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Cost-sensitive Multi-distribution Center Vehicle Routing Optimization Based on Improved Immune Clone Algorithm

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Abstract: In order to improve the efficiency of the multiple depots vehicle routing, Combines the advantages of immune clone algorithm with simulated annealing, brings forward a new algorithm based on simulated Annealing Immune Clone Algorithm in multiple depots vehicle routing optimization. The new algorithm provides not only with the strong global search capability of the immune clone algorithm, but also with the strong local capability of the simulated annealing algorithm. Give the multiple depots vehicle scheduling model and the coding method of the vehicle route. One the one hand, Accelerate the searching process by the tensile annealing of the affinity function. On the other hand, the new antibodies are accepted by the simulated annealing rule in the mutation and crossover and speed up the global searching ability. The optimal solution is got by simulated annealing regulation when the annealing temperature is tended to zero. The simulation results demonstrate that the solving result of the fusion algorithm is more excellent than the other algorithms and it improves the performance in searching speed and increases the global astringency compared with simple immune clone algorithm.

Key words: Multiple depots, immune clone algorithm, simulated annealing algorithm, vehicle routing optimization

INTRODUCTION

With rapid development of the economics globalization, the logistics impact on economic activity is more and more attention. The logistics distribution vehicle scheduling problem is a core problem, a direct impact on logistics service quality and economic benefits. In the actual situation, there are often multiple logistics distribution center, therefore distribution center logistics distribution problem more optimization is of great significance. The multi-distribution center vehicle routing problem has become intelligent logistics scheduling of research hot spots (Dondo and Cerda, 2009). Vehicle routing problem is a very important link in multiple depot logistics scheduling. This problem effectively resolved can improve logistics scheduling scientific level, lower transport cost and increase economic effectively (Aras *et al*., 2011). Distribution is an important element in modern logistics system. It includes picking up goods from distribution center and delivering goods to the customers on time. In real-life world, there have many factors with cost factor. Therefore, multi-depot vehicle routing problem with cost factor is discussed in this study.

Among distribution business there are many optimizing strategies. The vehicle routing problem has great effect on improving distribution speed, quality of service and economy benefit. According to the number of distribution center, the vehicle scheduling problem can be divided into single-depot vehicle routing problem and multi-depot vehicle routing problem. The modern city logistics system usually has more than one depot. So, this study has both theoretical and practical value.

There are two methods for solving the multi-depot vehicle routing problem. One is the exact algorithm and the other is the heuristic algorithm (Mirabi *et al*., 2010). The exact algorithm includes the branch and bound method, the cutting plane method, the network flow algorithm, the dynamic programming, etc. The heuristic algorithm is structured by the experience, so its solution is satisfied and isn't necessarily the optimal under the acceptable time and space for the multiple depots vehicle routing. The heuristic algorithm of vehicle routing has become an important direction and a large number of algorithms have emerged (Nishimura and Nishimori, 2004). For example, the genetic algorithm, the taboo search, the simulated annealing algorithm, intelligent heuristic algorithm, etc. Nagy puts forward a solution to the

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corresponding VRP problem and modifies this solution to make it feasible for the VRPPD. Kuo proposes a Variable Neighborhood Search (VNS) for solving the multi-depot vehicle routing problem with loading cost. Narasimha brings forward a variant of MDVRP, called min-max MDVRP, where the objective is to minimize the tour-length of the vehicle traveling the longest distance in MDVRP. Rodolfo presents an MDVRPTW local search improvement algorithm that explores a large neighborhood of the current solution to discover a cheaper set of feasible routes. Aras formulates two mixed-integer linear programming models for this problem which we refer to as the selective MDVRP with pricing. Nilay proposes a new type of geometric shape based genetic clustering algorithm is proposed.

