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A Modified Discreet Particle Swarm Optimization for a Multi-level Emergency Supplies Distribution Network

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ABSTRACT

Currently, the research on emergency supplies distribution and decision models mostly focus on deterministic models and exact algorithm. A few of studies have been done on the multi-level distribution network and metaheuristic algorithm. In this paper, random processes theory is adopted to establish emergency supplies distribution and decision model for multi-level network. By analyzing the characteristics of the model, a modified discrete particle swarm optimization metaheuristic algorithm (MBPSO) is proposed to solve the problem. In MBPSO, appropriate degradation mechanism and parallel global search structure is designed. MBPSO has capability of global optimum search and fast convergence property for hybrid integer programming model with multi-constrained and weighted single objective.

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NOMENCLATURE

T	Set of total time of distribution.	h
x_{id}	Set of amount of emergency supplies to be distributed to demand point d at supply point i ,where $i \in I$, $d \in D$.	t
dis_{id}	Set of distance between supply point i and demand point d ,where $d \in D$.	km
dis_{ih}	Set of distance between supply point i and transit point h ,where $i \in I$, $h \in H$.	km
dis_{hd}	Set of distance between transit point h and demand point d ,where $h \in H$, $d \in D$.	km
v_k	Set of velocity of transport facility k ,where $k \in K$.	km/h
t_{zz}	Set of transshipment time.	h
C	Set of total cost of distribution.	
c_{inv}^{k}	Set of fixed cost of transport facility k .	
c_{v}^{k}	Set of variable cost of transport facility k , where $k \in K$.	
c_{zz}	Set of the transshipment cost.	
p	Set of probability of being found by enemy in delivery paths.	
S	Set of random risk from enemy in delivery paths.	

Greek Symbols

λ_{id}	Set of Poisson intensity between supply point i and demand point d , where $i \in I$, $d \in D$.
λ_{ih}	Set of Poisson intensity between supply point i and logistics transit point h , where $i \in I$, $h \in H$.
λ_{hd}	Set of Poisson intensity between transit point h and demand point d , Where $h \in H$, $d \in D$.
$\lambda_{i?d}$	1,if transport facility does not get through any transit point;0 otherwise, where $i \in I$, $d \in D$.
$\lambda_{i?k}$	1,if transport facility k will be chosen,0 otherwise, on condition that $\lambda_{i?d} = 1$. where $i \in I$, $k \in K$.

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$\lambda_{i?h}$	1,if the transit point h be chosen,0 otherwise. where $i \in I$, $h \in H$.
$\lambda_{ih?k}$	1,if transport facility k will be chosen,0 otherwise, on condition that $\lambda_{i?h} = 1$,from supply point i to logistics transit point h , where $i \in I$, $h \in H$, $k \in K$.
$\lambda_{hd?k}$	1,if transport facility k will be chosen,0 otherwise, on condition that $\lambda_{i?h} = 1$, logistics transit point h to demand point d , where, $d \in D$ $h \in H$, $k \in K$.
Subscripts	
i	supply point. $i \in I$
h	transit point. $h \in H$
d	demand point. $d \in D$
k	transport facility. $k \in K$
v	velocity
inv	invariable
?	choose which one

1. INTRODUCTION

Modern information emergency support has the characteristics of high intensity, fast-paced information transmission and shorter time. It is very difficult to deliver emergency supplies for disaster area in this complex emergency environment. Emergency supplies distribution has been extensively studied in literature and mainly focus on single-level network, deterministic models and planning algorithm. However, less research has been done on uncertainty in the emergency environment, the multi-level distribution network and intelligent heuristics algorithm under uncertainty environment. In consideration of uncertainties of supply and demand, an integer programming model is presented to formulate the problem, and a Lagrangian heuristic algorithm is developed to solve the problem. The results show that the proposed algorithm can get approximate optimal solutions in a short time period [1]. Toyoglu Karasan & Kara, provide an ammunition distribution algorithm. In this paper, with respects to a factor of hard time windows, designing a three-layer commodity-flow location routing formulation that distributes multiple products, and demand points allowed to be supplied by more than one transportation or depot. They develop a static mixed integer programming model and solve nine problem instances in a reasonable amount of time [2]. Naval warfare is studied in this literature, mainly concentrating on logistics center location, emergency supplies presets and emergency supplies distribution optimization problem [3]. Three-index formulations were proposed for solving the problem of locating regional blood banks to serve hospitals [4], and in literature [5] for designing the division's distribution system, in consideration of the system number, size, and locations of central depots.

