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Supply Chains of Spare Parts Distribution in Clone Immune Algorithm

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Abstract: Based on the distribution characteristics of spare parts service, this study studies supply chains of spare parts distribution allocation problem using customers' satisfaction quantization method and integration of cost function method. The huge population size the genetic algorithm requires will inevitably lead to much slower evolution, which is a systematical limitation of traditional Genetic Algorithm (GA). So, this study proposes an improved clone immune genetic algorithm. Based on the merit-based selection of different fitness individuals, this improved method adaptively clones the superior individuals, thus increase the operation efficiency, decrease the time of iteration and could obtain the optimal solution as soon as possible. Therefore, the performance of the algorithm can be improved significantly. The result of the experiments proves that the improved clone immune genetic algorithm shows better consequence than the traditional GA.

Key words: Supply chains, spare parts, allocation, satisfaction, clone immune

INTRODUCTION

Service supply chain management refers to the professional services which start from the suppliers to the final customers. It includes the information management, process management, capacity management, service performance and financial management (Ellram *et al*., 2004). Previous researches are mainly focus on two issues: The first is the supply chain with service-related activities, which run by the lowest cost and best service model; the second is the supply chain working on service activities specifically. Referring to the manufacturing supply chain business model, it intends to find the operating mode of service supply chain (Guo, 2012). The service supply chain investigated in this study belongs to the former category and focuses on the service supply chain of spare parts. In spare parts service market, customers extremely concern the timeliness of the spare parts supply service. How to choose an appropriate Distribution Center (DC) which can satisfy customers' demand in time is the main issue in spare parts logistic service researches.

Currently, service supply chain has some problems, such as the varieties of spare parts continually increase, transportation costs remain high and low customer satisfaction, along with other prominent problems. Considering the importance of delivery time, Wang and Wang, (2013) and Huang (2010), respectively proposed supply chain logistics model based on the limitation of the variability of lead time and the ordering cost. This study, based on previous studies, investigates a wide range of service spares and spare parts distribution centers, in order to build a multi-parts and multi-DC cost function model. Most importantly, this study also proposes a service time based satisfaction quantization method to promote the distribution model of service spare parts logistics network.

Considering the algorithms, a series of solving algorithms of supply chain allocation problem have been suggested by previewed researches, for example, the gravity method and Baumol-wolfe method. Later, Genetic Algorithms are widely used to solve such problems (Wang and Wang, 2002). The huge population size which Genetic Algorithm requires will inevitably lead to much slower evolution, which is a systematical limitation of the traditional Genetic Algorithm (Mi *et al*., 2009). In recent years, Immune Algorithm (Hong, 2013) has been widely used to solve all kinds of problems (Liu *et al*., 2012). However, using Immune Algorithms to solve Service Parts Logistics planning problem is relatively deficient. Based on spare parts model's characteristics, this study cites the principle of Clone Immune Genetic Algorithm (Zhou and Zhang, 2005) and improves the traditional Clone Immune Genetic Algorithm by limiting the number of clone antibody dynamically. Thus, it can greatly improve the computational efficiency and avoid getting the partly optimal solution which is caused by precocity. And the global optimal solution can be got quickly. Both the model and algorithm proposed in this study are verified by numerical samples.

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MODELING

This study researches supply chain networks of service spare parts, which is much timelier than that of the other kinds of logistics networks. Since the delivery time is a significant factor to influence customers' satisfaction, this study cites a time-satisfaction model (Ma, 2005). In this model, the delivery time is divided into five time intervals by four time point (Te_k, Te_k, Tl_k, Tl_k). The interval (Te_k, TL_k) is the satisfactory interval and interval (Te_k, Tl_k) is the acceptable interval. If the delivery time is earlier than Te_k or later than Tl_k, it assumes that the customers are not satisfactory.

