European Online Journal of Natural and Social Sciences 2014;
vol.3, No.1, pp. 92-101 ISSN 1805-3602

Integrated and periodic relief logistics planning for reaction phase in uncertainty condition and model solving by particles swarm optimization algorithm

Siamak Ghiasvand, Babak Ejlaly

Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran

Received for publication: 14 November 2013.
Accepted for publication: 10 January 2014.

Abstract

Disaster relief logistics is considered to be one of the major activities in disaster management. This research studies response phase of the disaster management cycle. To do so, a multi-purpose integrated model for a three-level relief cycle logistics is provided under an uncertainty condition and on a periodic basis. In this model, inventory transfer, vehicle routing, distribution and sending relief goods are modeled on a periodic basis. In addition, in order to solve the proposed mathematical model, ultra-initiative particles swarm algorithm in combination with variable neighborhood search based on Pareto archive is proposed. To prove the efficiency of the proposed particles swarm algorithm, several sample problems are randomly selected considering the solved problems in the literature and are solved by particles swarm algorithm. These problems are also solved by genetic algorithm and the results obtained from these two algorithms are compared in terms of quality, dispersion and integrity indices. The results show that compared to genetic algorithm, particles swarm algorithm is more capable of producing more integrated, qualified and dispersed responses. Moreover, the results show that the solution time of genetic algorithm is less than that of the proposed algorithm.

Keywords: Relief logistics, Swarm Optimization Algorithm

Introduction

Each year, millions of people are affected by natural or manmade disasters around the world. In recent decade, the number of victims has significantly been increased. (Burton 2007, Swiss Reinsurance 2010, Thomas 2005). Most of relief organizations help and support the affected persons by providing them such relief goods as food, water, drug and medical equipment as well as building shelter and relief tents. A wide range of logistics-related issues are becoming humanitarian. Some studies estimate that logistics and supply cycle management comprises more than 80% of the whole operations. (Van Wassenhove 2006). This article studies a particular event which may happen during response phase or reconstruction phase. Some of regional warehouses should be established for storage and distribution of the relief goods. These regional warehouses receive services from central warehouses or adjacent regional warehouses and the central warehouses receive services from global warehouses. A warehouse may be destroyed due to a disaster, firing, theft or other reasons and this also leads to supply shortage. So the demand for special goods may suddenly increase. For example disease outbreaks require the drugs and the related equipment. Sudden increasing of a demand results in shortage of a local warehouse which can be compensated through central warehouses but since this takes a long time, this shortage can be supplied by means of regional warehouses as well.

In some cases, several disasters occur simultaneously that may cause additional losses like 2010 Haiti Earthquake which first earthquake occurred and followed by storm. Therefore, periodic events involve a complicated planning. (Balaisyte 2006) .

Relief logistics planning involves contradictory goals. Its first goal is to minimize the unfulfilled de-

Corresponding author: Siamak Ghiasvand, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran, Email: Lrpars.lm@gmail.com

mand and its second goal is to minimize the distribution cost which is inconsistent with the first goal and so there should be a balance between them. As the literature shows operations research models have a successful application in supporting different kinds of humanitarian operations.

Literature Review

Given the importance of logistics in humanitarian operations, many articles have been published in this field during recent years and several operations research methods have been proposed. For example facility location planning, transporting routing, planning for solving the proposed problems such as maximum coverage and network flow model or the shortest route of the initiative and exact methods have been provided. Sometimes location problem has been combined with transporting routing (Afshar, 2007) and in some cases inventory planning has been combined with location problem. Chng (2007) proposed two possible models for warehouses location in relation to the urgent response following earthquake as well as inventory assignment to warehouses.

Yi and Kumar (2007) proposed ant colony optimization algorithm to solve logistics problems in relief measures during crisis. Tzeng and colleagues (20070 proposed a deterministic multi-criteria model to distribute the necessary goods within the damaged regions considering cost of response time and customer's satisfaction and to solve it by means of multi-purpose fuzzy planning approach. given the importance of uncertainty in disasters relief management, some researchers raised uncertainty discussion. Barbarosoglu and Arda (2004) proposed the uncertainty modeling for relief response. Chang and his colleagues (2007) proposed two random planning models in order to determine warehouse centers and the amount of necessary equipment as well as equipment distribution. Mete and Zabinsky (2010) proposed a random optimization model for planning the warehouse and distributing medical products in emergency conditions. Balcik and Beamon (2008) expanded facility location model and inventory planning model for disaster relief. Fiedrich and colleagues (2000) proposed an inventory model to deal with the disasters. Periodic routing problem is another routing problem for which it is necessary to provide service to customers on a periodic basis and in line with planning horizon. Periodic routing aims to make clear the routs for servicing to customers in each period so that all costs related to routing in planning horizon be minimized. Periodic routing was first proposed by Beltrami and Bodin (1974).

