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RESEARCH PAPER

Design a Relief Transportation Model with Uncertain Demand and Shortage Penalty: Solving with Meta-Heuristic Algorithms

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ABSTRACT

In this paper, a fuzzy multi-objective optimization model in the logistics of relief chain for response phase planning is addressed. The objectives of the model are: minimizing the costs, minimizing unresponsive demand, and maximizing the level of distribution and fair relief. A multi-objective integer programming model is developed to formulate the problem in fuzzy conditions and transformed to the deterministic model using Jime'nez approach. To solve the exact multi-objective model, the ε-constraint method is used. The resolved results for this method have shown that this method is only able to find the solution for problems with very small sizes. Therefore, in order to solve the problems with medium and large sizes, multi-objective cuckoo search optimization algorithm (MOCSOA) is implemented and its results are compared with the NSGA-II. The results showed that MOCSOA in all cases has the higher ability to produce higher quality and higher-dispersion solutions than NSGA-II.

KEYWORDS: *Relief chain; Response phase planning; Inventory displacement; MOCSOA; NSGA-II.*

1. Introduction

The inherent uncertainty and the unpredictability of natural disaster (especially earthquakes) require that comprehensive disaster management plans be presented to reduce and mitigate the risks and consequences of the disaster [1]. Based on the importance of logistics in humanitarian operations, many papers have been published in this context over the last decade. The operations research methods have been proposed to formulate the issues in this context such as facilities location planning, transportation planning, vehicle routing, inventory planning, etc. Exact solution methods and heuristics are provided to solve the problems such as the maximal covering, network flow, or the shortest route. The location problem is combined with the vehicle routing problem [2], and also with inventory planning. In 2007, Chang presented two possible models for warehouses location for emergency response after earthquake and also inventory allocation to the warehouses [3]. Rawls and Trunquist (2012) studied the problem of pre-location and dynamic supply in disasters. They considered the demand for relief goods as uncertain and modeled on different scenarios [4]. Ozdamar and Demir (2012) provided a model in which a relief items were sent to the disaster zone and the injured people would be evacuated and sent to the hospitals [5].

Rottkemper et al. (2012) studied the distribution and displacement of inventory in humanitarian operations under uncertainty conditions. They have provided a multi-period mixed-integer

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mathematical model with the objectives of minimizing the cost of inventory displacement and minimizing unresponsive demand in all periods [6]. Rezayi Malek and Tavakkoli-Moghadam (2014) presented a mathematical model where the facilities location, determining the level of inventory in depots, and distributing and sending relief goods have been addressed. Their mathematical model has two objectives of minimizing the time of sending the goods and minimizing the total cost of the network [7]. Safeer et al. (2014) analyzed the distribution and transportation network in relief logistics. They categorized and reviewed the models of transportation and distribution of relief goods in the literature based on transportation costs, parameters and considered constraints and objectives [8]. Duffis et al. (2015) simulated a relief operation and provided an efficient system for helping the injured people under different conditions and scenarios [9]. Battini et al. (2016) have addressed the sustainable closed-loop supply chain problem in humanitarian operations. They designed the supply chain for relief operations considering the aspects of sustainability. They presented a mathematical model based on the scenario consideration with capacitated constraints for facilities and vehicles [10]. Alem et al. (2016) proposed a two-stage stochastic model for relief logistics planning in Brazil. In the proposed model, the routing phase is considered with a variety of transportation vehicles as well as the supplying of relief goods for injured people are considered with limited resources. They also take into account the risk factors in their model [11]. Rezaie Malek et al. (2016) surveyed the issue of relieving, and provided a robust mathematical model for modeling of relief logistics considering perishable goods [12]. Sebatli et al. (2017) addressed the issue of determining the amount of demand in the relief supply chain as well as the allocation of facilities to supply the relief items. They provided an integer mathematical model for the studied problem [13]. Baskaia et al. (2017) investigated the problem of pre-location problem in the relief supply chain logistics. They formulated the problem considering the limited capacity of facilities and also relief goods at different levels of quality [14]. Haghi et al. (2017) developed a robust multi-objective mathematical model for relief planning in pre/post disaster under demand and resource uncertainty. They considered the location of distribution centers, hospitals and temporary depots in their model, as well as the failure of some facilities due to disaster. The combination of genetic algorithms and simulated annealing is used in order to solve the model [15]. Salvado et al. (2015) investigated the sustainable performance criteria in the humanitarian supply chain. They studied the necessary criteria for creation of sustainable development in humanitarian operations [16]. Cannes and Gold (2017) studied the sustainable supply chain in humanitarian operations. They provided a framework for planning the relief supply chain considering socio-economic-environmental objectives, and tested it for four case studies [17]. Alfredo & Douglas (2018) have presented a novel model to optimize location, transportation, and fleet sizing decisions. In contrast with existing models, vehicles can be reused for multiple trips within micro-periods (blocks of hours) and/or over periods (days). Uncertainty regarding demand, incoming supply, and availability of routes is modeled via a finite set of scenarios, using two-stage stochastic programs. 'Deprivation costs' are used to represent social concerns and minimized via two objective functions [18]. Aliakbar Hasani and hadi Mokhtari (2019) simultaneously investigated inventory groups' number and corresponding service levels, assignment of relief commodities to groups, relief facility location, and relief service assignment. The proposed model aims to minimize the risk and the total cost of network management and simultaneously maximize the network population coverage [19]. Fatemeh Sabouhi,Zeinab Sadat Tavakoli (2019) have considered the most important relief services, including the transportation of injured people to hospitals, the transportation of evacuees from affected areas to shelters, and the supply of required relief commodities to these evacuees. To provide these services effectively, a multi-objective mathematical programming model for locating transfer points and shelters is proposed.

The model considers the demand for evacuation as an uncertain parameter [20]. Yufeng Zhou , Bin Zheng (2020) Considering the characteristics of the two-level emergency logistics system including uncertain demand, uncertain transportation time, multiple varieties of relief materials, shortage of supply, multi-transportation modes and different urgencies of relief material demand, the integrated issue with the concern of transfer facility location and relief material transportation have studied [21]. Meilinda F.N.Maghfiroh (2020) have presented in this study a multi-modal relief distribution model using a three-level chain composed of (1) supply nodes, (2) logistics operational areas, and (3) affected areas, while considering multiple trips for disaster response operations. The model determines the location of logistics operational areas, modes of transport utilized, and amount of relief goods allocated for each mode of transport. In addition, the model considers the different phases of essential response factors, such as network and infrastructure conditions, as well as accessibility of supplies and modes of transport [22]. Jia Shu and Wenya Lv (2021) presented a humanitarian relief supply network design model for large-scale natural disasters such as flood and hurricane. The -expander structure guarantees that either the network can satisfy the total demand among affected areas or utilize at least proportion of the total pre-positioned relief supply. The model optimizes the decisions of emergency facility location and relief supply pre-positioning simultaneously under uncertain demand in each affected area [23].