The objective function of the model to be established below is to find the minimum value, but the satisfaction function we established is to seek the maximum value. In order to meet the minimum requirements of the objective function, this study establishes a penalty function. Thus, the target of the penalty function converts from maximizing the satisfaction of the time into minimizing the penalty cost. The satisfaction penalties function as follows:

$$P(t_k)=\begin{cases} W(Te_k-t_k), 0\le t_k<Te_k \\ 1-\left(\dfrac{t_k-Te_k}{TE_k-Te_k}\right)^{\alpha_k}, Te_k\le t_k<TE_k \\ 0, TE_k\le t_k<TL_k \\ 1-\left(\dfrac{Tl_k-t_k}{Tl_k-TL_k}\right)^{\alpha_k}, TL_k\le t_k<Tl_k \\ M, t_k>Tl_k \end{cases} \quad (1)$$

Equation 1, W (Te_k-t_k) is the waiting cost when the delivery time is earlier than Te_k. M is an infinite positive number. α_k = (1, 2, 3,. ...., n) is a sensitive factor and α_k is more sensitive to time when it greater.

In the model, there are two factors which are considered as objective, customer satisfaction and the cost. Thus, it is a multi-objective problem. This study focuses on minimizing customers' satisfaction using penalty functions. And in the model, based on different distributors and customers have different preference on the factors, different weights are allocated on different ones. Considering the satisfaction penalty function and the cost function have different magnitude, the model uses cost function normalization method divided by the maximum cost as F_{max}. The objective function can be expressed as:

$$E=Min(\theta_1(F/F_{max})+\theta_2P) \quad (2)$$

Including:

$$F=\sum_{j\in J}(G_j+C_j)U_j+\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}W_{ijt}H_{ijt}Z_{ijt}+\sum_{j\in J}\sum_{K\in k}\sum_{T\in t}W_{jkt}H_{jkt}Z_{jkt} \quad (3)$$

$$P=\sum_{j\in J}\sum_{k\in K}P(t_k)Z_{jkt} \quad (4)$$

Equation 2, θ_1 and θ_2 represent the weight of the two functions, $\theta_1\ge 0$, $\theta_2\ge 0$ and $\theta_1+\theta_2=1$, the higher value of θ is, the higher the priority consideration.

Subject to:

$$\sum_{j\in J}\sum_{k\in K}W_{jkt}=\sum_{k\in K}Q_{kt}, \forall t\in T \quad (5)$$

$$\sum_{k\in K}W_{jkt}\le A_{jt}, \forall j\in J, \forall t\in T \quad (6)$$

$$\sum_{i\in I}W_{ijt}=\sum_{k\in K}W_{jkt}, \forall t\in T, \forall j\in J \quad (7)$$

$$\sum_{j\in J}W_{ijt}\le A_{it}, \forall i\in I, \forall t\in T \quad (8)$$

$$\sum_{i\in I}\sum_{j\in J}Z_{ijt}=1, \forall t\in T \quad (9)$$

$$\sum_{j\in J}\sum_{k\in K}Z_{jkt}=1, \forall t\in T \quad (10)$$

$$t_k=(T_j+T_{jk})Z_{jkt}, \forall j\in J, \forall k\in K, \forall t\in T \quad (11)$$

$$P(t_k)\le\alpha, \forall k\in K \quad (12)$$

$$Z_{ijt}, Z_{jkt}, U_j\in\{0,1\}, \forall i\in I, \forall j\in J, \forall k\in K, \forall t\in T \quad (13)$$

Parameter description:

I : Supplier
j : Distributor
k : Customer
α : The highest value limits of customer satisfaction penalty function
I : Supplier set
J : Distributor set
K : Customers set
G_j : Distribution center fixed costs

C_j : Distribution center warehousing costs
Q_{kt} : Customer-k needs the amount of spare parts-t
W_{jkt} : Distributor-j delivers the amount of parts-t to the customer-k
W_{ijt} : Supplier-i supplies the amount of parts-t to the distributor-j
H_{jkt} : The unit costs from distributors-j delivers parts-t to the customer-j
H_{ijt} : The unit costs from supplier-i delivers parts-t to the distributors-j
A_{it} : The maximum production capacity of spare parts for supplier-i
A_{jt} : The maximum storage capacity of spare parts for distributor-j
T_j : Loading time of parts required for distributor-j
T_{jk} : Travel time from distributor-j to the customer-k

Equation 5 indicates that customers' total demand for one kind of spare parts is equal to the total supply of the parts by distributors; Eq. 6 represents each kind of spare parts that a distributor supplied cannot exceed the distribution center's maximum storage capacity of that kind of ones; Eq. 7 indicates that each distributor has the same in and out amount for one kind of parts; Eq. 8 represents the limitation of suppliers' capacity; Eq. 9 indicates one kind of spare parts which a distribution center needed can be only supplied by one supplier; Eq. 10 means that one kind of spare parts that a customer demanded can be only offered by one distributor; Eq. 11 means the equation of the arriving time; Eq. 12 represents the highest constraint of the satisfaction penalty function; Eq. 13 is the decision variables.

