Journal of Quality Engineering and Production Optimization

Vol. 6, No. 2, Summer & Autumn 2021

http://jqepo.shahed.ac.ir

Research Paper

DOI: 10.22070/JQEPO.2021.14796.1195

Decentralized Multi-Commodity and Multi-Period Mathematical Model for Disaster Relief Goods Location and Distribution using HACO-VNS Hybrid Algorithm

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Abstract *– Logistics makes up one of the significant parts of humanitarian organizations. Regarding the natural disasters' increasing growth, coordination and cooperation in the logistics sector get more and more critical in order to minimize costs and enhance relief effectiveness. Thus, the current study proposes a decentralized multi-commodity and multi-period mathematical model for disaster relief commodities' location and distribution. The major players of the research are the relief warehouses and the third-party logistics (3PL) organizations. These two players interact through a coordination mechanism, which keeps going until the time no shortage pops up in the system. The involved innovations encompass considering the simultaneous location, inventory, and distribution of aid supplies and relief provision outsourcing and relief goods' transportation services to 3PL companies. The proposed HACO-VNS hybrid approach-based model has been solved for a case study in Tehran. The results indicate that as the demand increases, the number of established distribution centers increases. Besides, the budget increase leads to the reduction of the relief commodities' shortage. Moreover, consequently, the present study extracted results that have been made accessible for disaster management practices.*

Keywords*– Decentralized Mathematical Model, Location and Distribution, HACO-NVS Hybrid Approach, Disaster Relief .*

I. INTRODUCTION

Nowadays, despite the present technological advances, natural disasters incurred catastrophes (earthquake, flood, storm, thunderbolt, avalanche, tornado, fire, volcano, etc.) and unnatural ones (war, terrorist acts, road accidents, industrial accidents, political unrest, refugee migration and so forth) are considered of the basic obstacles to the sustainable development in the countries (Fathalikhani et al.2020). Not being prepared to tackle such disasters can bring about demanding life and financial losses (Liu et al. 2019). A couple of days after Haiti was struck by an earthquake in 2020, the United Nations announced it as the most devastating quake ever experienced (Sakiani et al.2020). Six months later, the UN declared the same issue about the Pakistan flood and forecasted the cost of about $ 0.5 billion for the short-term relief course (Tavana et al., 2018). In addition to such disasters, in recent decades, we have witnessed several

Manuscript Received:28- August -2021 & Revised: 17- Nov -2021 & Accepted: 12- December -2021
ISSN: 2423-3781

massive disasters, including the Indian Ocean earthquake and tsunami in 2004, and Sichuan province storm and cyclone and earthquake in 2008, and the Kermanshah earthquake in 2018(Ghasemi et al.2020).

Under the post-disaster conditions, vital resources like food, water, tent, clothing, relief aids and etc., are not sufficient for saving the injured victims (Toyasaki et al., 2017). In other words, the pre-stored supplies lack the potential to meet the disaster-affected victims, and the relief organizations face a shortage of items. Under such conditions, to continue aid provision and save the victims, it is highly critical to supply and purchase relief resources. Also, locating the distribution centers can minimize the system costs and minimize the relief time and, consequently, its incurred losses and damage (Alinaghian et al., 2019).

The supply chain control algorithms are divided into three categories: centralized, decentralized, and partial coordination algorithms. In the centralized algorithm, it is hypothesized that the whole supply chain is controlled by a central decision-maker, and the entire system operates as an integrated unit. The supply chain controlled by a centralized algorithm is termed as the centralized supply chain (Li et al.2019). In the decentralized algorithm, each of the supply chain members is taken as the independent economic institution independently seeking to optimize their profit. The supply chain under the control of a decentralized algorithm is known as the decentralized supply chain (Kahraman & Oztaysi,2014). While the two above algorithms are the limit modes of control algorithms in real-world supply chains, the partial coordination algorithm is the intermediate model of the two. In the decentralized supply chain, the conflict of interests, the goals, and the priorities of the supply chain members are at the maximum possible level. The Bullwhip effect and bilateral finalization can be mentioned as two adverse phenomena in the decentralized supply chains (Balcik et al. 2010)

In 2004, the United Nations Development Program reported Iran with the highest number of annual earthquakes induced deaths across the world, and in the same report, Iran is considered among the 15 worldwide disaster-prone countries. Thus, determining the appropriate models for preparedness and responding to disasters can facilitate disaster management (Babaei et al., 2019).

The rapid growth of the world's population and the increase in the number of people in dangerous environments has led to an increase in the number and severity of natural disasters, followed by an increase in the number of people affected by these disasters. For example, between 2010 and 2019, the number of natural disasters reported was approximately 960 per year, indicating a sharp increase (Ahmadi Choukolaei et al., 2021). Also, the number of affected people is generally between 100 million and 400 million per year in the world (Ghasemi and Babaeinesami, 2019). Due to the severity and scale of the disasters, the demand for rescue operations is high and usually exceeds the supply; therefore, relief centers that normally meet the needs of the city in times of disaster will not be able to meet the needs created at the right time. Therefore, there is a need for comprehensive and robust planning to manage disaster relief and its costs. Therefore, a decentralized mathematical model has been taken into account in the present research for relief commodities' location, inventory, and distribution in Tehran, Iran. In the first stage, the third-party logistics companies are located, and in the second stage, the warehouses are situated. The coordination mechanism also outlines how the two stages of the model are related. The main challenge of this research is to determine the best balance between the members of the disaster relief supply chain so that they can achieve a cost balance between the warehouse model and 3pl. Therefore, to manage this challenge, a coordination mechanism has been provided so that supply chain actors can provide services at optimal costs and in the shortest golden time. The main reason for using the coordination mechanism is the security of information between different organizations during the disaster relief process. Therefore, the present study contributions encompass the following:1-Presenting a mathematical model for coordination among disaster relief supply chain members using decentralized decision-making algorithm 2-Considering the location, inventory, and distribution of relief commodities-related decisions simultaneously 3- Relief outsourcing and relief commodities' delivery service to 3PL companies.

This study is organized into six sections. The first and second sections cover the introduction and literature. The 3rd section involves the problem statement, and the 4th section presents the mathematical model. The solution approach is given in section 5, and the numerical example is presented in section 6. The case study is provided in section 7 and the conclusion in section 8.