Above these are some research achievements on distribution of emergency supplies. The main differences of our approach with other proposals existing in the literature are that in this paper random processes theory is adopted to establish emergency supplies distribution and decision model in multi-level network. Meanwhile, a modified discrete particle swarm optimization (MBPSO) metaheuristic algorithm is proposed to solve this multi-constrained and weighted single objective.

The paper is organized as follows. In section 2, we formulate the problems of emergency supplies distribution and propose modified discrete particle swarm optimization algorithm (MBPSO). In section 3, through a instance discussing different performance among three algorithms. Finally, section 4 contains some conclusions and future research development.

2. MATHEMATICAL MODEL

Multi-level emergency supplies distribution network is generally composed of three layers, supply points, transit points (depots) and demand points as shown in Figure 1**.** In real case, emergency supplies distribution always is affected by transport distance, warehouse storage and transport capacity restrictions. So, emergency supplies distribution usually involves cooperation of supply points and transit points. Specially, emergency supplies distribution in uncertain environment, some important factor of time, cost and random risk from uncertain environment will be taken into consideration.

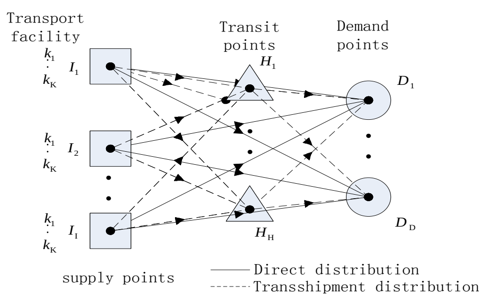

Figure 1. Three layers distribution network

In this section, we will establish models based on these factors.

2. 1. Model Formulation

❖ Time and Cost Model

Transport time and cost are divided into direct part and transshipment part. Every route in multi-level distribution network, different transport facility will generate different transport time and cost, but only allowed to choose one of the transport facilities in one route. If a route passes through a transit point, it will generate transshipment time and transshipment cost, which are associated to its value. The larger amount of emergency supplies will expend more time and cost. The total time and total cost of emergency supplies distribution are shown in Equations (1) and (2).

$$T=\begin{cases}\sum_{d\in D}\sum_{i\in I}\sum_{k\in K}\lambda_{i?d}\lambda_{i?k}\left(\frac{dis_{id}}{v_k}\right) & \lambda_{i?d}=1\\ \sum_{d\in D}\sum_{i\in I}\sum_{h\in H}(1-\lambda_{i?d})\lambda_{i?h}\begin{pmatrix}\sum_{k\in K}\lambda_{ih?k}\left(\frac{dis_{ih}}{v_k}\right)+\cdots\\ x_{id}t_{zz}+\sum_{k\in K}\lambda_{hd?k}\left(\frac{dis_{hd}}{v_k}\right)\end{pmatrix} & \lambda_{i?d}=0\end{cases} \tag{1}$$

$$C=\begin{cases}\sum_{d\in D}\sum_{i\in I}\sum_{k\in K}\lambda_{i?d}\lambda_{i?k}\left(c_{inv}^k+c_v^k x_{id}dis_{id}\right) & \lambda_{i?d}=1\\ \sum_{d\in D}\sum_{i\in I}\sum_{h\in H}(1-\lambda_{i?d})\lambda_{i?h}\begin{pmatrix}\sum_{k\in K}\lambda_{ih?k}\left(c_{inv}^k+c_v^k x_{id}dis_{ih}\right)+\cdots\\ x_{id}c_{zz}+\cdots\\ \sum_{k\in K}\lambda_{hd?k}\left(c_{inv}^k+c_v^k x_{id}dis_{hd}\right)\end{pmatrix} & \lambda_{i?d}=0\end{cases} \tag{2}$$

❖ Random Risk Model

Random process is a set of random variables, which represents the evolution of random variables in some system over time. The Poisson process is one of the most important random processes in random processes theory. It is widely used to formulate the random points process in a period of time, such as the arrival times of customers at a service center, and the positions of flaws in a piece of material. In this paper, we use Poisson process to describe the times of destroy from uncontrollable factor in environment.

