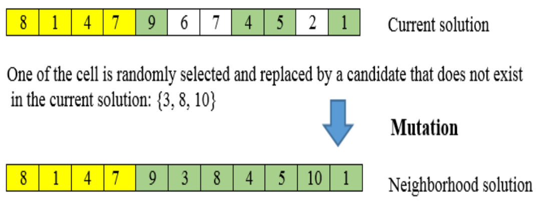

Figure 6. Neighbor search operator

Statistical Center of Iran website based on the Population and Housing Census (2016). The Iranian Code of Practice for Seismic Resistant Resign of Building, Standard No.2800 was used to calculate the earthquake risk of the cities (ER).

$$udw_k = ER_k * PO_k \tag{21}$$

In this paper, to calculate the distances matrix between nodes (urd_{ij}, lrd_{jk}), road distance was obtained from the Google Maps Platform and Distance Matrix API service. A code was written in Python programming language to determine the distance matrix of nodes (urd_{ij}, lrd_{jk}).

5. 2. Computational Results The small size problem was solved by FE-EA, and the optimal location and allocation were reported. When the lower-level problem was solved to optimality, the performance assessment of the bi-level problem was conducted using the upper-level objective [33]. Table 3 reports the numerical results obtained by NG-ES and NLS-ES algorithms for the upper-level. As Table 3 show, two algorithms from NG-ES and one from NLS-ES were obtained as the optimal solution.

Owing to the inefficiency of FE-EA in large-size problems, it is only solved by NHLS-S and NG-ES. Tables 4 and 5 report the best and the average values for all algorithms. The minimum value of the leader's objective function is related to NG-ES with the DE-AD code. This algorithm uses the DE and AD algorithm to allocate facilities at upper and lower levels, respectively. As Figures 7 and 8 show, based on the best and average value, NG-ES (DE-AD) outperforms other algorithms and is selected as the appropriate algorithm for BL-EW-LAP. According to Figure 9, all types of NG-ES algorithm have better performance than NHLS-ES for standard deviation. In addition, NHLS-ES is converged much faster than NG-ES is (Figure 10). Since BL-EW-LAP is a strategic and long-term problem, CPU time is not considered the important criterion to select an appropriate algorithm.

Figure 11 illustrates the behavior of the objective functions and the effect of the leader's response on the follower for different solutions. The leader is monotonically decreasing, while the follower has some fluctuation. Table 6 depicts the effect of parameters $(umax, lmax)$ change on the value of the objective function. With the increasing number of national warehouses, the objective function of both levels is reduced, but the increase in the number of regional warehouses does not affect the objective function of the leader and follower models.

TABLE 3. Results of all algorithm for the upper-level in the small size problem

NHLS-ES	NG-ES	Algorithm code
912589320.2	912589320.2	DE-DE
946221123	912589320.2	DE-AD
946221123	946221123	AD-DE
946221123	1101597134	AD-AD

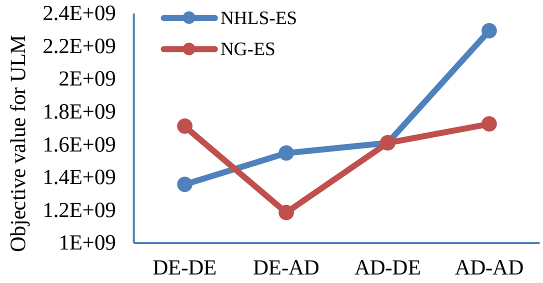

Figure 7. Best solution (NG-ES,NHLS-ES)

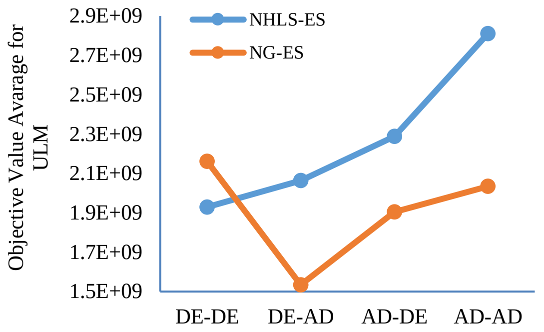

Figure 8. Average of solutions (NG-ES,NHLS-ES)

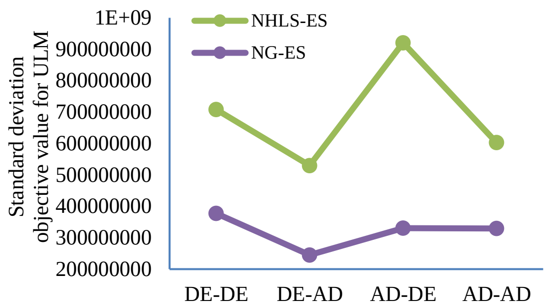

Figure 9. Standard deviation of solutions (NG-ES,NHLS-ES)