CLONING IMMUNE GENETIC ALGORITHM

Clone immune genetic algorithm was a cloning selection theory which was first proposed by Burnet according to Darwinian evolution theory (Tauber and Podolsky, 1994). The core content of clonal selection is using vaccination approach in the candidate solution space to produce a set of good solution colony. Filtering out good antibodies by cloning, mutation approaches. And finally the optimal solution can be got after several iterations. However, as the colony is still immature for the initial general algorithm iterations, fixed affinity indicators are still used to determine the scale of clonal proliferation. It will inevitably lead the post-avidity of different antibodies become similar earlier. Lacking of diversity makes antibodies premature convergence. This study proposes that investigating antibodies of different fitness and different affinity should use different cloning scale, which ensures not only the scale of cloning, but also the diversity of the population, while avoid premature convergence of the algorithm. This method improves the calculation accuracy substantially. The steps of the algorithm are as follows.

Step 1: Antibody coding: According to the characteristics of the model, assume the number of suppliers is A, the number of distributors is B and the number of customers is C. The length of the coded chromosome is the sum of A, B and C. The former bits A are adopted by binary encoding method. And 1 represents selected, 0 represents unselected. The bits after A are distributor series which are conducted by integer encoding method. The distributors are sorted from Y_1 to Y_b. And each value of Yn ranges from (0, A). To the same, customer series the value of Z_n range from (0, B). 0 means no distribution center can supply delivery service. (1, A) and (1, B) respectively means the corresponded supplier and distributor to a specific customer. As shown in Table 1.

Step 2: Initial population generate: This study uses randperm function by MATLAB software. It randomly generates a matrix which is constituted of N chromosomes. Each row represents an antibody. N is the initial number of antibody of the population.

Step 3: Vaccine extraction: This study takes the overall immune method by calculating the fitness of current population. And it picks out the antibody with the highest fitness. The entire gene is treated as an initial sequence V of the vaccine.

Step 4: Calculation of fitness and affinity: Since the allocation problem is to find the minimum solution, this study converts the objective function E into a maximize fitness function, fitness function as follows:

$$\text{Fit(a)}=\begin{cases} C_{max} - F(a), F(a) < C_{max} \\ 0, \text{otherwise} \end{cases} \tag{14}$$

C_{max} can be an input value or a maximum theoretical estimator.

In addition, we introduce the concept of affinity, namely the affinity relationships between two antibodies. It can determine the numbers of antibodies need to clone. There are many metrics for affinity and this study uses the Euclidean Distance as the metric. The Euclidean Distance of antibodies-a_i and antibodies-a_j is shown below:

Table 1: Coding sequence

1		A	A+1		A+B	A+B+1		A+B+C
X_1	•••	X_a	Y_1	•••	Y_b	Z_1	•••	Z_c

$$D_{ij} = \sqrt{\sum_{\substack{1\le i\le n\\1\le j\le n}} (F(a_i)-F(a_j))^2} \quad (15)$$

where, $F(a_i)$ and $F(a_j)$ represent the fitness of antibodies-a_i and antibodies-a_j, respectively. The smaller of D_{ij} the higher degree of the similarity between antibodies it is.

Step 5: Termination condition selection: The loop is terminated by limiting evolution generation approach, in order to output the optimal solution.

Step 6: Clonal proliferation: Clonal proliferation is a major step of the algorithm process. The clone number of antibodies is determined by their fitness as Fit (a), antibody affinity as D and the total number of clones as M.