I. LITERATURE REVIEW

Alizadeh et al. (2021) proposed a multi-period model for locating the natural disasters relief facilities. The study mainly pursues the goal of maximizing the coverage level of hospitals and distribution centers. The Lagrange approach was employed to solve the suggested model. The question case study derived results suggest that increasing the demand lowers the covering level of the affected areas. Ghasemi et al. (2021) provided a robust mathematical model for locating the distribution centers, controlling the relief goods inventory, and allocating the centers to hospitals under earthquake conditions. Estimating computer-assisted simulation of relief commodities' demand and designing the interaction of the fundamental urban infrastructures are considered of their innovations. The simulation-optimization model has been solved by robust optimization. The question case study is Tehran. The results indicate that the proposed model is performing appropriately. Khalili-Damghani et al. (2021) presented a methodical model to minimize pre-disaster costs and maximize the post-disaster relief coverage area. Their objective was to develop a bi-objective multi-echelon multi-supplies mathematical model for location-allocation. The model is solved with an epsilon-constraint method for small and medium-scale problems and the invasive weed optimization algorithm for large-scale problems. Alinaghian et al. (2021) dealt with the pre-and post-quake disaster relief centers' location and allocation. Taking the temporary relief centers into account to prevent the swarming of the injured individuals is of the present study innovations. The harmonic algorithm and the Tabu search, along with the neighborhood search, have been used to solve the presented model. Several numerical examples solved with robust optimization indicate the proposed model is performing favorably. Manopiniwes & Irohara (2021) introduced a mathematical model for locating the temporary relief centers under flooding. The main goal is to minimize the supply chain costs such as location and transportation. Thus, the presented model has been considered as multi-period being analyzed in several periods. Of such innovations taken into account here is multi- transportation mode. The case study solution extracted results revealed the proper performance of the proposed model. Dunn & Gonzalez (2021) developed an adaptive algorithm to raise resilience and location and allocation of relief bases under flood conditions. Paying attention to the stochastic uncertainty and reliability for the centers is of the considered innovations. For locating the centers, ArcGIS software has been applied. The major goal of the research is to minimize the total system costs, including the location costs. The introduced system has been solved for various examples resulting in fulfilling performance results. Cavdur et al. (2021) provided novel strategies for the distribution of relief commodities and the human workforce under disaster circumstances. Therefore, a two-stage stochastic model has been proposed for the temporary relief centers' location and allocation. The 1st stage has been the pre-disaster phase and the 2^{nd} of the post-disaster phase. Minimizing the chain costs is done in the 1^{st} phase and allocating the resources to the centers in the 2^{nd} phase. The case study sensitivity analysis results imply that as the demand quantity increases, the allocation costs dramatically rise. Zhan et al. (2021) developed a mathematical model for locating and allocating the relief bases under supply-demand uncertainty. The basic goals pursued in the study are to minimize the shortage and the unmet demand. They focused on the case study of Zhengyang County, south of China. The Particle Swarming Optimization (PSO) algorithm has been used to solve the suggested model, the results of which denote that by the suppliers' number increase, the unsatisfied demand gets lower. Ghasemi et al. (2019) presented a multi-objective multi-commodity methodical model to location-allocation decisions in disaster conditions. Their main objectives were locating the temporary care and accommodation centers, allocation of the affected areas to the located centers. Finally, their model was solved using modified particle swarm optimization and Non-Dominated Sorting Genetic Algorithm-II. Davoodi et al. (2019) dealt with locating the distribution centers and routing emergency vehicles under disaster situations. The study phase included the pre-and post-disaster phases where the study suppliers' positioning has been investigated in the pre-phase. The main study goal has been to maximize the probability of meeting the disaster-affected points through facilitating the supplier. The study's major innovation involves considering the transportation network failure. Nagurney et al. (2019) presented a two-stage mathematical model for locating the distribution centers under uncertainty. They proposed an ideal planning in which the location, the facility capacity, and the stored commodity quantity are determined in the first stage, and the routing capacity is given in the second stage. In this model, it is possible that accessing a route is impossible in a scenario, and it is accessible in another scenario. Torabi et al. (2018) provided a multi-objective mathematical model for disaster relief management in earthquakes. The study phases encompassed preparedness and response phases. Their major goal was locating the temporary shelters and relief vehicles routing for victims' evacuation. Of the innovations in this research was considered a support shelter for any destroyed one. Noham et al. (2018) suggested a mathematical model for locating relief headquarters and controlling pre-disaster relief goods' inventory. The post-disaster stochastic routing has been given as well. The main goal of the research was to find out the location and the number of the local distribution centers and the inventory quantity to guarantee the proper response when disaster-stricken. The sensitivity analysis results suggest that higher demand remarkably raises the transportation costs. Loree et al. (2018) designed a logistics network for controlling the flow of relief commodities. The study phase was the response one, and the temporary relief facilities were optimally located in this phase. The significant goal in this study was routing the relief vehicles for delivery and the relief goods' loading in the short-term constructed centers. The numerical examples signify the proposed model performing satisfactorily. Li et al. (2017) developed a multi-objective model for the location and management of the relief vehicles transportation in the distribution network, where they have focused on the goal to minimize the relief goods' time, to minimize the required relief personnel number in the established relief centers and to minimize the unmet demand. The proposed model has been solved via the Epsilon limit. Haghi et al. (2017) presented a multi-objective and multi-stage model in the disaster response phase. Their desired goal was to maximize the effectiveness and justice in relief goods distribution and optimal resource allocation. Considering the demand, transportation vehicle fleet size and commute infrastructure accessibility simultaneously are viewed as their innovations. And ultimately, the sensitivity analysis implies that by demand increase, the distribution costs drastically rise.

With respect to the literature review table in appendix A, the research gap is compiled as the following:

- Not considering coordination among the disaster relief supply chain elements and using a decentralized decision-making algorithm
- Not concurrently considering the decisions about location, inventory control, and relief goods distribution
- Not considering outsourcing issue in aid provision by 3PL companies
- Not considering the real-world case study for customizing the model
- Not considering efficient hybrid metaheuristic algorithms for solving the proposed models

III. STATEMANET OF PROBLEM

In the present research, a decentralized mathematical model has been presented for the inventory management, location, and distribution of disaster relief commodities. Relief commodities include water, medicine, tent, and food. The first-stage model consists of the third-party logistics companies making efforts to minimize the transfer costs between the supplier and distribution points, distribution to the affected area, inventory, unsatisfied demand, and allocation. The two stages of the model interconnect using a coordination mechanism. The supply chain coordination is mainly put forth about the supply chain decentralized structure, whose goal is to create coordination and cooperation in decision making and the prioritization among the supply chain members so that they could encourage supply chain for the overall performance improvement. In other words, the goal behind the supply chain coordination can be considered to enhance the performance of the decentralized supply chain so that the decentralized chain's performance approaches the centralized mode as much as possible. The major reason behind employing a coordination mechanism is to secure the information among various organizations during the disaster relief process. Therefore, the present study contributions encompass the following:

- Presenting a mathematical model for coordination among disaster relief supply chain members using a decentralized decision-making algorithm
- Considering the location, inventory, and distribution of relief commodities-related decisions simultaneously
- Relief outsourcing and relief commodities' delivery service to 3PL companies

IV. MATHEMATICAL MODEL

The first stage assumptions are related to the location and capacity of the vehicles. The second level of assumptions is related to the shortage of relief commodities and budget allocation. The assumptions are all taken from the real world and customized for the case study.

Assumptions of First-Stage Model:

- Locating is performed discretely, and the optimal location is picked out of the candidate ones.
- In case of the desired demand is not being met, the special penalty is taken into account for each demand unit.
- The mathematical model is multi-period, multi-commodity, and single-objective.
- Relief vehicles have limited capacity.