The expression $\{N(t),t\ge 0\}$ means random times of destroying from uncontrollable factor in an environment during a period $[0,t)$. Assume that $\{N(t),t\ge 0\}$ obey strength λ for the Poisson Process, where the strength λ is mean to random times of destroy from uncertain environment to one of the routes in unit time. In once destroy process, The probability of our emergency supplies being destroyed is denoted by p, where $0<p<1$, and whether the environment will destroy emergency supplies within each time is a mutual independence event.

Definition 1: $\{N(t),t\ge 0\}$ means random times of destroy from uncontrollable factor in environment during a period $[0,t)$, where $Y(t)=\sum_{n=1}^{N(t)}X(n)$ and $X(n),(n=0,1,2\cdots)$ is independent identically distributed. Then, $\{Y(t),t\ge 0\}$ belongs to compound Poisson process, which obeys the strength λp.

Proof 1:

$$X(n)=\begin{cases}1 & \text{be destroyed in } n\text{th}\\ 0 & \text{notbe destroyed in } n\text{th}\end{cases}$$

The times of being destroyed by environment in one of the routs during a period in $[0,t)$ is denoted by $Y(t)=\sum_{n=1}^{N(t)}X(n)$.then $P\{X(n)=1\}=p$ and $P\{X(n)=0\}=1-p$.

So,

the characteristic function of $X(n)$ is denoted by $\varphi_{X(n)}(v)=pe^{iv}+(1\text{-}p)$.

$\because Y(t)$ belongs to compound Poisson process

$\therefore$ Characteristic function of $Y(t)$ is denoted by $\varphi_{Y(t)}(v)=e^{\lambda t[\varphi_{X(1)}(v)-1]}=e^{\lambda t[pe^{iv}-p]}=e^{\lambda pt[e^{iv}-1]}$

Because of the unique principle of Poisson Process, we know that $\{Y(t),t\ge 0\}$ belongs to Compound Poisson Process which obey the strength λp.

So, we have known that $\{Y(t),t\ge 0\}$ belongs to compound Poisson process, which obey the strength λp. In order to investigate the random risk degree in a transport process, we have to investigate some characteristic functions of this Poisson Process. In this paper, we choose the mean function as a target to evaluate the random risk degree of emergency supplies distribution. $\{Y(t),t\ge 0\}$ is shown in Equation (3).

$$m_N(t)=E\left[Y(t)\right]=\gamma pt \tag{3}$$

Through Equation (3) we can conclude that the expectation value of compound Poisson process is proportional to Poisson intensity, subsystems probability and duration time. Based on the above deduction, the random risk of emergency supplies distribution in multi-level network is shown below.

$$S=\begin{cases}\sum_{d\in D}\sum_{i\in I}\sum_{k\in K}\lambda_{i?d}\lambda_{i?k}\left(\frac{dis_{id}}{v_k}\right)\lambda_{id}p & \lambda_{i?d}=1\\ \sum_{d\in D}\sum_{i\in I}\sum_{h\in H}(1-\lambda_{i?d})\lambda_{i?h}\begin{pmatrix}\sum_{k\in K}\lambda_{ih?k}\left(\frac{dis_{ih}}{v_k}\right)\lambda_{ih}p+\cdots\\ \sum_{k\in K}\lambda_{hd?k}\left(\frac{dis_{hd}}{v_k}\right)\lambda_{hd}p\end{pmatrix} & \lambda_{i?d}=0\end{cases} \tag{4}$$

The objective function is shown in Equation (5) .It consists of time, cost and random risk, on which we will put corresponding weight factor to cater to a different scenario, where $\alpha+\beta+\lambda=1$. Some constraints are shown below.