As can be seen, it has not been addressed in the previous research to provide an integrated fuzzy relief logistics model in the response phase, taking into account the simultaneous location, routing, distribution and sending relief goods, observance of fairness in the distribution of goods, allocating inventory to depots and sudden changes the demand and the displacement of inventory. In this paper, an integrated model for the phase- response in the relief chain in fuzzy conditions is presented. The issues that will be presented in this model simultaneously include designing a transportation network, temporary facility location, inventory management, distribution and sending of relief goods, and observance of fairness in the distribution of relief goods.

In the real world, in the crisis management reaction phase, places are determined for the establishment of intermediary warehouses for the storage of relief goods and are allocated to any place according to the projected demand for a level of inventory and this inventory will be supplied from supply points. Due to the inherent of uncertainty of demand, in different periods, the demand level may suddenly increases in some areas; however, in the case of insufficient inventory in the warehouse for those areas, shortages of inventory could be supplied through other warehouses. In fact, in actual world issues, part of the demand will be predicted with regard to the information gathered from the occurred disaster, and the other part of the demand, which is also Indeterminate, may suddenly occur in some damaged areas. In fact, a sudden change in supply or demand does not allow part of the demand to be answered and it causes dissatisfaction. If such a change occurs, there will be a need for re-programming. . Therefore, in order to reduce the cost of re-planning and increase the level of people's satisfaction, an approach that would help to reduce unresponsive demand without extensive production costs, is needed. For this reason, in order to solve this problem, the other issue that will be considered in the model of this research is the transportation model, inventory displacement and re-programming for the distribution of relief goods. In this research, in order to model this case, in different periods, depending on the demand in different areas, inventory displacement from one storage location (warehouse) to another location (another warehouse), reallocation of inventory to the warehouses and re-programming distribution will also be modeled.

the items presented in this model are: (1) Important relief logistics decisions such as inventory phase, transportation, location, distribution and delivery of relief goods, as well as fairness in the distribution of relief goods; (2) Due to the uncertainty of the demand for relief goods and the possibility of a sudden change in the amount of demand, the issue of shifting inventory between relief depots; (3) penalties for shortage of goods; (4)Periodic and dynamic planning are considered side by side, This model can help managers and officials in crisis management to make decisions in the event of a crisis, and the existence of such a model is very important and necessary in providing relief.

Therefore, conducting this research and applying the proposed model (due to the proximity of the model to real-world problems) is very useful in times of crisis.

This paper has been set up in several sections; in the first section, the introduction and research background are described; in the second section, the full description of the problem studied and the mathematical model are presented; in the third section, the structure of the solving algorithm is described; in the fourth section, the solution results and finally in the fifth section, the final conclusion is presented.

2. Problem Formulation

In this research, the relief logistics have reviewed in the response phase of relief management. The proposed model includes three levels: I supplier, A central warehouses and J regional warehouses. . In this model, relief goods are shipped from suppliers to central warehouses and from central warehouses to regional warehouses. Given that in the real world, in sometimes, regional warehouses may have inventory shortage, they can compensate for the Inventory shortage through central warehouses or other regional warehouses. In this model, demand is considered in two parts: projected demand and unpredicted demand. The purpose of this model is to plan the distribution and inventory displacement, location, and observance of fairness in the distribution of relief goods periodically. Also, the model presented in this research has three objectives: 1) minimizing the total transportation fuzzy costs and hold inventory; 2) minimizing unresponsive demand; and 3) maximizing the minimum of estimated demand ratios. To design the model, a number of assumptions is considered that are as follows:

- In this research, relief logistics operations are in the phase- response, and the proposed model has considered as to be periodic planning (during the time).
- The number of locations for temporary facilities is not fixed and will change over the different periods; the number of depots that are located are fixed and predetermined; the number of available equipment in each period is determined and predetermined.
- Vehicles have a weighted capacity constraint and do not necessarily return to the same origin as they have left it.
- The model is a multi-commodity and the relief goods will be distributed fairly among damaged groups. That is, all relief groups must receive a minimum level of predetermined from all relief goods. Demand for relief goods is also different in different periods.

In this section, the mathematical modeling of the considered problem has been paid. In this regard, first, the structure of the problem is described and then a fuzzy three-objective mathematical model is presented. Finally, at the end of this section, the fuzzy mathematical model has become to the definitive model of its kind using the fuzzy numbers ranking method.

2.1. Indices and parameters

I: Suppliers Points (i and i' the supplier index)

A: Number of central warehouses (a and a' central warehouse indices)

J: Depots points (j and j' depot index)

C: Number of relief goods (c goods index)

M: number of types of vehicles (m type of vehicle index)

T: Planning horizons (t and t' period index)

αmin_{ct}: The minimum coverage level of goods c during period t, which is determined based on emergency degree

w_c: Weight of a goods unit c

d^1_{jct}: Value of projected demand of goods c in depot j in period t

$\tilde{d}^2_{jct}(d^{2l}_{jct}, d^{2m}_{jct}, d^{2u}_{jct})$: value of fuzzy demand of goods c in the depot j in period t

$vcap_{\mathrm{m}}$: Vehicle capacity of type m

$Vpcap^{\mathrm{m}}_{\mathrm{at}}$: Parking capacity of the central warehouse a for the vehicle m in period t

$Vpcap^{\mathrm{m}}_{\mathrm{j't}}$: Parking capacity of the warehouse j' for the vehicle m in period t

$cy^{\mathrm{m}}_{\mathrm{j'0}}$: The number of vehicles in the depot j' in the first stage

$\mathrm{cy}^{\mathrm{m}}_{\mathrm{a0}}$: The number of vehicles in the central warehouse a in the first stage

$cfix^m$: Fixed cost of vehicle *m*

$\tilde{c}_{jj'm} = (c^l_{jj'm}, c^m_{jj'm}, c^u_{jj'm})$: The fuzzy cost of transportation goods from depot *j* to depot *j*'

$\tilde{c}_{ajm} = (c^l_{ajm}, c^m_{ajm}, c^u_{ajm})$: The fuzzy cost of transportation goods from central warehouse *a* to depot *j*

$\tilde{c}_{iam} = (c^l_{iam}, c^m_{iam}, c^u_{iam})$: The fuzzy cost of transportation goods from supplier *i* to central warehouse *a*

cap_{at}: Capacity of central warehouse *a* in period *t*

cap_{jt}: Capacity of warehouse *j* in period *t*

s_{jc0}: Initial inventory of goods *c* in warehouse *j* in the first period

s_{ac0}: Initial inventory of goods *c* in central warehouse *a* in the first period

$\tilde{h}$ =(h^l, h^m, h^u) Fuzzy cost of holding inventory

$\tilde{p}_{1ct}$ =($p^l_{1ct}, p^m_{1ct}, p^u_{1ct}$) Penalty of projected demand in period *t* which has not satisfied.