However, the first mathematical model for periodic routing problem was proposed by Christofides and Beasley (1984). Hadjiconstaninou and Baldacci (1988) proposed multi-warehouses periodic routing. Cordeau and colleagues (1997) presented a forbidden search algorithm in order to solve multiple warehouse and multi-period problem. Kang and colleagues (2005) proposed an exact solution algorithm for periodic scheduling problem with multiple warehouses. Ho and colleagues (2008) expanded genetic algorithm in order to solve multiple warehouse routing problem. Salhi and Sari (1997) presented an initiative three-step method in order to solve multiple warehouse routing problems.

Mathematical Model Description

This article studies relief logistics during reaction phase of relief management. For this purpose, a three-level model including supplier (I), central warehouses (A) and regional warehouses (J) is provided. In this model, the relief goods are transferred from central warehouses to regional warehouses. Since in real world, the regional warehouses may deal with inventory shortage, such warehouses can compensate this shortage from central warehouses or other regional warehouses. According to this model, two kinds of demand – predicted and unpredicted- are considered. This model aims to study inventory transfer and distribution planning as well as vehicle routing on periodic basis. This model is designed as a three-purpose model under fuzzy uncertainty conditions. All components of this model will be described in the next section.

Model Indices

I: Points related to suppliers (i and i› refer to supplier index)

A: Number of central warehouses (a and a› refer to central warehouses index)

J: Points related to Depot (j and j› refer to Depot index)

C: Number of relief goods (c refers to goods index)

M: Types of vehicles (m refers to vehicle type index)

T: planning Horizon (t and t› refer to period index)

Model Parameters

αmin_{ct}: Minimum coverage of goods (c) during period (t) which is determined based on the urgency level.

w_c: Weight of a unit of the c^th^ goods

d^1_{jct}: The rate of the predicted demand for goods (c) in depot (j) during period (t)

$\tilde{d}^2_{jct} = (d^{2l}_{jct}, d^{2m}_{jct}, d^{2u}_{jct})$: The rate of fuzzy unpredicted demand for goods (c) in depot (j) during period (t)

$vcap_m$: Capacity of vehicle (m)

$Vpcap^m_{at}$: Parking capacity of central warehouse (a) for vehicle (m) during period (t)

$Vpcap^m_{j't}$: Parking capacity of warehouse () for vehicle (m) during period (t)

$cy^m_{j'0}$: Number of vehicles available on depot () at the first step

cy^m_a: Number of vehicles available on central warehouse (a) at the first step

$cfix^m$: Fixed cost of vehicle (m)

$\tilde{c}_{jj'm} = (c^l_{jj'm}, c^m_{jj'm}, c^u_{jj'm})$: Fuzzy transportation cost per unit goods from depot (j) to depot ()

$\tilde{c}^m_{ajm} = (c^l_{ajm}, c^m_{ajm}, c^u_{ajm})$: Fuzzy transportation cost per unit goods from central warehouse (a) to depot (j)

$\tilde{c}_{iam} = (c^l_{iam}, c^m_{iam}, c^u_{iam})$: Fuzzy transportation cost per unit goods from supplier (i) to central warehouse (a)

cap_{at}: Capacity of central warehouse (a) during period (t)

cap_{jt}: Capacity of warehouse (j) during period (t)

s_{jc}: The initial inventory of goods (c) in warehouse (j) during the first period

s_{ac}: The initial inventory of goods (c) in central warehouse (a) during the first period

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

$\tilde{p}_{1ct} = (p^l_{1ct}, p^m_{1ct}, p^u_{1ct})$: Fuzzy penalties for the predicted demand during period (t) which have not been fulfilled yet.

$\tilde{p}_{2ct} = (p^l_{2ct}, p^m_{2ct}, p^u_{2ct})$: Fuzzy penalties for the unpredicted demand during period (t) which have not been fulfilled yet.

Model variables

x^{mt}_{iac}: The amount of goods (c) sent from supplier (i) to central warehouse (a) by vehicle (m) during period (t)

x^{mt}_{ajc}: The amount of goods (c) sent from central warehouse (a) to the jth depot by vehicle (m) during period (t)

$x^{mt}_{jj'c}$: The amount of goods (c) sent from depot (j) to depot () by vehicle (m) during period (t)

$y^{mt}_{jj'}$: Number of vehicle (m) sent from depot (j) towards depot () during period (t)

y^{mt}_{aj}: Number of vehicle (m) sent from central warehouse to depot (j) during period (t) and arrives at (j) during period (t+1)

y^{mt}_{ia}: Number of vehicle (m) sent from supplier (i) to central warehouse (a) during period (t) and arrived at (a) during period (t+1)