Immune clone algorithm was proposed by Burnet (1959) and His central idea is that the antibodies around the cell surface will react selectively with antigens (Riff *et al*., 2013). The immune algorithm is a calculating model which combines the main features of biological immune system with engineering application (Sun *et al*., 2009). The immune clone algorithm is the greedy search in process and it duplicates the antibodies with high affinity. In order to keep the diversity of individuals, the immune clone algorithm mutates blindly and the inactivated individuals are eliminated for finding the optimal solution. Simulating polyclonal mechanism of the biological immune system, the immune clone algorithm can exchange information between antibodies by the mutation and crossover and get the better solution and feasible solution in the counting process (Yang *et al*., 2010). The using of simulated annealing algorithm provides a new method for the MDVRP and prevents it from the local best solution. The immune clone algorithm is applied into the vehicle routing problem with common defects of early convergence and it easily falls into the local minima (Hasan and Wu, 2011). Therefore, on the basis of building the model of multi-depots vehicle scheduling problem, this study studies to solve the problem with the simulated annealing immune clone algorithm and the new stochastic approach is proposed to solve the vehicle routing problems. The new antibodies are accepted by the simulation annealing rule in the mutation and crossover and speed up the global searching ability. The optimal solution is got by simulated annealing regulation when the annealing temperature is tended to zero.

MATHEMATICAL MODEL

The mathematical model for the cost-sensitive multi-logistics center distribution is as follows:

$$\left.\begin{aligned}
&\min Z = \alpha\, \mathrm{cost}_{total_distance} + \beta\, \mathrm{cost}_{wait_time} + \lambda\, \mathrm{Cost}_{vehicle_number} \\
&\mathrm{cost}_{total_distance} = \sum_{k=1}^{M}\sum_{i=1}^{n_k}\left(\sum_{i=1}^{N+M}\sum_{j=1}^{N+M} d_{ij}X_{ij}^{mk} + g_{mk}y_{mk}\right) \\
&\mathrm{cost}_{wait_time} = CA\times\left(\sum_{k=1}^{K}\sum_{m=1}^{n_k} WT_{km} + \sum_{k=1}^{K}\sum_{m=1}^{n_k} UWT_{km}\right) \\
&\mathrm{Cost}_{vehicle_number} = p_1\sum_{i=1}^{N}\max\left[(ET_i - s_i), 0\right] + p_2\sum_{i=1}^{N}\max\left[(s_i - ET_i), 0\right]
\end{aligned}\right\} \tag{1}$$

M is the multi-logistics center and the vehicle number $K_m(m = 1,\ldots, M)$ render services for the clients N. $g_i(i = 1,\ldots, N)$ is the weight the customer i demands and it doesn't exceed g_{mk}. The customer number is 1, 2,..., N and the multi-logistics center is N+1, N+2,..., N+M. $[ET_i, LT_i]$ is time range that the vehicle reach. S_i is the time that the customer i demands. The Eq. 1 is the total objective function of the multi-logistics center and the shortest path is the final goal. $\mathrm{cost}_{total\_distance}$ is the total distance and $\mathrm{cost}_{wait\_time}$ is the forfeit for the waiting loading and unloading. $\mathrm{Cost}_{vehicle\_number}$ is the total rent for the vehicle. α, β, λ is the cost-sensitive weigh. The constrains of Eq. 1 is as follows:

$$\sum_{j=1}^{N}\sum_{m=1}^{M}\sum_{k=1}^{K_m} X_{ij}^{mk} \le \sum_{m=1}^{M} K_m, i = m \in \{N+1, N+2,..., N+M\} \tag{2}$$

$$\left.\begin{aligned}
&\sum_{i=1}^{N+M}\sum_{j=1}^{N+M} X_{ij}^{mk} = \sum_{i=1}^{N+M}\sum_{j=1}^{N+M} X_{ji}^{mk} \le 1, \\
&i = m \in \{N+1, N+2,..., N+M\}, k \in \{1, 2,..., K_m\}
\end{aligned}\right\} \tag{3}$$