$\tilde{p}_{2ct}$ =($p^l_{2ct}, p^m_{2ct}, p^u_{2ct}$) : Penalty of fuzzy demand in period *t* which has not satisfied.

2.2. Decision variables

x^{mt}_{iac}: The amount of goods *c* which from the supplier *i* in period *t* is sent by the vehicle type *m* to the central warehouse *a*.

x^{mt}_{ajc}: The amount of goods *c* which from the central warehouse *a* in period *t* is sent by the vehicle type *m* to the depot *j*.

$x^{mt}_{jj'c}$: The amount of goods *c* which from the depot *j* in period *t* is sent by the vehicle type *m* to the depot *j'*.

$y^{mt}_{jj'}$: The number of vehicles of type *m* which going from depot *j* to the depot *j'* in period *t*.

y^{mt}_{aj}: The number of vehicles of type *m* which going from central warehouse *a* to the depot *j* in period *t* and arrived at *j* in the period *t*+1.

y^{mt}_{ia}: The number of vehicles of type *m* which going from supplier *i* to the central warehouse *a* in period *t* and arrived at a in the period *t*+1.

$cy^{m}_{j't}$: The number of vehicle of type *m* which transfer from period *t* to period *t*+1, and to the depot *j'*.

cy^{m}_{at}: The number of vehicle of type *m* which transfer from period *t* to period *t*+1, and to the central warehouse *a*.

s_{jct}: Inventory of depot *j* of the goods *c* which remaining from the *t*-1 period and available at the beginning of period *t*.

s_{act}: Inventory of central warehouse *a* of the goods *c* which remaining from the *t*-1 period and available at the beginning of period *t*.

SD_{jct}: The amount of responsive demand of goods *c* at the depot *j* in period *t*.

UD_{jct}: The amount of unresponsive demand of goods *c* at the depot *j* in period *t* which transfer to period *t*+1.

CUD_{jct}: Part of the projected demand of goods *c* at the depot *j* in period *t*, which has not been satisfied.

$UCUD_{jct}$: The amount of unpredicted demand of goods *c* at the depot *j* in period *t*, which has not been satisfied.

2.3. Mathematical model

$$\min f1 = \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{\substack{j'=1\\ ,j'\neq j}}^{J}\sum_{m=1}^{M}[\tilde{c}_{jj'm}\left(\sum_{c=1}^{C} x^{mt}_{jj'c}\right) + y^{mt}_{jj'} * cfix^m] + \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{a=1}^{A}\sum_{m=1}^{M}[\tilde{c}_{ajm}\left(\sum_{c=1}^{C} x^{mt}_{ajc}\right) + y^{mt}_{aj} * cfix^m] + \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{a=1}^{A}\sum_{m=1}^{M}[\tilde{c}_{iam}\,(\sum_{c=1}^{C} x^{mt}_{iac}) + y^{mt}_{ia} * cfix^m] + \tilde{h}\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{c=1}^{C} s_{jct} + \tilde{h}\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{a=1}^{A} s_{act} \tag{1}$$

$$\min f2 = \sum_{t=1}^{T}\sum_{c=1}^{C}[\tilde{p}_{1ct}\sum_{j=1}^{J} CUD_{jct} + \tilde{p}_{2ct}\sum_{j=1}^{J} UCUD_{jct}] \tag{2}$$

$$\max\ f3 = \sum_{t}\sum_{c} min_j\ \frac{SD_{jct}}{(d^1_{jct} + \tilde{d}^2_{jct})} \tag{3}$$

Subject to:

$$s_{jc1} = SD_{jc1} + \sum_{m=1}^{M} \sum_{j \neq j' \in J} X_{jj'c}^{m1} + s_{jc2} \quad \forall j, c \tag{4}$$

$$s_{jct} + \sum_{m=1}^{M} \sum_{a=1}^{A} X_{ajc}^{mt-1} + \sum_{m=1}^{M} \sum_{j', j' \neq j} x_{j'jc}^{mt} = SD_{jct} + \sum_{m=1}^{M} \sum_{j \neq j' \in J} X_{jj'c}^{mt} + s_{jct+1} \quad \forall j, c, t = 2,3 \dots, T \tag{5}$$

$$s_{ac1} = \sum_{m=1}^{M} \sum_{j=1}^{J} X_{ajc}^{m1} + s_{ac2} \quad \forall a, c \tag{6}$$

$$s_{act} + \sum_{m=1}^{M} \sum_{i=1}^{I} X_{iac}^{mt-1} = \sum_{m=1}^{M} \sum_{j=1}^{J} X_{ajc}^{mt} + s_{act+1} \qquad \forall a, c, t = 2,3, \dots, T \tag{7}$$

$$d_{jct}^{1} + \tilde{d}_{jct}^{2} + UD_{jct-1} = SD_{jct} + UD_{jct} \; \forall j, c, t = 2,3, \dots, T \tag{8}$$

$$d_{jc1}^{1} + \tilde{d}_{jc1}^{2} = SD_{jc1} + UD_{jc1} \quad \forall j, c \tag{9}$$

$$\sum_{j=1}^{J} \left(s_{jcT+1} + \sum_{t=1}^{T} \left(d_{jct}^{1} + \tilde{d}_{jct}^{2}\right)\right) + \sum_{a=1}^{A} s_{acT+1} = \sum_{j=1}^{J} \left(s_{jc1} + UD_{jcT}\right) + \sum_{a=1}^{A} s_{ac1} + \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{a=1}^{A} \sum_{m=1}^{M} x_{iac}^{mt} \quad \forall c \tag{10}$$

$$CUD_{jc1} = d_{jc1}^{1} - SD_{jc1} \qquad \forall j, c \tag{11}$$

$$CUD_{jct} = d_{jct}^{1} - SD_{jct} + \max\{0, CUD_{jct-1}\} \;\; \forall j, c, t = 2,3, \dots T \tag{12}$$

$$\sum_{m} \sum_{j'} \sum_{c} w_c * x_{j'jc}^{mt} + \sum_{m} \sum_{a} \sum_{c} w_c * x_{ajc}^{mt-1} + \sum_{c} w_c * s_{jct} \leq cap_{jt} \;\; \forall j, t = 2,3, \dots, T \tag{13}$$