$cy^m_{j't}$: Number of vehicle (m) transferred in depot () from period (t) to period (t+1)

cy^m_{at}: Number of vehicle (m) transferred in central warehouse (a) from period (t) to period (t+1)

s_{jct}: The amount of inventory of goods (c) in depot (j) remained from period (t-1) and is available in the beginning of period (t)

s_{act}: The amount of inventory of goods (c) in central warehouse (a) remained from period (t-1) and is available in the beginning of period (t)

SD_{jct}: The amount of demand for goods (c) which has been fulfilled in depot (j) during period (t)

UD_{jct}: The amount of demand for goods (c) in depot (j) during period (t) which has not been fulfilled and has been postponed to period (t+1)

CUD_{jct}: A part of the predicted demand for goods (c) in depot (j) during period (t) which has not been fulfilled

$UCUD_{jct}$: The amount of the unpredicted demand for goods (c) in depot (j) during period (t) which has not been fulfilled

Objective Functions

The first objective function is to minimize total fuzzy costs related to transportation and storage of the inventory.

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

The second objective function is to minimize the unfulfilled demand:

$$\min f2 = \sum_{t=1}^{T}\sum_{c=1}^{C}[\tilde{p}_{1ct}\sum_{j=1}^{J} CUD_{jct} + \tilde{p}_{2ct}\sum_{j=1}^{J} \mathrm{UCUD}_{jct}] \quad (2)$$

The third objective function is to maximize the least ratio of the fulfilled demand:

$$\max \sum\sum min_j \frac{SD_{jct}}{(d^1_{jct} + \tilde{d}^2_{jct})} \quad (3)$$

Model Limitations

$$s_{jct} + \sum_{m=1}^{M}\sum_{a=1}^{A} X_{ajc}^{mt-1} + \sum_{m=1}^{M}\sum_{j',j'\neq j} x_{j'jc}^{mt} = SD_{jct} + \sum_{m=1}^{M}\sum_{j\neq j'\in J} X_{jj'c}^{mt} + s_{jct+1} \quad \forall j,c,t = 2,3\dots,T \tag{4}$$

This limitation ensures the balance of goods flow in depots. For each goods in each period, total amount of goods stored in a depot during that period, the amount of goods which that depot receives from central warehouses and the amount of goods which receives from the other depots equals to total amount of goods which that depot uses in order to fulfill the demand, the amount of goods which sends to other depots and the amount of goods stores in the warehouse for the next period.

$$s_{jc1} = SD_{jc1} + \sum_{m=1}^{M}\sum_{j\neq j'\in J} X_{jj'c}^{m1} + s_{jc2} \quad \forall j,c \tag{5}$$

This limitation ensures the balance of goods flow in depots during the first period.

$$s_{act} + \sum_{m=1}^{M}\sum_{i=1}^{I} X_{iac}^{mt-1} = \sum_{m=1}^{M}\sum_{j=1}^{J} X_{ajc}^{mt} + s_{act+1} \qquad \forall a,c,t = 2,3,\dots,T \tag{6}$$

This limitation ensures the balance of goods flow in central warehouses. The whole amount of goods (c) available on the central warehouse (a) during period (t) [the amount of goods (c) which has been remained from period (t-1) and is available in central warehouse (a) in the beginning of period (t) together with the amount of goods (c) which has been received from suppliers during period (t)] are sent to depots and the remaining amount will be stored in central warehouse (a) for the next period.

$$s_{ac1} = \sum_{m=1}^{M}\sum_{j=1}^{J} X_{ajc}^{m1} + s_{ac2} \quad \forall a,c \tag{7}$$

This limitation ensures the balance of goods in central warehouses during the first period.

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

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

This limitation shows all demands for goods (c) -whether definite and indefinite- in depot (j) during period (t) together with the unfulfilled demand for the same goods in the same depot from the previous period is equal to total demand– whether fulfilled or unfulfilled- for goods (c) in depot (j) during period (t).

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

This limitation deals with the balance of total goods flow in all depots during all periods and central warehouses. The amount of goods which is remained until the end of relief operations (in both depots and central warehouses) together with the distributed goods should be equal to total initial inventory of depots and central warehouses as well as the amount of goods which is received from suppliers. In fact, this limitation ensures that no goods are lost.

$$CUD_{jct} = d_{jct}^{1} - SD_{jct} + \max\{0, CUD_{jct-1}\} \quad \forall j,c,t = 2,3,\dots T \tag{11}$$

$$CDU_{jc1} = d_{jc1}^{1} - SD_{jc1} \qquad \forall j,c \tag{12}$$

This limitation shows a part of the certain demand for goods (c) which has not been fulfilled in depot (j) during period (t) is equal to all certain demands for goods (c) in depot (j) during period (t) excluding the fulfilled and unfulfilled demands from the previous period. By determining the amount of predicted and unfulfilled demands, one can calculate the unpredicted and unfulfilled demands as well. This could be done by the following relation:

$$UCUD_{jct} = UD_{jct} - CUD_{jct} \quad \forall j,c,t \tag{13}$$

This limitation is used to calculate the amount of unpredicted demand for goods (c) in depot (j) during period (t) which has not been fulfilled.