$$\min \quad Z=\alpha T+\beta C+\gamma S \tag{5}$$

$$S.T. \quad \sum_{h\in H}\lambda_{i?h}=1 \ \forall h\in H \ \forall i\in I \tag{6}$$

$$\sum_{k\in K}\lambda_{id?k}=1 \ \forall i\in I \ \forall d\in D \ \ \forall k\in K \tag{7}$$

$$\sum_{k\in K}\lambda_{ih?k}=1 \ \forall i\in I \ \ \forall h\in H \ \forall k\in K \tag{8}$$

$$\sum_{k\in K}\lambda_{hd?k}=1 \ \forall h\in H \ \forall d\in D \ \forall k\in K \tag{9}$$

$$\sum_{i=1}^{I}x_{id}=x_d \quad \forall i\in I \ \forall d\in D \tag{10}$$

$$\sum_{d=1}^{D}x_{id}\le X_i \quad \forall i\in I \ \forall d\in D \tag{11}$$

Constraint (6) describes that only one transit point can be chosen.

Constraint (7) demonstrate that we can choose only one transport facility, under condition $\lambda_{i?d}=1$. Constraint (8) ensures that we can choose only one transport facility from supply point i to transit point h, on the condition that $\lambda_{i?d}=0$.

Constraint (9) ensures that we can choose only one transport facility from supply point *h* to demand point *d*, on the condition that $\lambda_{i?d}=0$.

Constraint (10) guarantees that the distribution amount of all supply points I should be equal to the amount of demand point d. Constraint (11) exhibits that the total distribution amount in arbitrary supply point i should be less than their own inventory.

Distribution models in the multi-level network is a hybrid integer programming model, consist of equality constraints, inequality constraints and Non-negative integer solution space, which belongs to the typical multi-constrained and weighted single objective optimization problem. In general, the model in small size could be solved by the exact algorithm. But with increased size of the model, the exact algorithms such as Mixed Integer Programming would not get its exact solution. So, in this paper, metaheuristic algorithms is used and developed for the proposed model.

In recent years, many scholars proposed a variety of approaches like heuristic algorithm, bionic intelligent algorithm, the algorithm combined with the constraint condition, etc., to investigate the problem [6, 7]. But, the existing approach cannot solve our model. So, a new metaheuristic algorithm will be proposed in this paper. In next section, we will introduce a modified metaheuristic algorithm to solve this problem.

2. 2. Improved Discrete Particle Swarm Optimization

2. 2. 1. Standard PSO Algorithm The particle swarm optimization algorithm (PSO) is proposed by Kennedy and Eberhart [8]. In PSO, a potential solution for a problem is considered as a bird, which is called a particle, flies through a D-dimensional space and adjusts its position according to its own experience and other particles'. In PSO, a particle is represented by its position vector p and its velocity vector v. In time step t, particle i calculates its new velocity then updates its position according to Equation (12) and Equation (13), respectively.

$$v_i^{'d}=\omega v_i^d+c_1r_1\left(p_i^d-x_i^d\right)+c_2r_2\left(p_g^d-x_i^d\right) \tag{12}$$

$$x_i^{'d}=x_i^d+v_i^{'d} \tag{13}$$

where ω is the inertial weight, and c_1 and c_2 are positive acceleration coefficients used to scale the contribution of self-cognitive and social-sharing components, $v_i^{'d}$ and v_i^d are the current. the last speed values, respectively. p_i^d is the best position that particle i has been experienced in d dimensions. p_g^d is the best position found by all particles I in d dimensions. r_1 and r_2 are uniform random variables in range.

2. 2. 2. Discrete PSO Algorithm Standard PSO algorithm is suitable for continuous problem. In order to make the PSO algorithm more adaptive to solve discrete optimization problems, J. Kennedy and K. C. Eberhart [9-12], introduced a Binary-Particle Swarm Optimization (BPSO), which is more suitable for solving the problem of discrete.

BPSO algorithm inherits the velocity updating equation of the standard PSO algorithm. Firstly ,utilize Equation (12) to update the velocity value, then, SIGMOID function is used to convert velocity value into the probability of binary digit to get value 1.The process is shown below.

$$s\left(v_i^d\right)=\frac{1}{1+\exp\left(-v_i^d\right)} \tag{14}$$

$$x_i^d=\begin{cases}1 & if \ \ rand()\le s\left(v_i^d\right)\\ 0 & otherwise\end{cases} \tag{15}$$

where $rand()$ is uniform random variables in range [0,1]. It is necessary to set a maximum velocity $v_{\max}$ to limit the range of v_i^d, denoted by $v_i^d \in [-v_{\max}, v_{\max}]$.