3 PL Model:

Indices	***Details***
i	Warehouses
v	Vehicles
k	Commodities
r	Demand points
t	Time period
j	Distribution centers

Parameters	***Details***
pen_{krt}	Unmet demand penalty of commodity *k* in demand point *r* during period t
cos_{ijkvt}	Transportation cost of commodity *k* from warehouse *i* to distributor j by the vehicle *v* during period *t*
cv_v	Fixed cost of vehicle *v*
D_{krt}	Demand for commodity *k* at demand point *r* during period *t*
Q_v	Number of inventory vehicles *v*
cr_v	Capacity of vehicles *v*
ct_{irkvt}	Transportation cost of commodity *k* from warehouse *i* to demand point *r* by vehicle *v* during period *t*
g_{jt}	Capacity of distribution center *j* during period *t*
vol_k	Volume quantity of a unit of commodity *k*

in'_{kit}	Quantity of inventory commodity *k* in warehouse *i* during period *t*
cf_{kjt}	Storage cost of commodity *k* in distribution center *j* during period *t*

Variables	***Details***
o_{ijvt}	Number of vehicle v from warehouse i to distributor j during period t
o'_{irvt}	Number of vehicle v from warehouse i to demand point r during period t
u_{ijkvt}	Quantity of commodity k delivered from warehouse i to distributor j by vehicle v during period t
n_{krt}	Unmet demand quantity k at point r during period t
e_{kjt}	Inventory of commodity k at distribution center j during period t
m_{kjrvt}	Quantity of commodity k delivered distributor j to demand point r by vehicle v during period t
z_{jt}	1 if distribution center j is established during period t otherwise it's 0

$$Min\ z1 = \sum_i \sum_j \sum_k \sum_v \sum_t cos_{ijkvt}.u_{ijkvt}\, z_{jt} + \sum_i \sum_r \sum_k \sum_v \sum_t ct_{irkvt}.m_{kjrvt} + \sum_k \sum_j \sum_t e_{kjt}.cf_{kjt} + \sum_k \sum_r \sum_t pen_{krt}.n_{krt} + \sum_j \sum_r \sum_v \sum_t cv_v.(o'_{irvt} + o_{ijvt}) \tag{1}$$

$$\sum_k u_{ijkvt} \le o_{ijvt}.cr_v \qquad \forall j,i,v,t \tag{2}$$

$$\sum_k m_{kjrvt} \le o'_{jrvt}.cr_v \qquad \forall j,r,v,t \tag{3}$$

$$e_{kjt} = \sum_v \sum_t u_{ijkvt} + e_{kj(t-1)} - \sum_v \sum_r m_{kjrvt} \qquad \forall k,j,t \tag{4}$$

$$o_{ijvt} \le Q_v \qquad \forall j,i,v,t \tag{5}$$

$$o'_{jrvt} \le Q_v \qquad \forall j,r,v,t \tag{6}$$

$$\sum_v \sum_r m_{kjrvt} = D_{krt} - n_{krt} \qquad \forall k,r,t \tag{7}$$

$$\sum_{j} e_{kjt}\, vol_k \leq g_{jt} z_{jt} \qquad \forall j, r \tag{8}$$

$$\sum_{v}\sum_{j} u_{ijkvt} \leq in'_{kit} \qquad \forall k, i, t \tag{9}$$

$$\begin{aligned} &o'_{irvt}, o'_{jrvt} \in integer \\ &\mathrm{e}_{\mathrm{kjt}}, \mathrm{u}_{\mathrm{ijkvt}}, n_{krt}, m_{kjrvt} \geq 0 \end{aligned} \tag{10}$$

The objective function (1) minimizes the transfer costs between the supplier and distribution center, distribution to the affected area, inventory, unmet demand, and allocation. The constraints (2) and (3) define the capacity of vehicle *v*. Constraint (4) stands for the equilibrium in the distribution center. Constraint (7) calculates the dispatched goods k from the distributor *j* to the demand point *r* by the vehicle *k* during the period *t*. Constraint (8) defines the distribution center's volume limitation. Constraint (9) implies that the quantity of the relief commodity delivered from the warehouse to the distribution center is less than the warehouse inventory quantity. Constraint (10) depicts the type of the problem decision variables.

Assumptions of Second-Stage Model

- The mathematical model is a multi-period, multi-commodity, and single-objective one.
- In case of the relief goods' shortage in the question warehouses, the penalty is considered for the shortage of each commodity unit.
- For each commodity, a certain space limitation is considered.
- Each warehouse has its own allocated budget, which is able to continue its processes within the defined budget.

Warehouse Model:

Parameterss	***Details***
p_{kit}	Capacity of warehouse *i* for commodity *k* during period *t*
$re_{\ kit}$	Quantity of commodity *k* demanded for in warehouse *i* during period *t*
cp_{kit}	Purchase cost of commodity *k* by warehouse *i* during period *t*
bud	Budget
a'_{kit}	Shortage penalty of commodity *k* in warehouse *i* during period *t*
w_k	Space required for commodity *k*

Decision variable	***Details***
$y_{\ kit}$	Quantity of commodity *k* supplied in warehouse *i* during period *t*

$s_{\,kjivt}$ Quantity of commodity *k* delivered from warehouse *i* to distributor *j* by vehicle *v* during period *t*

$x_{\,kit}$ Shortage quantity of commodity *k* in warehouse *i* during period *t*

$$minz2 = \sum_{k}\sum_{i}\sum_{t} cp_{kit}.y_{\,kit} + \sum_{k}\sum_{i}\sum_{t} l'_{kit}.I'_{kit} + \sum_{k}\sum_{i}\sum_{t} a'_{kit}.x_{\,kit} \tag{11}$$

$$\sum_{k}\sum_{i}\sum_{t} p_{kit}.y_{\,kit} \leq bud \tag{12}$$

$$w_k.I'_{kit} \leq p_{kit} \qquad \forall k,i,t \tag{13}$$

$$I'_{kit} = I'_{ki(t-1)} + y_{\,kit} - \sum_{j}\sum_{v} s_{\,kjivt} \qquad \forall k,i,t \tag{14}$$

$$\sum_{j}\sum_{v} f_{\,kjivt} = re_{\,kit} - x_{\,kit} \qquad \forall k,i,t \tag{15}$$

$$y_{\,kit}, s_{\,kjivt}, x_{\,kit}.I'_{kit} \geq 0 \tag{16}$$

The objective function (11) minimizes the costs of purchase, storage, and shortage. Constraint (12) denotes that the costs of each warehouse should not exceed its total budget. Constraint (13) indicates that the stored good quantity in each warehouse should be lower than the capacity of each warehouse. Constraint (14) illustrates the inventory equilibrium among the warehouses. Constraint (15) shows the demand-shortage relationship in the proposed supply chain. Constraint (16) displays the type of the problem decision variables.