$$\sum_{m}\sum_{j'}\sum_{c} w_c * x_{j'jc}^{mt} + \sum_{m}\sum_{a}\sum_{c} w_c * x_{ajc}^{mt-1} + \sum_{c} w_c * s_{jct} \le cap_{jt} \quad \forall j,t = 2,3,\dots,T \tag{14}$$

This limitation deals with meeting the capacity of depot (j) during period (t).

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

This limitation deals with meeting the capacity of depot (j) during period (t).

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

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

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

This limitation deals with meeting the capacity of vehicle (m) during period (t).

$$\sum_{m=1}^{M}\sum_{c=1}^{C}\sum_{i=1}^{I} x_{iac}^{mt-1} * w_c + \sum_{c} w_c * s_{act} \le cap_{at} \quad \forall a,t \tag{19}$$

$$\sum_{m}\sum_{c}\sum_{j} w_c * x_{ajc}^{mt} + \sum_{c} w_c * s_{act+1} \le cap_{at} \quad \forall a,t \tag{20}$$

These limitations deal with meeting the maximum capacity of central warehouses during each period.

$$\sum_{j=1}^{J} y_{jj'}^{mt} + \sum_{a=1}^{A} y_{aj'}^{mt-1} + cy_{j't-1}^{m} = \sum_{j=1}^{J} y_{j'j}^{mt} + cy_{j't}^{m} \quad \forall j',m,t = 2,3,\dots,T \tag{21}$$

This limitation deals with the balance of vehicle flow in depots and shows that all vehicles get into warehouse () from warehouse (j) and central warehouse (a) together with those vehicles transferred from the previous period equals to all vehicles get out of warehouse () together with those vehicles transferred to the next period.

$$cy^{m}_{j'0} = \sum_{j=1}^{J} y^{m1}_{j'j} + cy^{m}_{j'1} \quad \forall\, j', m \tag{22}$$

This limitation is in relation to the first period.

$$\sum_{j=1}^{J} y^{mt}_{jj'} + \sum_{a=1}^{A} y^{mt-1}_{aj'} + cy^{m}_{j't-1} \le Vpcap^{m}_{j't} \quad \forall j', m, t = 2,3,\ldots,T \tag{23}$$

This limitation shows the limitation of parking capacity of warehouse () during period (t) for vehicle (m).

$$\sum_{i=1}^{I} y^{mt-1}_{ia} + cy^{m}_{at-1} = \sum_{j'}^{J} y^{mt}_{aj'} + cy^{m}_{at} \quad \forall a, m, t = 2,3,\ldots,T \tag{24}$$

This limitation deals with the balance of vehicle flow in central warehouses and shows that all vehicles get into central warehouse (a) from supplier (i) together with those vehicles transferred from the previous period equals to all vehicles get out of central warehouse (a) during period (t) together with those vehicles transferred to the next period.

$$cy^{m}_{a0} = \sum_{j'}^{J} y^{m1}_{aj'} + cy^{m}_{a1} \quad \forall a, m \tag{25}$$

This limitation is related to the first period.

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

This limitation shows the limitation of parking capacity of central warehouse (a) for vehicle (m) during period (t).

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

This limitation is related to the minimum coverage level of goods (c).

The limitations related to values and signs of variables include:

$$x^{mt}_{iac}, x^{mt}_{ajc}, x^{mt}_{jj'c}, y^{mt}_{ia}, y^{mt}_{aj}, y^{mt}_{jj'c}, s_{jct}, s_{act}, SD_{jct}, UD_{jct}, CUD_{jct}, UCUD_{jct} \ge 0 \tag{28}$$

Now, the model is de-phased by using Jime ´nez method:

The objective function (1) is written as follows:

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

The objective function (2) is written as follows:

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

$$W_{c,t} \le \frac{SD_{jct}}{(d^{1}_{jct} + \tilde{d}^{2}_{jct})} \qquad \forall j, c, t \tag{31}$$

The de-phased model is as follows:

$$W_{c,t} \le \frac{SD_{j,c,t}}{d^{1}_{jct} + \left[\beta\frac{d^{2l}_{jct} + d^{2m}_{jct}}{2} + (1-\beta)\frac{d^{2m}_{jct} + d^{2u}_{jct}}{2}\right]} \tag{32}$$

$$d^{1}_{jct} + \beta\frac{d^{2l}_{jct} + d^{2m}_{jct}}{2} + (1-\beta)\frac{d^{2m}_{jct} + d^{2u}_{jct}}{2} + UD_{jct-1} = SD_{jct} + UD_{jct} \; \forall j, c, t = 2,3,\ldots,T \tag{33}$$