The affinity μ_i of antibody-i is as follows:

$$\mu_i = \min(D_{ij}), i \neq j; i, j = 1, 2, ..., N \quad (16)$$

The clone number of antibody-i is as follows:

$$Q_i = \text{int}\left[M \cdot \frac{\text{Fit}(a_i)}{\sum_{i=1}^{M} \text{Fit}(a_i)} \cdot \mu_i\right], \quad (17)$$
$$i = 1, 2, ..., N$$

Step 7: Clonal mutation: This study uses a hypermutation method to the mutation operation. In terms of a specific antibody, it randomly selects two genes and inverts the whole genes between these two positions to form a new antibody. This operation is repeated continually. The advantage of this option is to make population to avoid getting local optimum solution. The mathematical description of clonal mutation operation as follows:

- Inversion operation of a_i, randomly select two swap genes a_h and a_p. For instance, the antibody is $a_i = \{a_1, a_2, \ldots, a_h, a_{h+1}, \ldots a_{p-1}, a_p, \ldots, a_m\}$ and the new antibody after the inversion approach is $a'_i = \{a_1, a_2, \ldots, a_p, a_{p-1}, \ldots, a_{h+1}, a_h, \ldots, a_m\}$

Step 8: Clonal selection: After finishing the mutation operation, compare the new antibody with the original antibody a_i. If Fit $(a_i)<$Fit (a'_i), then replace the original antibody by the new antibody-a'_i and update the population. Otherwise, leave the original antibody a_i.

Step 9: Vaccination and update: Randomly select a number of antibodies, which takes dynamic selection vaccination method. Specifically, it replaces the genes from the first position to the last one. Then it calculates the fitness of this antibody after one gene is replaced. The fitness of the new antibody is compared with the original one's fitness. If the new antibody's fitness is greater, it will replace the original one by the new antibody. After vaccinating, the antibody with the highest fitness is compared with the vaccine's fitness. If the fitness is greater than the vaccine's, replace the original vaccine, otherwise, no replace.

Step 10: Population update: After updating the vaccine, add the antibody with the greatest fitness to the antibody memory database. If the similar problem occurs, it can be extracted directly as a vaccine. Thus, it can improve the efficiency significantly.

EXPERIMENTS RESLUTS AND ANALYSIS

This study proposes an example to test the model in this part. The supply chain network consists of two kinds of spare parts. There are 2 suppliers, 4 distributors and 8 customers. The known conditions are shown below. The fixed costs of distribution centers are G_j and the running costs of distribution centers are C_j, as shown in Table 2. Table 3 shows that the supplier-i to the distributor-j costs are W_{ijt} * H_{ijt}. Table 4 shows that the distributor-j to the customer-k costs are W_{jkt} * H_{jkt}. Table 5 shows the loading time T_j. Table 6 shows the delivery time T_{ij}. And Table 7 shows the customer's demand Q_{kt}. Table 8 shows the maximum production capacity A_{it} of supplier-i for spare-t and the maximum storage capacity A_j of distributor-j for spare-t are shown in Table 9.

This part simulates the model, using matlab simulation software. The algorithm specifies the initial conditions. The popsize is 50, the termination condition for generation evolution as Gen is 300, θ_1 is equal to 0.6 and θ_2 is equal to 0.4, respectively. It also compares the

Table 2: Fixed costs G_j and running costs C_j

Variables	j_1	j_2	j_3	j_4
G_j	1500	1750	2000	1350
C_j	750	825	845	725

Table 3: Transportation costs of i to j

$W_{ij}H_{ij}(t_1,t_2)$	j_1	j_2	j_3	j_4
i_1	(135, 330)	(185, 275)	(146, 320)	(130, 265)
i_2	(150, 365)	(155, 250)	(137, 265)	(160, 245)

Table 4: Transportation costs of distributor-j to customer-k

$W_{ij}H_{ij}(t_1,t_2)$	k_1	k_2	k_3	k_4	k_5	k_6	k_7	k_8
j_1	(66, 125)	(65, 110)	(54, 103)	(46, 110)	(81, 114)	(53, 98)	(65, 105)	(78, 109)
j_2	(56, 110)	(45, 115)	(54, 123)	(69, 130)	(41, 111)	(50, 125)	(54, 131)	(58, 113)
j_3	(60, 118)	(41, 124)	(57, 105)	(63, 108)	(44, 112)	(45, 123)	(57, 127)	(60, 114)
j_4	(67, 117)	(75, 124)	(55, 131)	(64, 104)	(73, 112)	(65, 134)	(72, 109)	(55, 107)