The standard BPSO algorithm has fast convergence speed, but due to its following tendency phenomenon, the particle population is easy to fall into local extremum. In order to overcome the shortcomings, we improved the standard BPSO optimization algorithm, making BPSO algorithm more efficient to accurately search the global optimum solution.

2. 3. Structure of Modified BPSO Algorithm

2. 3. 1. Solution Structure As can be seen from Figure 2, the structure of the solution is divided into two parts. The first part is the accurate part, which means the amount of emergency supplies to be distributed. The second part is metaheuristic part, which means the combination of routes and transports. Furthermore, solving process is divided into two parts. Firstly, combination of routes and transports is generated by MBPSO algorithm. Then linear programming is used to solve the minimum value of objective function and corresponding amount of emergency supplies to be distributed in each supply point.

2. 3. 2. Neighborhood Structure of Swarm In the standard BPSO algorithm, the potential solution in every step is pulled to be current global optimum, which denoted by Gbest. In this way, making standard BPSO algorithm fast convergence, but easy to fall into local extremum and the algorithm becomes premature convergence. In this paper, the neighborhood structure of standard BPSO algorithm is improved. So, the Gbest of improved BPSO algorithm, not only from the current best solution, but also with a certain probability derive from one of select particles' best solution it experienced, is denoted by Pbest. In this mechanism, the BPSO algorithm makes appropriate degradation, thus increasing diversity of the population. At the same time, in order to avoid falling into local extremum, at every predetermined sampling point, another parallel global search mechanism will be triggered. Some separate population will be randomly initialized to get global optimum in sampling period.

2. 3. 3. MBPSO Implement Steps

Step1 Population initialization. In the problem definition domain , initializing population position and velocity value randomly, and calculating its fitness.

Step2 Stop judging. Stop and exit, if the algorithm meet stop condition., otherwise , continue.

Step3 velocity and position update. Equation (12), (14), (15) are used to update the velocity and position of populations and calculating new populations' fitness.

Step4 Parallel algorithm structure. At every predetermined sampling point, another parallel global search mechanism will be triggered in sampling period. Some separate population will be randomly initialized to get global optimum which is denoted by Gbest1. In sampling period, if Gbest1 is better than Gbest, replace it.

Step5 Population degradation mechanism. At every predetermined sampling point, in roulette random way, with a certain probability substitute one of select particles' best solution it experienced (Pbest) for current global optimum (Gbest). Meanwhile, Storing Gbest. When sampling period is over, if there is no other better optimal value updated, then give the last stored Gbest back to the current optimal value.

Step6 Evaluate fitness, turn to step 2.

3. RESULTS AND DISCUSSION

In order to verify the validity and practicability of the model and modified discrete particle swarm optimization algorithm (MBPSO), constructing a three level emergency supplies distribution network, consists of 4 supply points, 3 transit points, 5 demand points and two kinds of transport facilities. α=0.5、β=0.2、$\gamma=0.3$ are the weight of time, cost and random risk respectively. Transit costs and Transit time is that $c_{zz} = 20\$/t$ and $t_{zz} = 0.3h/t$. Other related parameters are shown in Tables 1 to 5.

MBPSO algorithm's performance is sensitive to parameters combination of c_1 , c_2 and w, which affects the convergence speed, accuracy and other properties. Therefore, combination of c_1 , c_2 and w is to be investigated first.

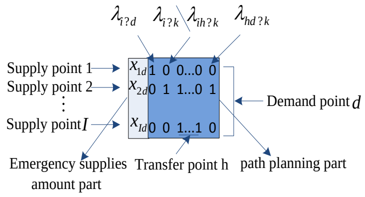

Figure 2. Solution structure

3. 1. Parameters Combination Experiment w is the inertial weight, and c_1 and c_2 are positive acceleration coefficients used to scale the contribution of self-cognitive and social-sharing. Lots of research have been done on PSO algorithm parameters analysis, but without unified conclusion. It is needed to retest the parameters for different question. According to the literature, parameter combinations test is designed for six groups, the result is shown in Figure 3 and Table 7.