Limitation (9) is written as follows:

$$d^{1}_{jct} + \beta\frac{d^{2l}_{jct} + d^{2m}_{jct}}{2} + (1-\beta)\frac{d^{2m}_{jct} + d^{2u}_{jct}}{2} = SD_{jc1} + UD_{jc1} \; \forall j, c \tag{34}$$

After de-phasing, limitation (10) is written as follows:

$$\sum_{j=1}^{J}(s_{jcT+1} + \sum_{t=1}^{T}(d^{1}_{jct} + [\beta\frac{d^{2l}_{jct} + d^{2m}_{jct}}{2} + (1-\beta)\frac{d^{2m}_{jct} + d^{2u}_{jct}}{2}])) + \sum_{a=1}^{A} s_{acT+1} = \sum_{j=1}^{J}(s_{jc1} + UD_{jcT}) + \sum_{a=1}^{A} s_{ac1} + \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{a=1}^{A}\sum_{m=1}^{M} x^{mt}_{iac} \quad \forall c \tag{35}$$

Limitation (27) is written as follows:

Particles Swarm Optimization Algorithm

PSO is a successful technique in artificial intelligence. Image a group of insects or a bunch of fish. If one of the group members finds a suitable route to progress (for example in order to get food, safe location and etc.), other members are also able to follow that route. This phenomenon is modeled using those members have their own position and velocity.

For the first time, PSO has been expanded by a social psychology named James Kennedy and an electronic engineer named Russell Eberhart based on the previous experiences in the field of modeling collective behavior observed in most kinds of birds.

In this article, in order to solve the understudy model, particles swarm optimization algorithm (PSO) is proposed in which variable neighborhood search structure are used in order to update the particles.

The proposed Structure

In this section, the designed components for the ultra-initiative PSO method are completely studied. The following figure shows the general structure designed for PSO method.

{Step1: initialization

Generate initial *N* feasible particles.

Initial pareto archive as empty set.

Apply improvement procedure for generated particles.

particles.

Initialize p_g and p_i.

Step 2: while number of iteration<= max_iteration

Update particle by VNS

Improve population of particles

Evaluate the updated particles to get the new and

Update pareto archive set

Select N best particles as next generation

End while.

Return the best solution.}

Response display method

In all ultra-initiative algorithms, due to the need to soluble at the beginning of the algorithm, it is necessary to save the soluble according to a certain structure. Such structure is known as response display method. In this research, in order to display response, a matrix structure is used so that for each model outputs, a matrix proportional to that variable is designed. For example, for variable $y_{jj'}^{mt}$ a four-dimensional matrix is designed two of which equals to number of the regional warehouses, the 3rd dimension equals to number of vehicles and the 4th dimension equals to number of periods.

Generating the Initial Responses

As previously mentioned particles swarm algorithm is population-based and operates with a population of responses on each of iterations. At the beginning of the algorithm, a population of responses should be generated as the initial responses. In this article, the initial population is randomly generated (considering limitations of the model). On the other hand, N possible response are randomly generated and used as the initial population of algorithm.

Improvement Trend

After generating the initial responses on each of iterations, improvement trend is applied on the available particles in the population which improves the particles as much as possible. In this study, improvement trend is designed as the parallel combination of two neighborhood search structure. In the next section, neighborhood search structure and improvement trend structure are explained.

The First Neighborhood Search Structure

In this structure, index (t) at integrated interval [1..T] (T refers to number of periods), indices (j and j') at integrated interval [1..J] (J refers to number of Depots), index (m) at interval [1..M] (M refers to types of vehicle) are randomly generated and the amount of goods sent from (j) to (j') during period (t) by vehicle (m) are replaced with the same amount of goods sent from (j') to (j) during period (t) by vehicle (m). However, limitations of model should be considered in this process.

The Second Neighborhood Search Structure

In this structure, index (t) at integrated interval [1..T] (T refers to number of periods), index (j) in integrated interval [1..J] (J refers to number of Depots), indices (a and a') in integrated interval [1..A] (A refers to number of central warehouses), index (m) in integrated interval [1..M] (M refers to types of vehicle) are randomly generated and the amount of goods sent from (a) to (j) during period (t) by vehicle (m) are replaced with the same amount of goods sent from (a') to (j) during period (t) by vehicle (m). However, limitations of model should be considered in this process.