Table 5: Loading time T

Time	j_1	j_2	j_3	j_4
T_j	4	3	2	3

Table 6: Delivery time T_{ij}

T_{ij}	k_1	k_2	k_3	k_4	k_5	k_6	k_7	k_8
j_1	12	15	9	12	16	21	12	13
j_2	16	12	11	18	14	10	15	13
j_3	16	12	11	18	16	13	13	12
j_4	14	15	12	11	10	9	20	9

Table 7: Customers demand Q_{kt}

$Q_{kt}(t_1,t_2)$	k_1	k_2	k_3	k_4	k_5	k_6	k_7	k_8
Q_t	(12, 40)	(11, 0)	(10, 50)	(0, 0)	(21, 10)	(0, 0)	(0, 0)	(25,15)

Table 8: Maximum production capacity A_{it} and maximum storage capacity A_j

$A_j(t_1,t_2)$	j_1	j_2	j_3	j_4
A_{jt}	(600, 1000)	(650, 880)	(750, 1100)	(660, 860)
$A_i(t_1,t_2)$	i_1		i_2	
A_{it}	(1100, 2100)		(1200, 2210)	

Table 9: Allocation matrix of distributors to customers

Variables	k_1	k_2	k_3	k_4	k_5	k_6	k_7	k_8
j_1	(0, 0)	(0, 0)	(10, 50)	(0, 0)	(0, 0)	(0, 0)	(0, 0)	(0, 0)
j_2	(12, 40)	(0, 0)	(0, 0)	(0, 0)	(21, 10)	(0, 0)	(0, 0)	(0, 0)
j_3	(0, 0)	(11, 0)	(0, 0)	(0, 0)	(0, 0)	(0, 0)	(0, 0)	(0, 0)
j_4	(0, 0)	(0, 0)	(0, 0)	(0, 0)	(0, 0)	(0, 0)	(0, 0)	(25, 15)

Table 10: Allocation matrix of suppliers to distributors

Variables	j_1	j_2	j_3	j_4
i_1	(10, 50)	(0, 0)	(0, 0)	(25, 0)
i_2	(0, 0)	(33, 50)	(11, 0)	(0, 15)

Table 11: Comparison of two algorithms results

Parameters	Optimal solution	Iterations (Gen)	Running time (sec)
Cloning immune genetic algorithm	0.637	125	2.231
Genetic algorithm	0.658	151	3.455

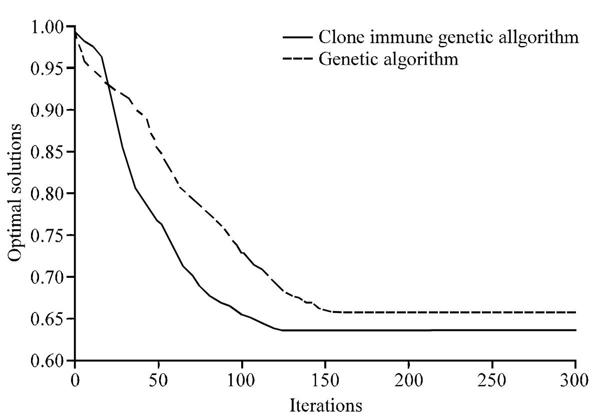

Fig. 1: Curve diagram of two algorithms

standard Genetic Algorithm with the improved algorithm in the same conditions. As a result, the minimum value that Cloning Immune Genetic Algorithm (CIGA) obtained is 0.637, while the minimum value of traditional Genetic Algorithm is 0.658. The demand assignment matrix of CIGA is showed in Table 9 and 10.

The results of two algorithms, as shown in Table 11.

Convergence curve diagram of two algorithms, shown in Fig. 1.

According to Table 11, in terms of the convergent generation and the running time, the new algorithms are greatly improved. And the optimal solution is much more accurate. From Fig. 1, it can be seen that, due to the advantages of the design of the algorithms, it not only maintains the diversity of the population, but also chooses the superior antibody. Thus, the new algorithm is much faster on convergence and more accurate to get the optimal solution.

CONCLUSION

Multi-product services for the allocation of spare parts supply chain are investigated by using a model of integrating customer satisfaction with cost evaluation, employing Clone Immune Algorithm. During the calculation, the cloning amount of superior antibodies is adjusted. In conclusion, the research presented in the study improves the efficiency of the population's evolution, while avoiding premature convergence and overcomes the confusion of local optimal solution.

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