We can see that group (a) is a Social Model, because it is parameter c1=0 which presents the group (a) does not have the cognitive part. Similarly. Group (b) is the cognitive model. Group (c) has neither society nor cognitive part, just has inertial weight. Group (d) has both society and cognitive part, without inertial weight.

Group (a) only has social sharing part, which makes a very close contact between the particles. As seen from the sub-graph (a) in Figure 3, the particle trajectories are compact from start to end. However, due to the lack of historical information, it reduces the ability of local optimization. Group (b) only has cognitive part, without social sharing part. Lack of information sharing between the particles, making 30 sets of particles became 30 independent individuals.

From the sub-graph (b) in Figure 3, it is also seen that the particle trajectory of the group (b) is more dispersed than group (a). Group (c) only has the inertia weight, without both cognitive and social sharing parts. It makes the 30 sets of mutually independent particles to search the optimal solution randomly. Group (d) does not have inertia weight, which makes the entire population lack sufficient power to improve the speed of evolution. Three parameters of the group (e) are not missing. It makes the algorithm to be able to moderately balance global and local search. From Table 7 can also be seen that group (e) is the best on convergence accuracy.

TABLE 1. Distance parameters (km)

	H_1	H_2	H_3	D_1	D_2	D_3	D_4	D_5
I_1	100	180	190	220	270	290	300	310
I_2	180	110	200	190	180	210	220	240
I_3	140	120	100	330	290	230	220	250
I_4	190	156	129	390	340	300	270	230
H_1	0	⁄	⁄	10	18	19	20	23
H_2	⁄	0	⁄	23	34	28	30	32
H_3	⁄	⁄	0	40	34	39	24	19

TABLE 2. Transport-related parameters

	k_1	k_2
velocity km/h	80	200
C_{inv} (fixed cost)	20	100
C_v (variable cost)	40	110
The probability of being found	0.3	0.6

TABLE 3. Emergency supplies reserves (t)

	I_1	I_2	I_3	I_4
reserves	10	200	300	20

TABLE 4. Demand quantity(t)

	D_1	D_2	D_3	D_4	D_5
Demand	30	50	60	12	30

TABLE 5. Intensity of poisson process parameters

	H_1	H_2	H_3	D_1	D_2	D_3	D_4	D_5
I_1	2	3	4	4	5	6	4	7
I_2	1.2	3	5	2	4	7	3	6
I_3	2.1	5	3	3	6	4	2	4
I_4	2	4	6	2	3	2	5	1
H_1	0	⁄	⁄	1.3	1.5	1.6	3	4
H_2	⁄	0	⁄	1.2	1.6	1.8	2	3
H_3	⁄	⁄	0	1	3	5	3	2

TABLE 7. MBPSO performance comparison with different parameter combinations

	C1	C2	W	Mean value
				*E+05
(a)	0	2	0.9	2.6422
(b)	2	0	0.9	2.6862
(c)	0	0	0.9	2.7542
(d)	2	2	0	2.7247
(e)	2	2	0.9	**2.5658**
(f)	2	2	0.9~0.1	**2.6365**

According to the literature [10], in group (f), the inertial weight decreases linearly. It makes the algorithm running in the early stages capable of carrying out large-scale global search, and later with a strong local search ability. From Table 7 it can also be seen that convergence accuracy of group (f) is preferred.

3. 2. Algorithms Comparison In order to verify the effectiveness of the algorithm, it is necessary to contrast (Modified Binary-Particle Swarm Optimization, MBPSO) with (Standard Binary-Particle Swarm Optimization, BPSO) and (Hill Climbing Algorithm, HCA), in terms of calculation accuracy and convergence. As shown in Figure 4 and Table 8. For comparison among the HCA, BPSO, MBPSO three algorithms were done in terms of calculation accuracy under different running times.