These two neighborhood structures are combined in parallel. Then improvement trend structure is composed as follows:

{for input particle s:

For i=1 to maximum iteration

S1=neighborhood search structure 1 (s)

S2=neighborhood search structure2(s)

S=acceptance (s1, s2, s)

End for

Return s}

As you see from above, when each of particles are given to improvement trend, the neighborhood search structures are applied on the input response in parallel (simultaneously) and the most qualified response is chosen among the three responses (input response, response generated from the first structure and response generated from the second structure). The qualified response is selected using non-dominate relations. In fact, that response which is not dominated by other responses is selected.

Particle Updates

Here, particle (X_i) is updated using variable neighborhood search (VNS) on each iteration. Variable neighborhood search structure (VNS) is generated by combining three neighborhood search operator, two of which are the same neighborhood search structure described on section (3-4). In the following, other neighborhood search operator and variable neighborhood search structure are explained.

The Third Neighborhood Search Structure

This structure takes two responses as the input and tries to search the first response neighborhoods so that be similar to the second response or on the other hand drive toward the second response. In fact, in this structure, the first response is directed to the second response. So, it can be said that the second response acts as the director of the first response.

Variable neighborhood structure is used in order to update the particles. This structure contains three inputs including x_i, p_i (the best neighborhood of i^{th} particle found in this iteration up to now) and p_g (the best response found in this iteration). The third neighborhood search structure is generated by combining the first and second neighborhood search structures. In this research, in the respective variable neighborhood search (VSN), the third neighborhood search structure is used twice and once p_i acts as the director of x_i and once p_g acts as the director of x_i. The variable neighborhood search structure designed in this study is as follows: (assume NSS_k represents K^{th} neighborhood search structure).

{for each input solution
K=1
While stopping criterion is meet do
n_ *S*=Apply NSS type k
s=choose solution by non-dominate relation
If *s* is improved then
K=1
Else
K=k+1
If k=4 then
K=1
Endif
Endif
Endwhile }

In the above structure, the first type of NNS is the first search neighboring structure, the second type of NSS is the second search neighboring structure, the third type of NSS is the third search neighboring structure with inputs of x_i and p_i, and at last the forth type of NSS is the third search neighborhood structure with inputs of x_i and p_g.

Updating p_i and p_g

For each of the i^{th} particle, if there is a neighboring better than p_i among the neighboring structures found for this response, p_i will be replaced with it. Otherwise, no change is made and it remains without any change.

If the best response is better than p_g among all the responses which have ever been found, p_g will be replaced with it. Otherwise, no change is made and it remains without any change.

Updating Pareto Archive

As it has already said, the solution method used in this research is based on Pareto archive. In the proposed algorithm, a collection is considered as Pareto archive which contains the non-dominated responses generated by the algorithm. This collection will be updated in each of the iterations. To do so, first the responses generated on that iteration and the responses available in Pareto archive are put into the response pool (answer pool) and are leveled. Then, among these responses, the responses available in the first level or the non-dominated responses are selected and considered as the new Pareto archive.

Selecting response collection for the next generation

Algorithm needs a population of responses in each of the iterations. In this research in order to select the next iteration population, the responses available in the population of that iteration together with the new responses generated by algorithm are put into the response pools. After leveling and calculating crowding distance for each response based on level of that response, N responses of the most qualified and dispersed are selected as the next iteration population of algorithm using Deb rule (Deb 2002).

Computational Results:

In this section, some sample problems are randomly generated and solved by the proposed particles swarm algorithm. To prove the efficiency of the proposed algorithm, results obtained from this algorithm and those obtained from genetic algorithm are compared based on three comparison metrics.

Comparison Metrics

There are various indices to evaluate the quality and dispersion of ultra-initiative multi-purpose algorithms. In this thesis, three indices are used for comparison purposes. In the next section, these indices are explained.

Quality Index: it is used to compare the quality of Pareto responses obtained from each method. In fact, all Pareto responses obtained by both methods are leveled based on quality index and the percent of the first level responses which belongs to each method are determined. The higher the percentage, the greater the quality of the algorithm.

Integration Index: it is used to test integration of the distributed Pareto responses which are generated on the border of responses. This index can be defined as follows:

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

In the above relation, d_i indicates Eucliadean distance between two adjacent non-dominated responses and d_{mean} indicates mean value of d_i.

Dispersion Index: it is used to determine the number of the non-dominated responses found on the optimal border. Dispersion index is defined as follows:

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

In the above relation, $\|x_t^i - y_t^i\|$ indicates Eucliadean distance between two adjacent responses (x_t^i and y_t^i) on the optimal border.