Equations 17 to 19 to linearize the first term of the first objective function. Variable w_{ijkvt} is also for linearization of this term.

$$w_{ijkvt} \leq M.z_{jt} \qquad \forall i,j,k,v,t \tag{17}$$

$$w_{ijkvt} \geq u_{ijkvt} - M.(1 - z_{jt}) \qquad \forall i,j,k,v,t \tag{18}$$

$$w_{ijkvt} \leq u_{ijkvt} \qquad \forall i,j,k,v,t \tag{19}$$

A. COORDINATION MECHANISM

The decentralized problems are set forth when the first-stage decision-makers cannot decide about all variables and lack the authority to verify all variables. In such decision-making, a decision-maker lacks the power to dictate their decisions to all parts of the system, and thus, decentralized decision making is presented. It is a special mode of two-stage decision making in which the first-stage decision-maker (S) is the division of the second-stage assuming that a decision-maker is selected for each division and each decision-maker independently controls a part of decision variables in the decision-making process (Khalili-Damghani and Ghasemi, 2016).

Decentralized decision-making starts working since all the divisions are located at one stage, then all are possessed with equal authority for decision making. As a result, in this study coordination mechanism is initiated with 3PL services. First off, the model is solved, and an initial solution is made available having estimated the commodity *k*'s inventory in the distribution point *j* during the period *t*, the second model in the run. After computing the initial solution, the cooperation mechanism terminates if the second-stage model has no shortage. Otherwise, the remaining amount of the commodity demanded from warehouse *i* during period *t* is calculated and delivered to the first-stage model. After that, the first-stage model is solved, and the quantities of the delivered goods are calculated. If the desired demand is met, the algorithm terminates. Otherwise, the new demand quantity gets into the second-stage model and the algorithm continues.

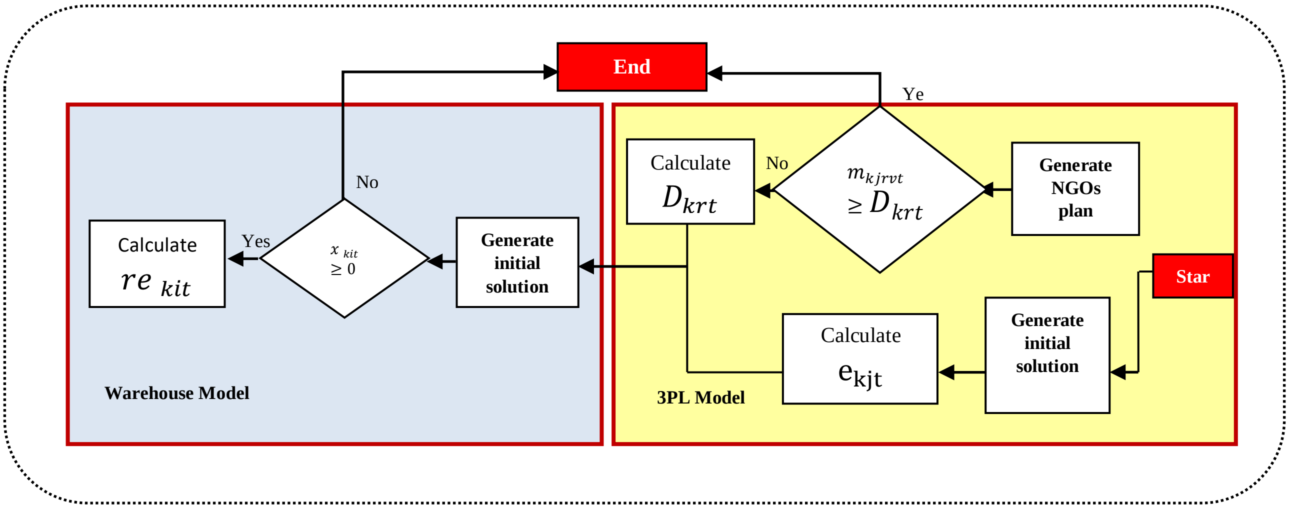

Fig.1: Coordination Mechanism of Model's two stages

V. SOLUTION

HACO-VNS hybrid algorithm has been applied to solve the proposed mathematical model. The hybrid algorithms are faster and solve highly accurately. Thus, first, the encoding and initialization structure of the Ant algorithm and then Variable Neighborhood Search (VNS) are described. One of the primary versions of the Ant algorithm is the Ant system, which besides its higher efficiency compared with the genetic one, does not approach the initial solution properly (Dorigo et al. 2006). VNS has been utilized to solve this problem. In this algorithm, unlike the Ant system where the ants have the permission to use the local pheromones, the ants are only allowed to use the global pheromones. In this approach, in each iteration, the edges with a higher amount of pheromone than the maximal are maximally reduced, and the edges with a lower amount of pheromone than the minimal level increase by the minimal quantity. Pheromone evaporation and probability-accident allow ants to find the shortest path. These two features make it flexible in solving any optimization problem. For example, in the graph of this paper problem, if one of the edges (or nodes) is removed, the algorithm has the ability to quickly find the optimal path according to the new conditions. In this way, if the edge (or node) is removed, the algorithm no longer needs to solve the problem from the beginning, but from where the problem is solved to where the edge (or node) is removed, we still have the best path, from now on ants can, after a short time, find the optimal (shortest) path. Besides, one of the advantages of the neighborhood search approach is fast convergence and the possibility of achieving higher-quality answers.

To increase the quality of the solutions produced by the ACO algorithm, it is possible to design hybrid ACO-local search algorithms. The local search algorithm improves a solution iteratively by looking at a defined neighborhood. During the search, if it finds a better solution, it replaces the current solution and the exploration moves to the new solution's neighborhood. The replacement can be done with the best solution found after exploring the whole neighborhood (best-improvement rule) or as soon as the solution improving the best one so far is found (first-improvement rule). Needless to say, the choice of a good neighborhood is crucial for the algorithm's performance. The hybridization of a local search algorithm within the ACO scheme will be described in the subsection Improvement Phase.

Improvement phase: It is common to hybridize the ACO with other heuristics aiming for better performance. Once a complete solution is obtained, a Local Search (LS) algorithm can improve it. The two approaches are complementary: the ACO explores the solution space in a coarse-grained way, and the LS refines the solution found. This combination may be crucial to achieving state-of-the-art performance. We developed a simple local search algorithm, which evaluates neighborhoods and iteratively improves the solution with the best neighbor found among them, using a best-improvement rule.

1-Initiate

2-Regulates algorithm parameters like evaporation coefficient

3-Position the ants in the relevant location

4-Create a feasible solution for each of the ants

5-Achieve the best current solution and update the best solution achieved so far

6-Update the pheromone of the edges and put the quantity according to the cases

7-Analyze the algorithm's termination condition. In case of meeting, go to the next stage, otherwise go to stage 3

8-Disply the best answer

9-Terminate

Fig.1 depicts Pseudocode of the Ant algorithm.

In order to design the hybrid algorithm's structure, the Random-key (RK) algorithm has been employed. For encoding the algorithm, a matrix with a uniform function in the range (0 and 1) is used. For instance, a solution code (0, 1, 4, 2, 5) shows the structure of allocating distribution centers to relief points. Fig.1 displays the encoding structure.

The concept called neighborhood and finding it is highly significant in the Ant algorithm. To discover the neighborhood, the possible transfers can be done on the present solutions, and the elements N(s) are set. It's worth mentioning that in most of the problems, the number of such transfers may be high, and it isn't feasible to estimate all of them in terms of the computing costs. For this reason, in the current study, a very small neighborhood is initially considered. Through this process, the presented algorithm can achieve quite a decent solution within a short time. Then the algorithm is able to change its neighborhood variety in case of the best solution being constant in a given number of iterations.Fig.2 demonstrates the structure of the variable neighborhood search algorithm. In figure 2, a separate selection is performed for each of the variables. Therefore, the VNS improves the current solution, replaces the current solution algorithm with new solutions, and starts the same neighborhood search structure again.