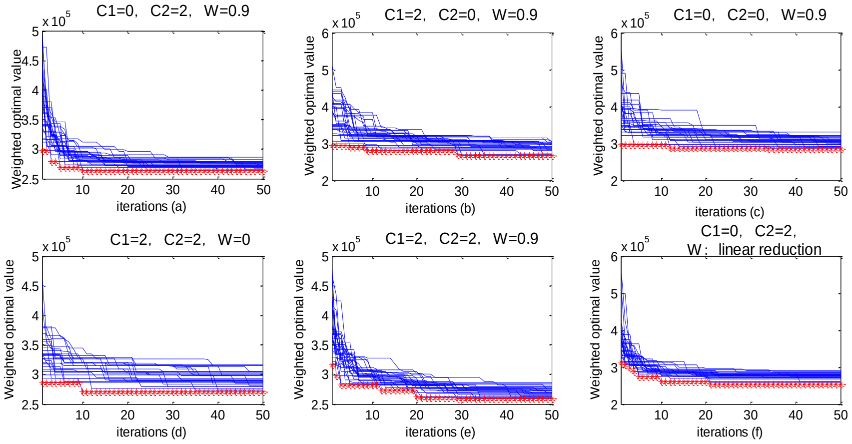

Figure 3. MBPSO particles convergence track under different parameter combinations

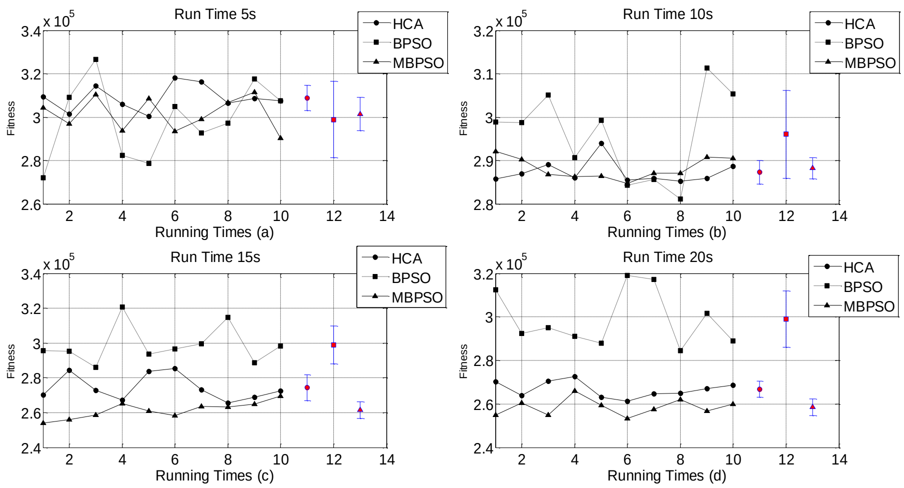

Figure 4. Algorithms' calculation accuracy comparison

TABLE 8. Mean value comparison of Algorithm calculation in 10 times run

run time	Algorithms	Mean value	run time	Algorithms	Mean value
		*E+05			*E+05
	HCA	3.0888		HCA	**2.873**
5s	BPSO	**2.9887**	10s	BPSO	2.9605
	MBPSO	3.0151		MBPSO	2.8822
	HCA	2.7439		HCA	2.6671
15s	BPSO	2.9893	20s	BPSO	2.99
	MBPSO	**2.6148**		MBPSO	**2.5854**

As can be seen from the sub-graph (a) in Figure 4, MBPSO algorithm is running under short of time, and its performance is just moderately. The calculation accuracy trajectories of the three algorithms are close. The reason for that is because MBPSO algorithm does not take full advantage of 'degeneration' mechanism and parallel global search function, its structure is similar to BPSO algorithm, so its performance is not the best. In some cases, MBPSO algorithm performance is even worse than the other two algorithms. However, with the longer running time, MBPSO algorithm 'degradation' mechanisms and parallel global search function comes into play. It makes all particles follow Gbest in local search, also can rush out of the local extremum restrictions to take global optimization. As can be seen from Figure 4, with the longer running time, the calculation accuracy trajectory of MBPSO algorithm have started better than the other two.

4. CONCLUSION

Poisson-Process was applied to establish emergency supplies distribution random risk and total model for multi-level network. By analyzing the characteristics of the model, based on the standard discrete particle swarm optimization algorithm (BPSO), the appropriate degradation mechanism and parallel global search are designed to improve BPSO's performance.