General Hypothesis of Algorithms

Values for the parameters related to both genetic and particles swarm algorithms are as follows:

- Population size for both algorithms in all problems equals to 100 and iteration number of algorithm equals to 600.
- Mutation operator rate and intersection operator rate in genetic algorithm equals to 0.1 and 0.8, respectively.
- For all problems, number of goods and types of vehicle equal to 3. In addition, weight of goods is randomly generated in integrated interval [1..10] and the predicted demand is generated in integrated interval [1..20]. In order to generate the unpredicted demand values as triangular distance [m1 m2 m3], number (m2) is firstly generated in integrated interval [1..20] and then numbers (m1) and (m3) are generated through relation (1-r)m2 and (1+r)m2 respectively. In both relation, (r) is considered as a random number in interval (0,1). This process is the same for generating rectangular values for transporting costs, inventory storage costs and penalties applied to the unfulfilled demand. The only difference is that the middle number is generated in integrated interval [1..40]. Moreover, vehicle capacity is randomly generated in integrated interval [150..300].
- In order to obtain parking capacity of depots and central warehouses, total weight for the necessary goods of the predicted demand is calculated as number (v1) and total weight for the predicted and the unpredicted demand is calculated as number (v2). Then for each vehicle (m), two numbers (w1 and w2) are calculated through these relations $w1 = \frac{v1}{vcap_m}, w2 = \frac{v2}{vcap_m}$ and at last parking capacity is randomly generated in integrated interval [w1..w2]. Also, capacity of depots and central warehouses are randomly obtained in integrated interval [v1..v2].
- The initial inventory values and number of the initial vehicles available in integrated interval [1..20] are randomly obtained.

Comparison Results

To prove the efficiency of the proposed algorithm, 10 sample problems are randomly generated and implemented by both genetic algorithm and particles swarm algorithm. The results obtained from comparing these 2 algorithms together with characteristics of these 10 problems are provided in the following table. Characteristics of each problem are represented by I/A/J/T format where I, A, J and T refer to number of suppliers, number of central warehouses, number of depots and number of planning periods respectively.

Table 1: Comparison results for genetic algorithm (GA) and hybrid particle swarm optimization algorithm (HPSO)

Run Time		Dispersion Index		Integration Index		Quality Index		Problem
GA	HPSO	GA	HPSO	GA	HPSO	GA	HPSO	
0.12	4.01	449.6	905.3	1.19	0.87	6	94	2/3/4/4
0.22	11.13	219.3	2375.4	0.1	0.38	11.76	88.24	5/4/6/4
0.28	10.98	1090.5	4518.9	0.46	0.19	9.9	90.91	5/4/8/4
1.13	19.61	1480.5	6499	1.34	1.29	15.62	84.38	7/4/15/5
1.45	25.67	2267.5	8774.7	0.99	0.67	9.3	90.7	7/8/15/5
2.71	45.8	7958	10785	1.54	0.81	38.1	61.9	7/10/18/6
3.27	52.1	6350	13980	1.72	0.81	24.24	75.76	7/10/20/6
3.95	72.59	3960	16786	0.94	0.49	11.36	88.64	8/10/20/8
9.76	132.02	12352	27734	1.47	0.96	18.52	81.48	9/12/24/10
11.77	155.09	10144	25209	0.45	0.98	33.33	66.67	9/12/30/10

As you see in the above table, compared to genetic algorithm, hybrid particle swarm optimization algorithm has more ability to generate the qualified responses close to the optimal boundary in all cases. Moreover, in all 10 problems, the response generated by hybrid particle swarm optimization algorithm is more dispersed than those obtained from genetic algorithm. In case of integration index, integration of responses generated by genetic algorithm is more than those generated by hybrid particle swarm optimization algorithm only in two problems. As you see, solution time of genetic algorithm is less than that of hybrid particle swarm optimization algorithm for all problems.

Conclusions

In this article, response phase from disaster management cycle is studied and a multi-purpose integrated model is provided for three-level relief cycle logistic under uncertainty condition and on a periodic basis for this phase. In order to solve the proposed mathematical model, an ultra-initiative particles swarm algorithm in combination with variable neighboring search algorithm based on Pareto archive. Results obtained from applying the proposed particle swarm algorithm and genetic algorithm on several problems are compared based on three quality, dispersion and integration indices. Results for this comparison shows that compared to genetic algorithm, particle swarm algorithm is more capable of generating more qualified, integrated and dispersed responses. Moreover, the results reflect this fact that solution time of genetic algorithm is less than that of the proposed algorithm.

References

Afshar, A, Haghani, A.(2012) Modeling integrated supply chain logistics in real-time large-scale disaster relief operations, *Socio-Economic Planning Sciences,* 1–12.