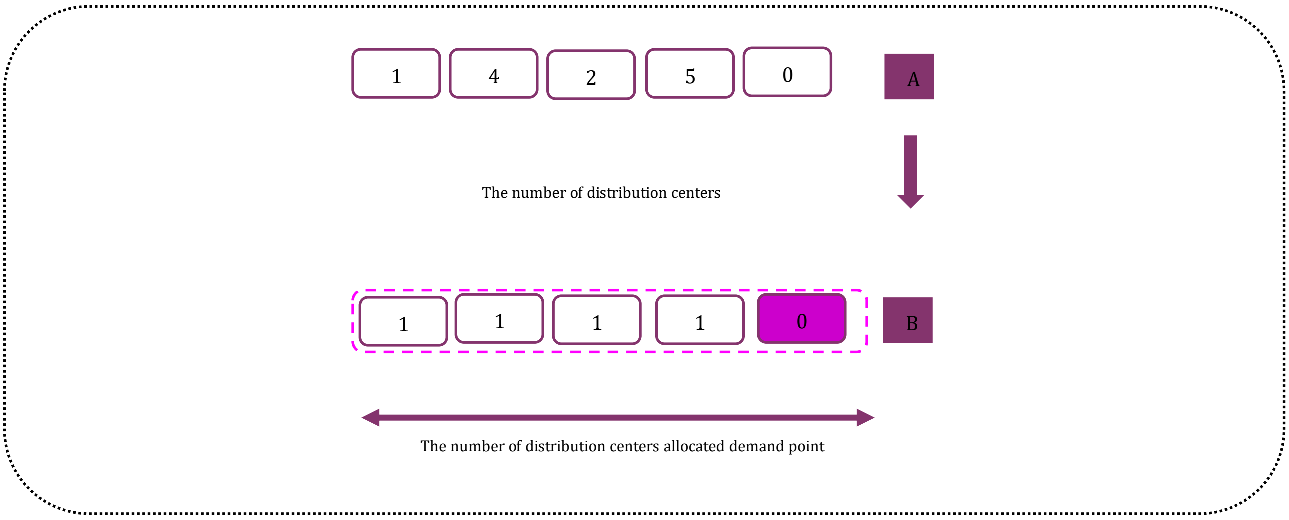

Fig.2: Relevant Algorithm Decoding

Initialization

Set Parameters $(nPop$, maximum number of iterations$(Maxitr))$

Consider a set of neighbourhood structures N_{ns} $(ns = 1, 2, \ldots, ns_{\max})$

Generate/recieve population with size $nPop$ and evaluate them

Pick up the best solution as initial solution S^*;

for $itr = 1$ **to** $Maxitr$ **do** // main loop

for $N_{ns} = 1$ **to** $ns_{\max}$ **do**

$S \leftarrow S^*$;

Determine a random solution S' from N_{ns} //shaking

Perform a neighborhood search N_{ns} on S' to find S''

Evaluate S'';

if $f(S'') < f(S^*)$

$S^* \leftarrow S''$ and Break;

elseif $f(S'') = f(S^*)$

Select one of them randomly;

endif

endfor

endfor

Report S^*;

end

Fig. 3: VNS algorithm pseudocode

The suggested algorithm adds the neighborhoods with quality to their previous neighborhoods. This process goes on until the algorithms find a better solution and or the final step of the algorithm terminates. Fig.3 depicts the HACO-NVS hybrid algorithm.

1-Start

2-Adjust algorithm parameters such as evaporation coefficient.

3-Place the ants in the appropriate places.

4-Create an answer for each of the ants

5-Get the best current answer and update the best answer so far.

6-Update the pheromone on the edges and place the amount on the edges according to what has been said

7-Examine the stop condition of the algorithm. If this condition is met, go to the next step, otherwise go to step 3.

8-Choose the best answer by variable searching the neighborhood

9-End

Fig.4: HACO-NVS algorithm pseudocode

VI. NUMERICAL EXAMPLE

In this section, numerical examples are provided to prove the proposed model is performing properly. Table I gives the parameters' values in the question example. As observed, all the parameters have been used from a uniform function in specified ranges.

Table I: Numerical example's parameters

Parameters	*Value*	*Parameters*	*Value*
pen_{krt}	$U\sim[5,10]$	in'_{kit}	$U\sim[100,200]$
cos_{ijkvt}	$U\sim[10,20]$	cf_{kjt}	$U\sim[10,20]$
cv_v	$U\sim[400,500]$	p_{kit}	$U\sim[6000,8000]$
D_{krt}	$U\sim[3000,5000]$	$re_{\ kit}$	$U\sim[1000,3000]$
Q_v	$U\sim[10,50]$	cp_{kit}	$U\sim[20,30]$
cr_v	$U\sim[1000,3000]$	bud	$U\sim[10000,15000]$
ct_{jrkvt}	$U\sim[5,10]$	a'_{kit}	$U\sim[10,15]$
g_{jt}	$U\sim[6000,8000]$	w_k	$U\sim[5,10]$
vol_k	$U\sim[1,5]$		

Table II shows the numerical examples' sizes and the comparison of the results of the exact algorithm solution and the hybrid algorithm. As defined, there are eight numerical examples. Examples 1-4 are for small sizes, and examples 5-8 are for medium size. The higher the problem size gets, the more problem nodes there are. For instance, in example 1, the number of warehouses, commodities, demand points, time period, and distributors is one, and the number of vehicles is 2. Besides, in example 8, the number of all facilities is 4. The last column of this table presents the comparison of the numerical examples' solution results through the exact and hybrid algorithms. As seen, the calculated error in all cases has been less than 1%, indicating the proposed hybrid algorithm's accuracy and the algorithm results' reliability.

Table II: Numerical examples' size and error percentage

Size	*Samples*	*Warehouse*	*vehicle*	*goods*	*Demand point*	*Period*	*Distribution center*	*Error%*
Small	Sample 1	1	2	1	1	1	1	0
	Sample 2	2	2	2	2	1	2	0.03
	Sample 3	2	2	3	2	1	2	0.09
	Sample 4	2	3	3	2	1	3	0.07
Medium	Sample 5	3	3	3	3	2	3	0.26
	Sample 6	3	3	4	3	2	3	0.15
	Sample 7	4	4	4	3	2	3	0.34
	Sample 8	4	4	4	4	2	4	0.38

Fig.5 displays the solution of the numerical examples. As indicated, by the numerical examples' size increase, the solution time increases, too. The first example's solution time for the exact solution is 18.21 s, and for the metaheuristic solution, it's 21.3 s. Moreover, as the problem size increases, the exact algorithm solution time suddenly starts rising from example 4. This built-up is up to the point where it increases exponentially. This build-up keeps increasing until the exact algorithm solution time gets 957.45, for example 8. Thus, it can be stated that regarding the solution time period, it is an np-hard problem, and considering the presented metaheuristic algorithm's efficiency, it can be employed for a case study.