$$UCUD_{jct} = UD_{jct} - CUD_{jct} \;\; \forall j, c, t \tag{14}$$

$$\sum_{m} \sum_{c} \sum_{j'} w_c * x_{jj'c}^{mt} + \sum_{c} w_c * s_{jct+1} \leq cap_{jt} \quad \forall j, t \tag{15}$$

$$\sum_{c} \left(x_{jj'c}^{mt} * w_c\right) \leq vcap_m \; * y_{jj'}^{mt} \qquad \forall m, j, j', t \tag{16}$$

$$\sum_{c} \left(x_{ajc}^{mt} * w_c\right) \leq vcap_m \; * y_{aj}^{mt} \qquad \forall a, j, m, t \tag{17}$$

$$\sum_{c} \left(x_{iac}^{mt} * w_c\right) \leq vcap_m \; * y_{ia}^{mt} \qquad \forall a, i, m, t \tag{18}$$

$$\sum_{m} \sum_{c} \sum_{j} w_c * x_{ajc}^{mt} + \sum_{c} w_c * s_{act+1} \leq cap_{at} \quad \forall a, t \tag{19}$$

$$\sum_{m=1}^{M} \sum_{c=1}^{C} \sum_{i=1}^{I} x_{iac}^{mt-1} * w_c + \sum_{c} w_c * s_{act} \leq cap_{at} \quad \forall a, t \tag{20}$$

$$cy_{j'0}^{m} = \sum_{j=1}^{J} y_{j'j}^{m1} + cy_{j'1}^{m} \quad \forall j', m \tag{21}$$

$$\sum_{j=1}^{J} y_{jj'}^{mt} + \sum_{a=1}^{A} y_{aj'}^{mt-1} + cy_{j't-1}^{m} = \sum_{j=1}^{J} y_{j'j}^{mt} + cy_{j't}^{m} \quad \forall j', m, t = 2,3, \dots, T \tag{22}$$

$$\sum_{j=1}^{J} y_{jj'}^{mt} + \sum_{a=1}^{A} y_{aj'}^{mt-1} + cy_{j't-1}^{m} \leq Vpcap_{j't}^{m} \;\; \forall j', m, t = 2,3, .., T \tag{23}$$

$$\mathrm{cy}_{a0}^{m} = \sum_{j'}^{J} y_{aj'}^{m1} + \mathrm{cy}_{a1}^{m} \quad \forall a, m \tag{24}$$

$$\sum_{i=1}^{I} \mathrm{y}_{ia}^{mt-1} + \mathrm{cy}_{at-1}^{m} = \sum_{j'}^{J} \mathrm{y}_{aj'}^{mt} + \mathrm{cy}_{at}^{m} \quad \forall a, m, t = 2,3, \dots, T \tag{25}$$

$$\sum_{i=1}^{I} \mathrm{y}_{ia}^{mt-1} + \mathrm{cy}_{at-1}^{m} \leq Vpcap_{at}^{m} \quad \forall a, m, t = 2,3, \dots, T \tag{26}$$

$$\frac{SD_{jct}}{(d_{jct}^{1} + \tilde{d}_{jct}^{2})} \geq \alpha min_{\mathrm{ct}} \qquad \forall j, c, t \tag{27}$$

$$x_{iac}^{\mathrm{mt}}, \mathrm{x}_{\mathrm{ajc}}^{\mathrm{mt}}, \mathrm{x}_{\mathrm{jj'c}}^{\mathrm{mt}}, \mathrm{y}_{\mathrm{ia}}^{\mathrm{mt}}, \mathrm{y}_{\mathrm{aj}}^{\mathrm{mt}}, \mathrm{y}_{\mathrm{jj'c}}^{\mathrm{mt}}, \mathrm{s}_{\mathrm{jct}}, \mathrm{s}_{\mathrm{act}}, \mathrm{SD}_{\mathrm{jct}}, \mathrm{UD}_{\mathrm{jct}}, \mathrm{CUD}_{\mathrm{jct}}, \mathrm{UCUD}_{\mathrm{jct}} \geq 0 \tag{28}$$

The expression (1) indicates the first objective function, which including minimizing the total fuzzy transportation and inventory holding costs. The expression (2) represents the second objective function as minimizing unsatisfied demand. The expression (3) maximizes the minimum estimated demand ratios. Constraint (4) ensures the balance of goods flow in depots in period one. Constraint (5) ensures the balance of goods flow in depots. Constraint (6) ensures the balance of goods in central warehouse in period one. Constraint (7) ensures the balance of goods in central warehouse. All goods in the central warehouse in period *t* is sent to depots (the amount of goods c which remained at the beginning of period *t* in the central warehouse a from period *t*-1, plus the amount of goods *c* which received from suppliers in period *t*) and the remainder will be stored in the central warehouse *a* for the next period. Constraints (8) and (9) state that all demand (given and indeterminate) for goods *c* in depot *j* in period *t*, plus the unresponsive demand for the same goods in the same depot from the previous period equals the sum of the answered and unresponsive demand from goods *c* in depot *j* in period *t*. Constraint (10) is also related to the balance of the total flow of goods in all depots in all periods and central warehouses. Constraints (11) and (12) state that part of the determined demand for goods *c* which has not been answered in the depot *j* in period *t* is equal to all the certain demand for goods *c* in the depot *j* in period *t*, minus the satisfied demand and a certain unresponsive demand from the previous period. Constraint (13) is related to observance the capacity of depot *j* in period *t*. Constraint (14) is used to calculate the unpredicted demand for goods c in the depot *j* which has not been answered in period t. Constraint (15) is related to observance the capacity of depot *j* in period 1. Constraints (16), (17) and (18) is related to observance the capacity of vehicles of type *m* in period *t*. Constraints (19) and (20) are related to observance the maximum capacity of central warehouses in each period. Constraint (21) is related to the balance of vehicle flow in depots for the first period. Constraint (22) is related to the balance of vehicle flow in depots. Constraint (23) express for the parking capacity constraint of warehouse *j* in period *t* for the vehicle m. Constraint (24) is related to the balance of vehicle flow central warehouse *j'* for the first period. Constraint (25) is related to the balance of vehicle flow central warehouse. Constraint (26) expresses for the parking capacity constraint of central warehouse *a* in period *t* for the vehicle *m*. Constraint (27) determines the minimum coverage level of goods *c*.