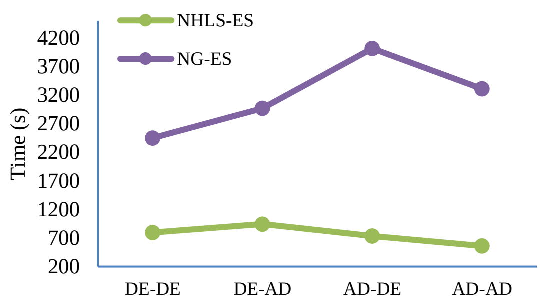

Figure 10. CPU time of Algorithms (NG-ES,NHLS-ES)

TABLE 4. Results of NHLS-ES algorithm for the large size problem

Algorithm code	Average of leader solutions	Best solution Leader	Best solution follower	Standard deviation	CPU time
DE-DE	1929385300	1356849145	19240511260	708256048.8	797.2
DE-AD	2062886677	1548416948	12505727872	529921735	943.8
AD-DE	2287684536	1610141001	16760613398	920550513	736.8
AD-AD	2810441087	2293225935	15642906833	602752285.6	560.3

TABLE 5. Results of NG-ES algorithm for the large size problem

Algorithm code	Average of leader solutions	Best solution Leader	Best solution follower	Standard deviation	CPU time
DE-DE	2161814222	1186002289	15220205195	377314775	2448
DE-AD	1665766868	2135123991	12515807758	449096980	2821
AD-DE	1904908088	1610141001	13067224449	330637134	4015
AD-AD	2033692902	1725735466	16780294548	329650646	3307

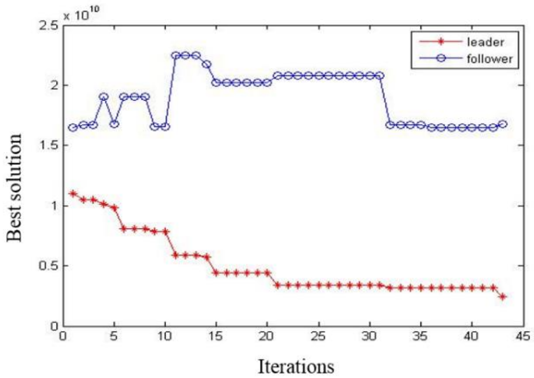

Figure 11. The variations of objective functions

TABLE 6. Impact of change $(umax, lmax)$ on objective functions

$umax$	$lmax$	Leader objective function	Follower objective function
2	3	912589320.2	2913096362
2	4	912589320.2	2913096362
2	5	912589320.2	2913096362
3	4	768888241.7	2709942156
3	5	768888241.7	2709942156

6. CONCLUSION

In this paper, a new bi-level programming model was designed for location-allocation emergency warehouses in the pre-positioning relief supply problem. In this model, the leader makes a decision on the location and allocation of national warehouses by predicting the location of regional warehouses and allocating them to demand cities. The application of this type of modeling suits countries where the design of the relief network is decentralized. The contribution of our problem in the pre-positioning literature is to model the location-allocation emergency warehouses problem in the framework of bi-level optimization. This model can also be used in the decentralized business supply chain. One requirement of logistic planning in disaster management is a limitation in the dispatch time of relief items from national warehouses to regional warehouses and the regional warehouse to service demand points. Accordingly, as a future suggestion, some constraints can be considered on the response time or coverage radius for national and regional warehouses. This helps the optimization model to become more realistic. Furthermore, there is more than one decision-maker at national and regional levels, leading to the design of multi-leader and multi-follower bi-level models. This kind of problem has more complexity than single leader/follower bi-level programming, especially for discrete problems. Another modeling suggestions is to consider various objective functions for upper-level and lower-level models. Furthermore, this problem can be modeled in the context of critical facility location.

Based on the comparison of NG-ES and NHLS-ES, it can be concluded that the developed algorithms compute the solution of the acceptable accuracy with a reasonable amount of time for a real problem. The NG-ES approach exhibited better results in this paper in terms of the standard deviation of solutions. The genetic algorithm exploits the well observed solutions, and it increases the intensification of the algorithm. NG-ES (DE-AD) outperformed all the sub-groups of NG-ES and NHLS-ES with the best, average and standard deviation of solutions for models with many variables. The main reasons behind the superiority of NG-ES (DE-AD) over three other nested genetic algorithms are concerned with the allocation method. The solution generation of all modes of NG-ES and NHLS-ES is a bottom-up approach (lower-level model to upper-level model), meaning that to calculate (X_{ij}), (Y_{jk}) must be calculated first. In certain cases, the generation of good solutions for the follower may exclude the generation of good solutions for the leader. This mechanism reduced the exploration of the search space (diversification), influencing its performance considerably. The development of nested evolutionary with different initial solution mechanisms and an exact method to solve these large size problems precisely can be a suggestion for further research.