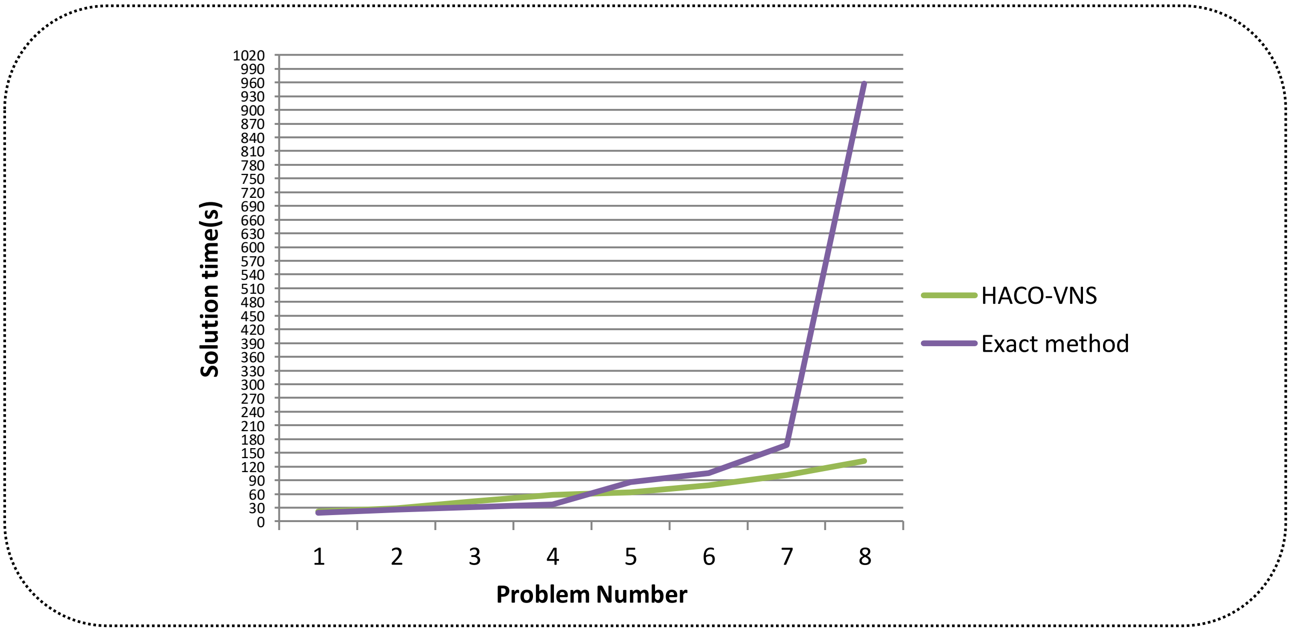

Fig.5: Numerical examples' solution time

According to the case study, the convergence of the Pareto's obtained from the HACO-VNS algorithm is depicted for the objective function. As shown in Figure 6, the proposed algorithm converges from iteration 85.

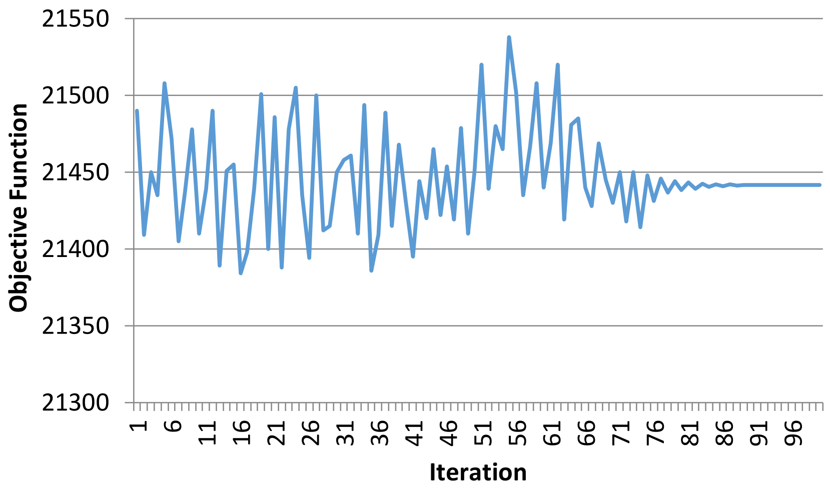

Fig .6: Convergence

VII. CASE STUDY

Earthquake is one of the major threats for Tehran. Various hazards are visualized for Tehran. The most critical and the most probable one is the earthquake. Disaster at any level and severity in a city with the characteristics of Tehran undeniably results in some damage, such as urban and residential buildings getting destroyed and naturally disrupting transportation and logistics networks. That means all facilities in charge of taking measures under disaster for aid provision will be affected. Then in this study, Tehran based district one has been focused on for the case study. Fig.7 shows the map of the case study. As specified, *L* stands for the demand points, *W* for the warehouses, and *D* for the distribution centers.

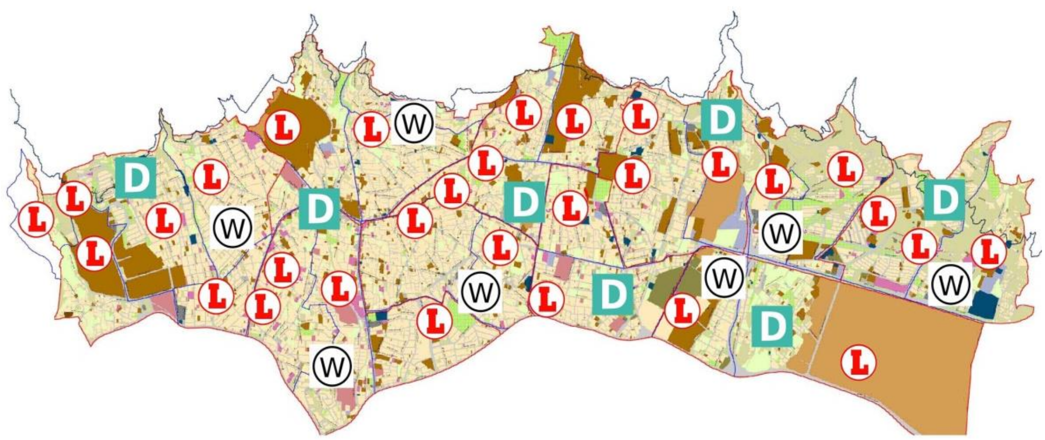

Fig .7: Case Study Map

Table III illustrates the relief commodities' demand quantity by the demand points. As indicated, there are 30 demand points and four relief commodities in the considered case study. For example, the demand quantities of the commodities 1- 4 in the Hekmat district are 87,248,229 and 44 kg, respectively.

Table IV stands for the warehouse capacity for the relief commodity. As clearly seen, warehouse 7 has been taken into account in the case study. For instance, the capacity of warehouse 1 for the relief commodity 1-4 is 2000, 1500, 2000, and 2000 kg, respectively.