2.4. Mathematical model defuzzification

In this paper, the Jimenez ranking method is used for defuzzification of the model. Based on this method, the first objective function is as follows:

$$\min f1 = \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{\substack{j'=1 \\ ,j'\neq j}}^{J}\sum_{m=1}^{M}\left[\frac{1}{4}\left(c_{jj'm}^{l} + 2*c_{jj'm}^{m} + c_{jj'm}^{u}\right)\left(\sum_{c=1}^{C} x_{jj'c}^{mt}\right) + y_{jj'}^{mt} * cfix^{m}\right]$$
$$+ \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{a=1}^{A}\sum_{m=1}^{M}\frac{1}{4}\left(c_{ajm}^{l} + 2*c_{ajm}^{m} + c_{ajm}^{u}\right)\left(\sum_{c=1}^{C} x_{ajc}^{mt}\right) + y_{aj}^{mt} * cfix^{m}]$$
$$+ \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{a=1}^{A}\sum_{m=1}^{M}\frac{1}{4}(c_{iam}^{l} + 2*c_{iam}^{m} + c_{iam}^{u})(\sum_{c=1}^{C} x_{iac}^{mt}) + y_{ia}^{mt} * cfix^{m}] \tag{29}$$
$$+ \frac{1}{4}\left(h^{l} + 2*h^{m} + h^{u}\right)\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{c=1}^{C} s_{jct} + \frac{1}{4}\left(h^{l} + 2*h^{m} + h^{u}\right)\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{a=1}^{A} s_{act}$$

The second objective function comes as follows:

$$\min f2 = \sum_{t=1}^{T}\quad\sum_{c=1}^{C}[\frac{1}{4}(p_{1t}^{l} + 2*p_{1t}^{m} + p_{1t}^{u})\sum_{j=1}^{J} CUD_{jct} + \frac{1}{4}(p_{2t}^{l} + 2*p_{2t}^{m} + p_{2t}^{u})\sum_{j=1}^{J} UCUD_{jct}] \tag{30}$$

Constraint (8) is defuzzifying as follows:

$$d_{jct}^{1} + \beta\frac{d_{jct}^{2l} + d_{jct}^{2m}}{2} + (1-\beta)\frac{d_{jct}^{2m} + d_{jct}^{2u}}{2} + UD_{jct-1} = SD_{jct} + UD_{jct}\ \forall j, c, t = 2,3, \dots, T \tag{31}$$

Constraint (9) also comes as follows:

$$d_{jct}^{1} + \beta\frac{d_{jct}^{2l} + d_{jct}^{2m}}{2} + (1-\beta)\frac{d_{jct}^{2m} + d_{jct}^{2u}}{2} = SD_{jc1} + UD_{jc1}\ \forall j, c \tag{32}$$

Constraint (10) after defuzzifying comes as follows:

$$\sum_{j=1}^{J}(s_{jcT+1} + \sum_{t=1}^{T}(d_{jct}^{1} + [\beta\frac{d_{jct}^{2l} + d_{jct}^{2m}}{2} + (1-\beta)\frac{d_{jct}^{2m} + d_{jct}^{2u}}{2}])) + \sum_{a=1}^{A} s_{acT+1}$$
$$= \sum_{j=1}^{J}(s_{jc1} + UD_{jcT}) + \sum_{a=1}^{A} s_{ac1} + \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{a=1}^{A}\sum_{m=1}^{M} x_{iac}^{mt} \quad \forall c \tag{33}$$

Constraint (27) comes as follows:

$$\frac{SD_{j,c,t}}{d_{jct}^{1} + \left[\beta\frac{d_{jct}^{2l}+d_{jct}^{2m}}{2} + (1-\beta)\frac{d_{jct}^{2m}+d_{jct}^{2u}}{2}\right]} \geq \alpha min_{ct} \tag{34}$$

2.5. ε-Constraint method

As we know, there are many methods for solving multi-objective problems that can be called the multi-objective problem solving based on Pareto Archive, weighting objectives method and ε-Constraint method (Fahimniya et al., 2017; Boonmi and et al., 2017). In this paper, as described in the next chapter, a multi-objective algorithm based on the Pareto Archive is presented. However, to investigate and prove the validity of the model as well as solving algorithm, the proposed three-objective model is converted to the single-objective model by using of the ε-Constraint method and then solved by the solving algorithm and accurate software Lingo. Finally, the results of solving a single-objective model by the solving algorithm and Lingo software are compared with each other. The function of ε-constraint method is described below. Suppose the multi-objective problem is as follows:

$$\max(f_1(x), f_2(x), \dots, f_p(x))$$
$$st$$
$$x \in S$$

Where S is the feasible solution space, and x is the set of model variables.

In the ε-constraint method, one of the objective functions is considered as a main objective and it will be optimized, and other objective functions are considered as constraints. The above multi-objective model transforms to a single objective model using the ε -constraint method as follows:

$$\max f_1(x)$$
$$st$$
$$f_2(x) \geq \varepsilon_2$$
$$f_3(x) \geq \varepsilon_3$$
$$\ldots$$
$$f_p(x) \geq \varepsilon_p$$
$$x \in S$$

According to the description, the presented three-objective model in this paper becomes as the following single-objective model:

$$\min f1 = \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{\substack{j'=1\\ ,j'\neq j}}^{J}\sum_{m=1}^{M}\left[\frac{1}{4}\left(c^{l}_{jj'm} + 2 * c^{m}_{jj'm} + c^{u}_{jj'm}\right)\left(\sum_{c=1}^{C} x^{mt}_{jj'c}\right) + y^{mt}_{jj'} * cfix^{m}\right]$$
$$+ \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{a=1}^{A}\sum_{m=1}^{M}\frac{1}{4}\left(c^{l}_{ajm} + 2 * c^{m}_{ajm} + c^{u}_{ajm}\right)\left(\sum_{c=1}^{C} x^{mt}_{ajc}\right) + y^{mt}_{aj} * cfix^{m}]$$
$$+ \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{a=1}^{A}\sum_{m=1}^{M}\frac{1}{4}(c^{l}_{iam} + 2 * c^{m}_{iam} + c^{u}_{iam})(\sum_{c=1}^{C} x^{mt}_{iac}) + y^{mt}_{ia} * cfix^{m}]$$
$$+ \frac{1}{4}\left(h^{l} + 2 * h^{m} + h^{u}\right)\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{c=1}^{C} s_{jct} + \frac{1}{4}\left(h^{l} + 2 * h^{m} + h^{u}\right)\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{a=1}^{A} s_{act}$$