Balaisyte, J, Pedraza Martinez AJ, Stapleton O, Van Wassenhove LN (2011) Responding to the Haiti earthquake disaster: one year on. http://www.insead.edu/facultyresearch/centres/isic/humanitarian/HaitiOneYearOn.cfm. Accessed 12 March 2011

Balçik, B, Beamon, BM (2008) Facility location in humanitarian relief. *Int J Logist:Res Appl, 11*(2),101–121

Barbarosoglu, G., Arda Y. (2004).A Two-Stage Stochastic Programming Framework for Transportation Planning in Disaster Response, *Journal of the Operational Research Society, 55,* 43-53.

Beamon, BM, Kotleba SA (2006) Inventory modelling for complex emergencies in humanitarian relief operations. *Int J Logist: Res Appl 9*(1),1–18

Beate Rottkemper, Kathrin Fischer, Alexander Blecken, Christoph Danne(2011), Inventory relocation for overlapping disaster settings in humanitarian operations.

Beltrami, E.J., Bodin, L.D.(1974). Networks and Vehicle Routing for Municipal Waste collection, *Networks, 4*(1), 65-94.

Burton, I (1997) Vulnerability and adaptive response in the context of climate and climate change. *Clim Change 36*(1–2),185–196

Chang MS, Tseng YL, Chen JW (2007) A scenario planning approach for the flood emergency logistics preparation problem under uncertainty. *Transp Res E 43,*737–754

Christofides, N., Beasley, J, E. (1984). The Period Routing Problem, *Networks, 14*(2), 237 – 256.

Cordeau, J.F., Gendreau, M., Laporte, G. (1997). A Tabu Search Heuristic for Periodic and Multi-Depot Vehicle routing problems, *Networks, 30*, 105-119

Fiedrich, F, Gehbauer F, Rickers U (2000) Optimized resource allocation for emergency response after earthquake disasters. Saf Sci 35:41–57

Hadjiconstantinou, E., Baldacci, R.(1998) A Multi-Depot Period Vehicle Routing Problem Arising in the Utilities Sector, *Journal of the Operational Research Society, 49*(12),1239– 1248

Deb, K. (2002). A fast and elitist multiobjective genetic algorithm:NSGA-II. *IEEE transaction evolutionary computation, 6*(2).

Kang, K.H., Lee, Y.H., Lee, B.K. (2005). An Exact Algorithm for Multi Depot and Multi Period Vehicle Scheduling Problem, In *Computational Science and Its Applications- ICCSA*, Lecture Notes in Computer Science, Springe

Kovács, G, Spens, KM (2007). Humanitarian logistics in disaster relief operations. *Int J Phys Distrib Logist Manag 37*(2), 99–114

Lai, Y., Hwang, C., “A New Approach to Some Possibilistic Linear Programming Problems”, Fuzzy Setsand Systems, Vol. 49, 1992, pp.121–133.

Mariano Jimenez, Mar Arenas, Amelia Bilbao, M. Victoria Rodriguez (2007). Linear programming with fuzzy parameters: An interactive method resolution, *European Journal of Operational Research, 177,* 1599–1609

Mete, O. H., Zabinsky, Z.B. (2010). Stochastic Optimization of Medical Supply Location and Distribution in DisasterManagement, *International Journal of Production Economics, 126*(1), 76-84

Salhi, S., Sari, M. (1997). A Multi-Level Composite Heuristic for the Multidepot Vehicle Fleet Mix Problem, *European Journal of Operational Research, 103*, 95-112.

Swiss Reinsurance Company (2010) Sigma no. 1/2010: natural catastrophes and man-made disasters in 2009. Catastrophes claim fewer victims, insured losses fall. Technical report. Swiss Reinsurance Company, Zurich. http://www.swissre.com/. Accessed 22 Oct 2010

The Sphere Project (2004) Humanitarian charter and minimum standards in disaster response. *The Sphere Project*. http://www.sphereproject.org/. Accessed 17 March 2009

Thomas, AS, Kopczak, LR (2005) *From logistics to supply chain management: the path forward in the humanitarian sector*. http://www.fritzinstitute.org/ PDFs/WhitePaper/ From Logisticsto.pdf. Accessed 10 Oct 2010

Tzeng, G.H., Cheng, H.J., Huang, T.D.(2007). Multi-Objective Optimal Planning for Designing Relief Delivery Systems, *Transportation Research Part E, 43*(6), 673-686

Van Wassenhove, LN (2006) Humanitarian aid logistics: supply chain management in high gear. *J Oper Res Soc, 57,*475–489

Van Wassenhove, LN, Pedraza Martinez, AJ (2010) Using OR to adapt supply chain management best practices to humanitarian logistics. *Int Trans Oper Res*

Yi, W., Kumar, A. (2007). Ant Colony Optimization for Disaster Relief Operations, *Transportation Research Part E, 43*, 660–672.

Zimmermann, H.J. (1978). Fuzzy Programming and Linear Programming with Several Objective Functions, *Fuzzy sets and Systems, 1,* 45–55.