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8. Appendix: Pseudo Code of Solution Algorithms

Input
Let $Sub-iter$ be internal loop iteration
Let $Lmax$ be number of local search method
Let CON be a counter that initially set to 0
Let $MaxCON$ be the maximum number of trials that the algorithm is not improved improve the solution*/
Generate an initial solution/*integer string* /
For all chromosomes
Calculate Y_{jk} by the allocation heuristic algorithm
Calculate $udw_j = \sum_k ldw_j Y_{jk}$
Calculate X_{ij} by the allocation heuristic algorithm
Let X_{ij} be as a parameters into the LLM
Calculate, Y_{jk}^* by an exact algorithm
Let Y_{jk}^* be as a parameters into the ULM
Update udw_j and calculate X_{ij} by the allocation heuristic algorithm based on chromosome
L=1
Best Solution = Current Solution
While $Con < MaxCon$
iter =1
Repeat
Create new neighborhood by mutation method
Calculate new neighborhood objective function
If $F_{New} \le F_{Best}$
Current solution = new neighborhood
Iter=iter+1
Until (iter ≤ Sub-iter)
If current solution < Best Solution
Best Solution = current solution
L=L
Con=0
Else
L=L+1
If L>Imax
L=1
Con=Con+1
End
Output best solution found

Figure 12. Pseudo-code of NHLS-ES

1. **Input**
2. **Let** p_c be the percentage of Crossovers population
3. **Let** p_m be the percentage of Mutation population
4. **Let** $npop$ be the size of population
5. **Let** spr be the percentage of Selection pressure rate
6. **Let** CON be a counter that initially set to 0
7. **Let** $MaxCON$ the maximum number of trials that the algorithm is not improved
8. Selection method of parent /*Roulette wheel selection*/
   Initial Solution generation
9. **Generate** an initial population of chromosomes (pop_0) /*integer string*/
10. **For** all chromosomes
11. **Calculate** Y_{jk} by the allocation heuristic algorithm
12. **Calculate** $udw_j = \sum_k ldw_j Y_{jk}$
13. **Calculate** X_{ij} by the allocation heuristic algorithm
14. **Let** X_{ij} be as a parameters into the LLM
15. **Calculate** Y_{jk}^* by an exact algorithm
16. **Let** Y_{jk} be as a parameters into the ULM
17. **Update** udw_j and calculate X_{ij} by the allocation heuristic algorithm
   Evaluation phase:
18. **While** $CON < MaxCON$
19. $n_c = npop * p_c$ / * number of chromosomes that will be generated by crossover*/
20. $i = 1$;
21. **While** $i \le n_c/2$
22. Select two chromosomes as parents based on Roulette wheel selection
23. Generate two offspring chromosomes by crossover operator
24. $n_m = npop * p_m$; / * number of chromosome that will be mutated*/
25. $j = 1$;
26. **While** $j \le n_m$
27. Select a random chromosome
28. Mutate chromosome
29. **For** each new chromosome
30. Repeat 10 to 17 steps
31. Calculate OF_{ULM} of each new chromosome
32. **Merge and sort population**
   Update stop condition
33. If the best solution not improve
34. $CON = CON + 1$
35. Else
36. $CON = 0$
37. **End**
38. **Output** best solution

Figure 13. Pseudo-code of NG-ES

Persian Abstract

چکیده

در برخ کشورها مدیران منطقه ای تلاش می کنند تسهیلات ملی را به نفع مناطق خود تخصیص دهند که این موضوع باعث اختلال در نظام تصمیم گیری دولت مرکزی می شود. با توجه به ساختار سلسله مراتبی این نوع تصمیم گیری ها، استفاده از مدلهای بهینه سازی کلاسیک از کارایی مناسبی در تصمیم گیری برخوردار نمی باشد و استفاده از رویکردهای بهینه سازی چند سطحی می تواند باعث افزایش اثربخشی برنامه ها شود. مقاله ما با هدف بکارگیری رویکرد برنامه ریزی دوسطحی در مساله مکانیابی انبارهای اضطراری بحران انجام شده است. یک زنجیره تامین امدادی سه لایه ای شامل انبارهای ملی، منطقه ای و نقاط تقاضا به عنوان شبکه امداد رسانی در نظر گرفته شده است. مدل سطح بالا در خصوص مکان یابی انبارهای ملی و تخصیص آنها به انبارهای منطقه ای تصمیم گیری میکند. مدل سطح پایین نیز مکان انبارهای منطقه ای و تخصیص آنها به نقاط تقاضا را مشخص میکند. ساختار هر دو مدل براساس مساله مکان یابی-تخصیص میانه تنظیم شده است. سه روش براساس رویکرد حل براساس شمارش کامل و دو الگوریتم تکاملی تودرتو (الگوریتم ژنتیک و جستجو همسایگی) ارائه شده است. مدل در ایران استفاده شده است و اثربخشی الگوریتمها برای دو سایز مساله تحلیل شده است. نتایج بدست آمده نشان دهنده عملکرد مناسب رویکردهای حل می باشد.