Subject to:

$$\sum_{t=1}^{T}\sum_{c=1}^{C}[\frac{1}{4}(p^{l}_{1t} + 2 * p^{m}_{1t} + p^{u}_{1t})\sum_{j=1}^{J} CUD_{jct} + \frac{1}{4}(p^{l}_{2t} + 2 * p^{m}_{2t} + p^{u}_{2t})\sum_{j=1}^{J} UCUD_{jct}] \leq e_2$$

$$\sum_{t}\sum_{c} min_j \frac{SD_{jct}}{(d^{1}_{jct} + \left[\beta \frac{d^{2l}_{jct} + d^{2m}_{jct}}{2} + (1-\beta)\frac{d^{2m}_{jct} + d^{2u}_{jct}}{2}\right])} \geq e_3$$

and the other constraints

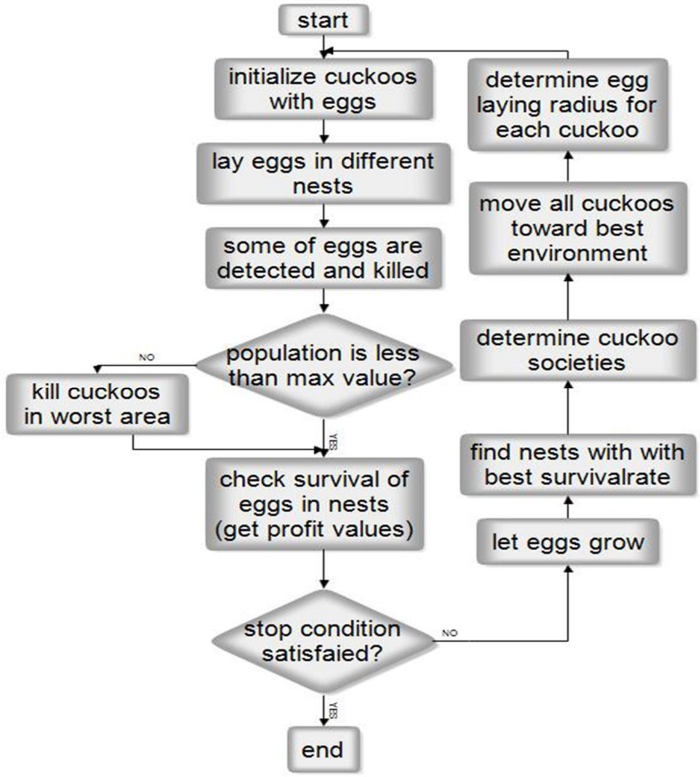

Fig. 1. Flowchart of the cuckoo algorithm

The steps of the ε-constraint method are as follows:

1. We select one of the objective functions as the main objective function.
2. Each time, according to one of the selected objective functions, we solve the problem and obtain the optimal values for each objective function.
3. We divide the interval between two optimal values of the sub objective functions into a pre-specified number and obtain a table of values for $\varepsilon_2,\ldots,\varepsilon_n$.
4. Each time, we solve the problem with the main objective function with each of the values $\varepsilon_2,\ldots,\varepsilon_n$.
5. We report the finding Pareto solutions.

3. Multi-Objective Cuckoo Search Optimization Algorithm

In this research, cuckoo optimization algorithm has been used to solve the presented multi-objective model.

The cuckoo optimization algorithm (COA) is one of the newest and most powerful evolutionary optimization methods that was presented in 2009 by Xin-she Yang and Suash Deb [26]. This algorithm is inspired by the life of a bird, called Cuckoo. The steps of the cuckoo optimization algorithm are as follows (see Figure 1):

1. Generate initial solutions as a population of cuckoos.
2. Initialization of algorithm parameters.
3. Define an empty set as an initial pareto archive.
4. Dedicate some eggs to each cuckoo.
5. Define Egg Laying Radius (ELR) for each cuckoo.
6. Cuckoo laying in the corresponding ELR of each cuckoo
7. Kill those eggs that are recognized by host bird.
8. Let Eggs hatch and chicks grow.
9. Evaluate of the habitats of all new cuckoos.
10. Control the cuckoo's maximum number in the environment and kill those who live worst habitats.
11. Cluster the cuckoos and find the best rank and select goal habitat.
12. Immigrate new cuckoo population toward goal habitat.
13. Apply the improvement procedure to the selected rank and improve them.
14. Update Pareto Archive.
15. Stop if condition is satisfied, if not go to step 4.

The COA is inherently designed to search for continuous space, and industrial engineering optimization issues, but a problem with discrete space can be solved using modified COA. Therefore, to apply the COA to a discrete search space, the standard COA computing operators require to be redefined.

3.1. Solution representation and generate the initial solutions

In this work, the matrix structure has used to represent the solution (create habitat), so that for each of the model outputs, a matrix is designed to fit that variable. For example, for variable a is a 4-dimensional matrix which the first two dimensions are number of suppliers and the number of goods, and third dimension equals the number of vehicles, and fourth dimension is equal to the number of periods, and for variable a, a 5-dimensional matrix which dimensions are respectively, depot number, depot number, number of goods, number of vehicles and number of periods, are designed. As previously stated, the Cuckoo algorithm is population-based, and in each iteration works with a population of solutions that a population of cuckoos is. In this research, the initial population is produced randomly (subject to model constraints). That means, N solutions are produced randomly and are used as the initial population of the algorithm.

3.2. Search by step 4 to 12 of the cuckoo algorithm

After produce the number of initial habitats, the fitness of all habits are calculated using a weighted method, we obtain a general solution for each habitat. To obtain these weights, first, based on the non-dominated relations and the Deb rule, solutions are ranked and then the Crowding distance criterion is calculated for each habitat according to the surface at which it is located and finally the weight of each habitat is calculated using the following equation:

$$c_s = \frac{rank}{crowding\ distance}$$

In the above equation, rank is the surface number that each solution (habitat) is located at it, and crowding distance is the distance of the crowding of each solution (habitat). After calculating the c_s index for the solutions, we normalize all the achieved fitness. Then select the number of cuckoos to start, this number is selected by the user. Then to each cuckoo randomly dedicate number of eggs in a certain interval, for example, between 2 and 4. Then calculate ELR for all cuckoos and add a tolerance $\pm\beta$ to ELR of each cuckoo. In this interval, if the number of habitats (solutions) is less than cuckoo eggs number, just the number of habitat, we dedicate solution to cuckoo, and if it is equal, all is dedicate to cuckoo and in case of more habitats in this interval than the number of eggs, we will dedicate random habitat to cuckoo. In the meantime, if a habitat is located in interval of two or more cuckoos, the algorithm continues and given that only one cuckoo egg is placed in each habitat, or all eggs are killed (according to principle of recognition host bird) or habitat is randomly dedicated to a cuckoo, and eggs of remained cuckoos are killed. In the meantime, a number of habitats have not been dedicated to cuckoos, which will be transferred to the next generation. Given the above steps and generate the initial population and the dedicate cuckoo eggs to the habitats, the next step is that after the eggs become chicks and matured (which represent the value of the habitat), the best habitat fitness which do laying at those , is chosen, which is usually clustering the number of cuckoo into k cluster (usually between 3 and 5), and the average fitness of the best rank as the goal environment and the best cuckoo habitat as the goal habitat, is selected and the immigration operations take place at this step. This operator that presented in Cuckoo's algorithm, is effective for continuous problems. Hence, in this paper, we will change this operator discretely and perform this operation as follows:

As we have read in the description of the algorithm, a number of cuckoo chicks that have matured are immigrate to the optimal habitat, percentage of them not take the whole path and they have a deviation equal to λ. But in a discrete environment, this operator is defined as:

$$Next\ habitat = Current\ Habitat + F(Goal\ Habitat - Current\ Habitat)$$

Here, F is a random number between 0 and 1 that determines the movement steps toward the goal point. Therefore, in a discrete COA, a method for modeling this movement and reaching the goal point in each iteration is required. Therefore, our proposed method is as follows:

After identifying the best habitat, rest of the matured cuckoo tend to immigrate to the optimal habitat with better conditions for them. Hence, next and new cuckoo habitat for immigration is characterized by the fact that the neighborhood search structure is applied to the current cuckoo habitat. This neighborhoods structure, two solutions (the current habitat of cuckoo and the goal habitat) are taken as an input and try to search for the first solution neighbors (current habitat), which is similar to the second solution (goal habitat), or in the other words moves toward second solution. In fact, in this structure, first solution structure is directed toward second solution, or second solution is directed to first solution; in fact, this procedure represents the immigration of cuckoo to goal habitat. How to search the solution neighborhood in this structure is as follows:

In this structure, the index t has been generated randomly in uniform interval $[1..T]$ (T is number of periods), the index j and j' in uniform interval $[1..J]$ (J is number of depots), and value of all goods Which are sent from j to j' in period t, are equal to value of same goods in the second solution which sent from j' to j in period t, due to the model's constraints is fitted. After immigration because of the increased number of cuckoos, for balance, a number of cuckoos must be destroyed and reduced to the number of reference cuckoos that are selected by the user. Hence, cuckoos that have worse fitness will be destroyed.

3.3. Improvement procedure

Designed improvement procedure in this work is a parallel combination of two neighborhood search structures. In the following, two neighborhood search structures and improvement procedure structure are explained. First Neighborhood Search Structure: In this structure, index t in uniform interval $[1..T]$ (T, number of periods), index j and j' in uniform interval $[1..J]$ (J, the number of depots) randomly are generated, and value of all goods which sent from j to j' in period t is equal to value of same goods which sent from j to j' in period t, taking into account the constraints of model, are replaced together.

Second Neighborhood Search Structure: In this structure, index t in uniform interval $[1..T]$ (T, number of periods), index j in uniform interval $[1..J]$ (J, number of depots), index a and a' in uniform interval $[1..A]$ (A, number of central warehouses) randomly are generated, and value of all goods which sent from a to j in period t is equal to value of same goods which sent from a' to j in period t, taking into account the constraints of model, are replaced together.

These two neighborhood structures are combined in parallel and make structure of improvement procedure. Neighborhood search structures are applied in parallel (simultaneously) on input solution, and a solution which is better in terms of quality than other solutions is selected from three solutions (input solution, solution generated by first structure and solution generated by second structure).

3.4. Pareto archive updates

In proposed algorithm, there is a set called Pareto Archive taking into account that keeps on herself the non-dominated solutions generated by algorithm. This set will be updated in each iteration of algorithm. How to update is that generated solutions in that iteration and solutions in Pareto archive are poured into a pool solutions and ranking together, then from among these solutions, solutions in the first rank or non-dominated is selected and considered as a new Pareto archive.

4. Computational Results

As mentioned, in order to solve proposed model, Cuckoo optimization algorithm based on Pareto Archive is proposed. In previous sections, components of this algorithm are fully described. In this paper, in order to prove efficiency of proposed algorithm, results of solving selected problems with different sizes by Cuckoo algorithm are compared with the results of solving these problems using the NSGA-II algorithm according to the quality, dispersion and uniformity indices. In this section, we will describe results of solution of the model by two Cuckoo algorithms and NSGA-II.

4.1. Comparison indices

There are several indices for quality assessment and multi - objective heuristic algorithms. In this paper, to perform a comparison, the three indicators described below will be considered.

The quality index - This index compares the quality of Pareto solutions obtained by each method. In fact, all the replies obtained by both methods together with the same level and specify that a few percentage points in the level of each method are owned by each method. The higher the percentage, the higher the algorithm.

A uniform index - This criterion tests the monotony of the distribution of Pareto solutions obtained on the boundary of the answers. The indicator is defined as follows

$$s = \frac{\sum_{i=1}^{N-1} \left| d_{mean} - d_i \right|}{(N-1) \times d_{mean}}$$

In the above equation, d_i depicts the Euclidean distance between the two non - recessive responses found in the vicinity, and d_{mean} defines the mean values of d_i.

dispersion index - this index is used to determine the amount of non - recessive responses found on the optimal boundary. The definition of the dispersion indicator is as follows:

$$D = \sqrt{\sum_{i=1}^{N} \max(\|x_t^i - y_t^i\|)}$$

In the above equation, $\|x_t^i - y_t^i\|$ indicates Euclidean distance between two neighbouring responses x_t^i and y_t^i over the optimal boundary.

4.2. Parameter tuning

To solve the model by algorithm, the model data are determined randomly and based on model constraints. The data values generated by the two algorithms are as follows:

- In all problems, number of goods is considered equal to 3.
- The value of projected demand has been generated in a uniform interval [1..20].
- To generate unpredicted demand values in a triangular distance [m_1, m_2, m_3], first, m_2 is generated in the uniform interval [1..20], and then m_1 with relation $(1-r)\times m_2$ and m_3 with relation $(1+r)\times m_2$ are generated. In these two relations, r is a random number in interval (0,1).
- In order to generate triangular values of transportation costs, holding costs of inventory and unresponsive demand penalties also act like the unpredictable demand, with difference that middle number in the uniform interval [1..40] is produced.
- Initial inventory values are generated randomly in a uniform interval [1..20].
- To running the Cuckoo algorithm, the number of neighborhood search iteration is 10, the population size is 200, and the number of cuckoo algorithm iteration is equal to 500.
- To running the NSGA-II algorithm, the population size is 200, the number of algorithms iteration is 500, and rate of mutation and crossover are 0.1 and 0.8, respectively.

4.3. Experimental results

In order to prove the performance of proposed algorithm, 10 sample problems were randomly generated and were run by proposed two genetic algorithm and cuckoo algorithm. The results of comparison of the two algorithms with the specifications of these 10 problems are shown in the table below. In this table, the specifications of each problem are represented by form *I*/*A*/*J*/*T* that in this form, *I* number of suppliers, *A* number of central warehouses, *J* number of depots, and *T* number of planning periods are.