A. COMPUTATIONAL RESULTS

Table V presents the results of the case study solution. As observed, the mathematical model in the first period has been solved with two iterations and the second period with three iterations. In the first period, the objective function of the 1st stage equals 501393, and the objective function of the 2nd stage is 316746 units. In the second period, the objective function of the first stage has shown the quantities of 192184 and that of the second stage as 2009492, respectively. In the second period, the objective function of the first stage has revealed the quantities as 36882,267022 and 218747. The second stage objective function has come up with 218410,156988 and 113515 quantities. Moreover, the model solution time equals 104 s in the first period and 186 s in the second period.

Table III: Relief Commodities' Demand Quantity in Each District

Demand point	*Commodity 1*	*Commodity 2*	*Commodity 3*	*Commodity 4*
Hekmat	87	248	229	44
Ozgol	68	198	215	56
Soohanak	70	119	131	23
Mahalati	69	101	238	49
Evin	72	210	213	34
Drake	36	178	140	34
Aqdasied	53	114	151	31
Elahieh	86	144	122	73
Andarzgu	73	189	162	40
Velenjak	76	172	104	47
Parkvey	95	204	190	34
Tajrish	51	140	150	32
Jamshidieh	100	123	188	20
Dibaji	77	203	149	59
Sadabad	44	156	105	20
Sahebqaranieh	66	105	156	27
Farmanieh	64	230	194	34
Qeitarieh	77	168	193	65
Mahmoodieh	68	146	179	42

Continue Table III: Relief Commodities' Demand Quantity in Each District

Demand point	*Commodity 1*	*Commodity 2*	*Commodity 3*	*Commodity 4*
Moghdas ardebili	100	111	241	68
Mini city	87	116	184	59
Nowbonyad	88	228	164	24
Valiasr	86	162	170	32
Darband	69	222	235	41
Golabdare	39	121	245	23
Jamaran	62	157	232	69
Dezashib	62	153	183	78
Niavaran	41	224	234	63
Araj	92	101	193	24
Kashanak	54	185	242	33

Table IV: Warehouse Capacity of Relief Commodities

Warehouse	*Comoditiy1*	*Comoditiy2*	*Comoditiy3*	*Comoditiy4*
Warehouse1	2000	1500	2000	2000
Warehouse2	3000	3000	3000	3000
Warehouse3	1000	1500	1500	1000
Warehouse4	2500	3000	4000	3000
Warehouse5	5000	4000	5000	4000
Warehouse6	7000	6000	6000	6000
Warehouse7	8000	8000	8000	8000

Table V: Case Study Results

Period	*Stage 1*		*Stage 2*		*Iteration number*
	f_1	*Time(s)*	f_1	*Time(s)*	
1	501393	23	316746	20	2
	192184	33	200492	29	
2	363882	28	218410	24	3
	267022	25	156988	26	
	218747	51	113515	32	

Table VI demonstrates the vehicles transferred from the warehouse to the distribution center. As indicated, under optimal conditions, it's not possible to establish two distribution centers, and there are five distribution centers. Say, the number of vehicles transferred from the warehouse 1 to 4 established distribution centers is 11, 13, 0, 25, and 0, respectively.

Table VI: Number of vehicles transferred from warehouse to distribution center

Warehouse/Distribution center	*DC1*	*DC2*	*DC3*	*DC4*	*DC5*
Warehouse 1	11	13	-	25	-
Warehouse 2	23	-	7	18	9
Warehouse 3	4	15	13	5	9
Warehouse 4	-	23	-	26	14
Warehouse 5	23	12	17	-	6
Warehouse 6	9	31	8	14	-
Warehouse 7	13	18	25	-	14

Table 7 shows the relief commodity shortage quantity in the warehouses. As perceived, the shortage quantity of commodity 1 in warehouse 1 is 25,0,0 and 36 kg, respectively.

Table VII: Shortage quantity of relief commodity in warehouses

Warehouse/Distribution center	*Commodity 1*	*Commodity 2*	*Commodity 3*	*Commodity 4*
Warehouse 1	25	-	-	36
Warehouse 2	-	-	26	52
Warehouse 3	21	15	32	-
Warehouse 4	-	17	-	19
Warehouse 5	11	29	34	-
Warehouse 6	35	-	-	14
Warehouse 7	19	42	-	30

Table VIII shows the unmet demand at the demand point. As perceived, the shortage quantities of commodities 1 and 2 in the Hekmat center are 3 and 9 kg, respectively.

B. SENSITUVITY ANALYSIS

In this section, to analyze the mathematical model, the sensitivity analysis has been carried out on the parameters influencing the case study model. Investigating these parameters' induced effect can provide an appropriate perspective for managers to make decisions. This section deals with the demand variation effect on the costs and the number of the established distribution centers. As displayed in Fig.8, the two models' costs rise as the demand increases. In contrast, the first-stage model's costs increase more sharply. And 30% decrease in demand accompanies the first-stage costs decline to 1025559 units and the second-stage costs to 952008 units. Moreover, under normal conditions after solving the model in the first stage, the costs get 1543228 units and 1006151 units in the second stage. Also, 10% demand increase leads to the first-stage cost increase of up to 1711618 units and of the second-stage cost as 1550643 units.

Table VII: Unmet demand at demand point

Demand point	*Commodity 1*	*Commodity 2*	*Commodity 3*	*Commodity 4*
Hekmat	3	9	-	-
Ozgol	68	-	-	56
Soohanak	70	-	-	-
Mahalati	12	15	-	-
Evin	72	32	14	4
Drake	36	16	20	3
Aqdasied	-	-	-	-
Elahieh	20	23	14	-
Andarzgu	-	-	-	-
Velenjak	-	-	-	3
Parkvey	-	-	-	-
Tajrish	3	11	13	-
Jamshidieh	-	-	-	-
Dibaji	-	-	-	-
Sadabad	7	3	8	12
Sahebqaranieh	16	13	14	10
Farmanieh	-	-	-	-
Qeitarieh	-	3	26	20
Mahmoodieh	-	-	62	11
Moghdas ardebili	-	36	16	30
Mini city	-	-	-	-
Nowbonyad	26	46	38	-
Valiasr	-	-	-	-
Darband	-	23	-	-
Golabdare	13	36	17	-
Jamaran	-	-	-	-
Dezashib	-	-	-	-
Niavaran	-	-	-	-
Araj	11	35	16	3
Kashanak	17	18	40	11

Fig.8: Sensitivity analysis of demand variation to cost variation

As clearly seen in Fig.9, the number of established distribution centers gets more as the demand quantity rises.Fig.1 shows 10% and 30% decline in demand results in the establishment of 3 distribution centers in the case study. Under normal conditions in the case study, five distribution centers are built. By 10% demand rise, six distribution centers, and 30% demand rise will lead to establishing seven distribution centers. Therefore, by its 30% increase, the established distribution centers will reach their maximum possible number.