In order to verify the effectiveness of the algorithm, contrasting (Modified Binary-Particle Swarm Optimization, MBPSO) with (Standard Binary-Particle Swarm Optimization, BPSO) and (Hill Climbing Algorithm, HCA) in terms of accuracy and convergence. The results show that MBPSO has the capacity of finding global optimum and a fast convergence property for multiple constrained integer programming models.

In summary, the proposed models and metaheuristic algorithm have a general and practical meaning for emergency supplies distribution under Multi-level network. Providing a new scheme to solve the multi-constrained high dimensional optimization combination problem.

5. ACKNOWLEDGMENTS

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6. REFERENCES

1. Ren, J. and Xiao-lei, Z., "Logistic supply network design in battlefield uncertain environment with enemy attack consideration", ***Fire Control & Command Control***, Vol. 39, No. 6, (2014), 126-130.
2. Toyoglu, H., Karasan, O. E. and Kara, B. Y., "Distribution network design on the battlefield", ***Naval Research Logistics (NRL)***, Vol. 58, No. 3, (2011), 188-209.
3. Gue, K. R., "A dynamic distribution model for combat logistics", ***Computers & Operations Research***, Vol. 30, No. 3, (2003), 367-381.
4. Or, I. and Pierskalla, W. P., "A transportation location-allocation model for regional blood banking", ***AIIE Transactions***, Vol. 11, No. 2, (1979), 86-95.
5. Perl, J. and Daskin, M. S., "A warehouse location-routing problem", ***Transportation Research Part B: Methodological***, Vol. 19, No. 5, (1985), 381-396.
6. Mezura-Montes, E. and Coello, C. A. C., "Constraint-handling in nature-inspired numerical optimization: Past, present and future", ***Swarm and Evolutionary Computation***, Vol. 1, No. 4, (2011), 173-194.
7. Singh, H. K., Ray, T. and Smith, W., "C-PSA: Constrained pareto simulated annealing for constrained multi-objective optimization", ***Information Sciences***, Vol. 180, No. 13, (2010), 2499-2513.
8. Kennedy, J., "Particle swarm optimization, in Encyclopedia of machine learning", Springer, (2011), 760-766.
9. Kennedy, J. and Eberhart, R. C., "A discrete binary version of the particle swarm algorithm", in Systems, Man, and Cybernetics, 1 Computational Cybernetics and Simulation, IEEE International Conference on, IEEE. Vol. 5, (1997), 4104-4108.
10. Akbarpour, H., Karimi, G. and Sadeghzadeh, A., "Discrete multi objective particle swarm optimization algorithm for FPGA placement", ***International Journal of Engineering Transactions C: Aspects***, vol. 28, No. 3, (2015), 410-418..
11. Deepa, S., Babu, S. R. and Ranjani, M., "A robust statcom controller using particle swarm optimization", ***International Journal of Engineering-Transactions B: Applications***, Vol. 27, No. 5, (2013), 731-738.
12. Hashemi, F. and Mohammadi, M., "Combination continuous action reinforcement learning automata & PSO for design of PID controller for AVR system", ***International Journal of Engineering-Transactions A: Basics***, Vol. 28, No. 1, (2014), 52-59 .

A Modified Discreet Particle Swarm Optimization for a Multi-level Emergency Supplies Distribution Network

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چکیده

در حال حاضر، تحقیقات بر روی مدل های توزیع اضطراری و تصمیم بیشتر بر روی مدل‌های قطعی و الگوریتم دقیق تمرکز می‌کنند. تعداد کمی از مطالعات بر شبکه توزیع چند سطح و الگوریتم فراابتکاری انجام شده است. در این مقاله، تئوری فرایندهای تصادفی را برای ایجاد توزیع تدارکات اضطراری و مدل تصمیم گیری برای شبکه چند سطحی انتخاب کردیم. با تحلیل ویژگی‌های مدل، برای حل مشکل اصلاح ذرات گسسته بهینه سازی الگوریتم فراابتکاری ارائه شده است. درMBPSO، مکانیسم تخریب مناسب و ساختار جستجوی جهانی موازی طراحی شده است. MBPSO دارای قابلیت جستجوی بهینه‌ی جهانی و همگرایی سریع برای مدل برنامه ریزی عدد صحیح ترکیبی چند محدودیتی و تک هدفه وزن-دار است.

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