In the ε-constraint method, three grid points are considered for each objective function. Because the problem is NP-hard, the ε-constraint as an exact solution method does not have the ability to solve the model in large scales. Table (1) shows the results obtained by three solution methods for small-sized problems. The best solution is shown for the first, second, and third function between Pareto points of the ε-constraint and values associated with NSGA-II and COA. Table (2) represenets the resulting error from these methods. In Table (2), as can be seen from quality point of view, the COA algorithm can produce more qualitative solution than NSGA-II and ε-constarint.

Table (3) includes the comparison of the algorithms based on the *quality*, *diversity* and *spacing* metrics and *CPU time*.

Tab. 1. The parameters values of both mataheuristic approaches

Parameters	NSGA-II algorithm parameter values	MOCSOA algorithm parameter values
Population size	200	200
Number of iterations of the algorithm	500	500
Number of repetitions of neighborhood search	---------	10
Crossover rate	0.8	---------
Mutation crates	0.1	---------

Tab. 2. Comparison results of three methods

Prob.	Size	Ɛ-constraint			NSGA-II			MOCSOA		
		f_1	f_2	f_3	f_1	f_2	f_3	f_1	f_2	f_3
1	2/1/2/1	1181491	563261	0.76536	1252640	586355	0.72365	1132521	560632	0.77326
2	2/1/3/1	1226598	715647	0.82512	1355365	756329	0.78656	1154969	709585	0.82863

Tab. 3. The error of results of the NSGA-II and MOCSOA versus results of the ε-constraint

Prob.	Size	NSGA-II			MOCSOA		
		First objective	Second objective	Third objective	First objective	Second objective	Third objective
1	2/1/2/1	0.06	0.04	-0.054	-0.04	-0.005	0.01
2	2/1/3/1	0.1	0.05	-0.046	-0.06	-0.001	0.004

Tab. 4. Comparison of results obtained by NSGA-II and MOCSOA based on given metrics

Prob.	Quality metric		Diversity metric (uniform)		Spacing metric (dispersion)		Run time	
	NSGA-II	MOCSOA	NSGA-II	MOCSOA	NSGA-II	MOCSOA	NSGA-II	MOCSOA
2/3/4/4	6	94	449.6	905.3	1.19	0.87	0.12	4.01
5/4/6/4	11.76	88.24	219.3	2375.4	0.10	0.38	0.22	11.13
5/4/6/4	9.9	90.91	1090.5	4518.9	0.46	0.19	0.28	10.98
7/4/15/5	15.62	84.38	1480.5	6499	1.34	1.29	1.13	19.61
7/8/15/5	9.3	90.7	2267.5	8774.7	0.99	0.67	1.45	25.67
7/10/18/6	38.1	61.9	7958	10785	1.54	0.81	2.71	45.8
7/10/20/6	24.24	75.76	6350	13980	1.72	0.81	3.27	52.1
8/10/20/8	11.36	88.64	3960	16786	0.94	0.49	3.95	72.59
9/12/24/10	18.52	81.48	12352	27734	1.47	0.96	9.76	132.02
9/12/30/10	33.33	66.67	10144	25209	0.45	0.98	11.77	155.09
Average	17.81	82.27	4627.14	11756.73	1.02	2.63	3.47	52.9

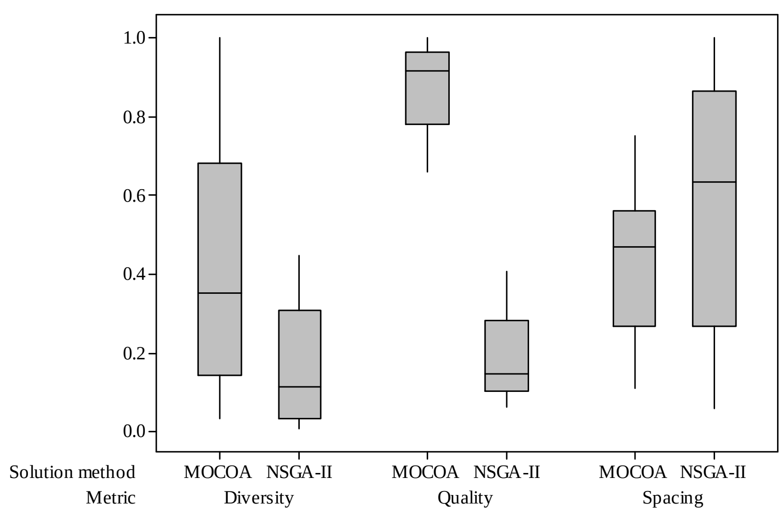

Fig. 2. Boxplot for the value of metrics obtained by NSGA-II and MOCSOA

As shown in Table (3) and Figure (1), multi-objective cuckoo optimization algorithm in all cases has higher ability to generate high-quality solutions near the optimal boundary than NSGA-II algorithm, also in every 10 problems, dispersion of solutions generated by cuckoo algorithm is higher than dispersion of solutions generated by the NSGA-II algorithm. In the case of uniformity index, also only in two cases, the NSGA-II algorithm has produced higher uniformity than the cuckoo algorithm. Comparison of running time of the two algorithms shows that the NSGA-II in all cases has less time to solve than the cuckoo algorithm. It should be noticed that ε-constraint as an exact solution method could not solve all sample problems despite the spend of over 10,800 seconds. This method is unable to find the feasible solution even for small sizes.

5. Conclusions and Future Works

In this research, the design of the response-phase relief transportation model from the disaster management cycle has been investigated and a multi-objective integrated model for three-level relief chain logistics is presented under uncertainty conditions. For solving the mathematical model, the cuckoo search optimization algorithm based on the Pareto archive is proposed to handle multi-objective problem. The results of running of several problems with the implemented cuckoo algorithm and the NSGA-II algorithm have been compared with respect to the quality, dispersion and uniformity indices with together. The results of the model showed that in all solved problems, the percentage of quality solutions in the cuckoo algorithm is more than the NSGA-II algorithm, which indicates that the cuckoo algorithm is more capable of finding optimal and near optimal solutions in the solving of the proposed model. As the same way, the results of these comparisons show that cuckoo's algorithm has a higher ability to produce solutions with more dispersion and uniformity than the genetic algorithm. Also, the results indicate that the NSGA-II has less running time than the COA. For future research, a number of suggestions are presented as follows:

- Providing and solving the robust optimization model for the relief supply chain.
- Using intelligent decision-making and expert systems to provide relief supply chain planning.
- Providing and solving sustainable supply chain logistics integrated model in uncertain conditions

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