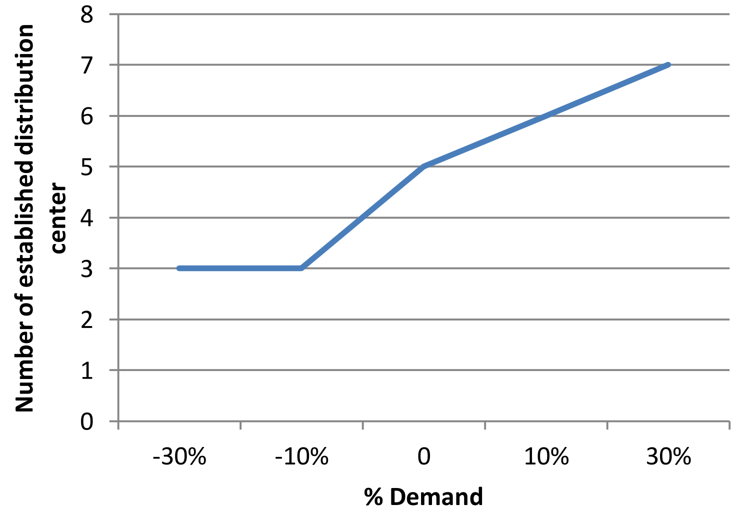

Fig.9: Sensitivity analysis of demand variation to distribution centers' number variation

Fig.10 depicts that as the budget increases, the relief commodity shortage quantity drops. According to Fig.1, 30% budget decline will increase the shortage quantity up to 506 units. In addition, 10% budget decline will increase the shortage quantity to 249 units. With 10 % budget rise, the shortage quantity gets down by 98 units, and 30% increase will reduce the shortage quantity to 67 units.

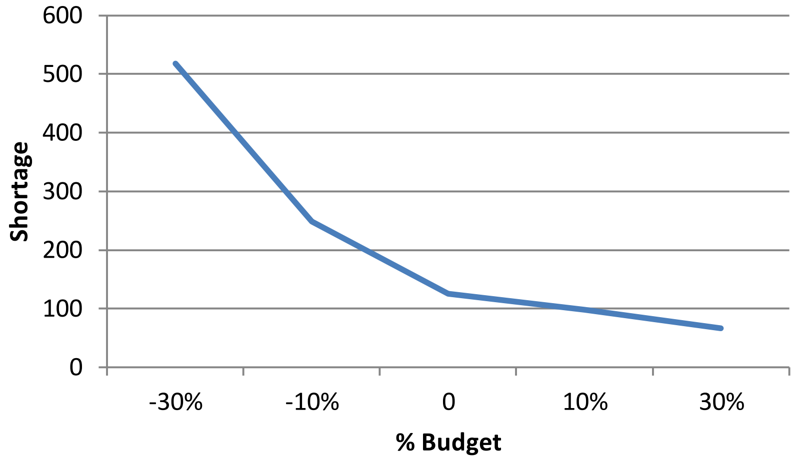

Fig.10: Sensitivity analysis of budget variation to shortage variation

VIII. CONCLUSION

Although logistics has been originally extracted from a military background, the central point of logistics in the current study focuses on the cooperation network of various organizations. The cooperation approach is due to this matter that logistics leads to increasing the productivity and competitiveness of the companies by lowering the service provision time, improving service quality, reducing costs, and raising flexibility. To cope with earthquake-induced uncertainty, we require a reaction in which higher cooperation and the specialization of operations not only takes place at the level of armed forces, governments, and humanitarian organizations, but also the benevolent individuals get more willing to cooperate with the humanitarian NGOs working in the same affected region so that to prevent resuming the operations. Consequently, cooperation and coordination among the humanitarian NGOs are required more than before. So in the continuation of the relief and rescue debate, the managers and decision-makers should be aware of this matter that:

- Cooperation among the humanitarian agencies boosts the effectiveness of the whole process of relief.
- Lack of and poor cooperation leads to wasting the resources and or the valuable reaction time loss.
- Cooperation among humanitarian agencies is tough and demanding due to various obstacles.

Hence, the present study-derived results can be proved beneficial for the organizations such as disaster management, hospitals, relief and rescue foundations, emergency and etc. At the time of catastrophes outbreak, the efforts to rescue and provide aid can reduce casualties and stock them with welfare by providing relief to the survivors. Thus, the current study proposes a decentralized mathematical model to minimize various disaster relief process associated costs. The main goal pursued here is locating, controlling the inventory, and distributing the relief goods in Tehran based district 1. At the first stage of the presented model, the third-party logistics companies are positioned for which the logistic activities have been outsourced. At the second stage, there are the warehouses mainly in charge of minimizing the costs of purchase, storage, and shortage. To relate the two stages of the model, a coordination mechanism has been developed. The mechanism defines the two models' interactions. Coordination goes on until the time there is no shortage, and the relief commodities' demand is satisfied. The model has been solved for numerical examples and for Tehran case study in large sizes. The model solution result implies that five distribution centers have been established.

The sensitivity analysis result indicates that as demand quantity increases, the costs of the two models increases, too. While in the first-stage model, the costs rise more sharply. The demand increase will lead to establishing more distribution centers. This process continues until the point that by 30% demand increase, the number of the established distribution centers gets 7. Besides, as the budget quantity increases, the relief commodity shortage declines. Accordingly, the decision-makers are recommended to raise the relief budgets as much as possible to be able to control the inventory and prevent a shortage.

The following tips are suggested for the would-be studies:

- Employing uncertainty algorithms such as fuzzy and stochastic
- Consider a competitive game to routing vehicles
- Considering other hybrid algorithms and using machine learning algorithms
- Considering relief related traffic and simultaneously dealing with the flow of the injured and the flow of relief commodities
- Considering the inference system to estimate the required relief commodity demand

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Appendix 1

Table a. literature review

Author	*Solution procedure*			*Commodity*		*Objective Function*					*Period*		*Decision level*				*Echelon Number*		*Game theory*	
	Exact	*Heuristic*	*Meta Heuristic*	*Single*	*Multi*	*Covering*	*Cost*	*humanitarian*	*Distance*	*time*	*Single*	*Multi*	*recovery*	*response*	*preparedness*	*prevention*	*Single*	*Multi*	*Coordination*	*Competition*
Alizadeh et al. (2021)	•			•			•				•			•				•		
Ghasemi et al. (2021)	•				•		•					•		•				•		
Khalili-Damghani et al. (2021)	•			•			•			•		•		•				•		
Alinaghian et al. (2021)	•				•		•	•				•		•				•		
Manopiniwes & Irohara (2021)	•			•			•			•		•	•	•				•		
Dunn & Gonzalez (2021)			•							•	•				•		•			
Cavdur et al. (2021)	•			•		•	•				•			•	•			•		
Zhan et al. (2021)	•				•		•					•		•	•			•		
Ghasemi et al. (2019)		•			•				•		•				•	•	•			
Davoodi et al. (2019)	•			•					•		•			•			•			
Nagurney et al. (2019)	•				•			•			•		•					•		
Torabi et al. (2018)		•		•					•		•		•	•			•			
Noham et al. (2018)		•		•		•					•		•				•			
Loree et al. (2018)	•			•			•			•		•	•	•				•		
Li et al. (2017)			•							•	•				•		•			
Haghi et al. (2017)	•			•		•	•				•			•	•			•		
This Research	•	•			•		•	•				•		•	•			•	•	