$$\sum_{j=1}^{N+M}\sum_{m=1}^{M}\sum_{k=1}^{K_m} X_{ij}^{mk} = 1,\ i \in \{1, 2,..., N\} \tag{4}$$

$$\sum_{i=1}^{N+M}\sum_{m=1}^{M}\sum_{k=1}^{K_m} X_{ij}^{mk} = 1,\ j \in \{1, 2,..., N\} \tag{5}$$

$$\left.\begin{aligned}
&\sum_{i=1}^{N} g_i \sum_{j=1}^{N+M} X_{ij}^{mk} \le q_{mk}, \\
&m \in \{N+1, N+2,..., N+M\},\ \ K \in \{1, 2,..., K_m\}
\end{aligned}\right\} \tag{6}$$

$$\left.\begin{aligned}
&\sum_{j=N+1}^{N+M} x_{ij}^{mk} = \sum_{j=N+1}^{N+M} x_{ji}^{mk} = 0 \\
&i = m \in \{N+1, N+2,..., N+M\}, k \in \{1, 2,..., K_m\}
\end{aligned}\right\} \tag{7}$$

$$x_{ij}^{mi}\left(x_{ij}^{mi} - 1\right) = 0,\ i = 1, 2,..., N, j = 1, 2,..., N \tag{8}$$

$$y_{i}^{mi}\left(y_{i}^{mi} - 1\right) = 0,\ i = 1, 2,..., N, j = 1, 2,..., N\ldots \tag{9}$$

k is the vehicle for the clients and d_{ij} is the cost of transportation form clients i-j. The Eq. 2 shows that the vehicles of each logistics center don't exceed the total number. The Eq. 3 gives the vehicles start form the logistics center and return. Each client is served by one vehicle form the Eq. 4-5. The load of vehicle doesn't exceed the maximum from the Eq. 6. The Eq. 7 shows the vehicle must pass at least one distribution centre. The Eq. 8-9 shows the variable confirm to the constraint.

ROPOSED SCHEME

Metropolis rule: Metropolis discovered that the important sampling method assumed that the new state was accepted by probability in 1953. In other word, the current state produce the new and the both energy is E_i and E_j. If $E_j<E_i$ and:

$$p_r = \exp\left(\frac{E_j - E_i}{kT}\right)$$

is more than the random number of the [0, 1], the new state is the current. Otherwise, the current state is kept.

In 1982, Kirkparrick introduced Metropolis criterion into the combinatorial optimization area and put forward the Simulated Annealing Algorithm for solving the large-scale combinatorial optimization problem. It is the simulation of solid annealing process and translates from the current I to J by the probability p(r) of the Metropolis rule. p(r) is as follows:

$$p(r)(i \Rightarrow j)\begin{cases} 1 & f(i) \le f(j) \\ \exp\left(\frac{f(i)-f(j)}{t}\right), & \text{otherwise} \end{cases} \tag{10}$$

f(i) belongs to the fitness of the present solution. f(j) is the new and $t \in R^+$ is the control parameters.

Encoding methods: According to the model of the multi-logistics distribution center, the common binary encoding is improved. The antibody code is (w_1, w_2,..., w_N) and w shows the client is serviced by the vehicle in multi-logistics center. w_i is constituted by (d_num, v_num, s_num) and d_num is the number of the distribution center. v_num is the number of the vehicle and s_num is the service sequence number in the distribution route.

For example, the antibody code is g(122, 221, 121, 312, 321, 222, 311, 323, 322) and it means the client number is nine. The first gene 122 corresponds to the first client and 221 is the second customer. The first gene 122 means the distribution center with number one sends the vehicle with number two and the service sequence number is second.

Tensile annealing of the affinity function: The random initial solution is corresponding to the vehicle route. If the route doesn't meet the constraint, the path is infeasible. M_i is the infeasible number of the antibody. The affinity function is as follows Eq. 17:

$$\text{Affinity}(A_i) = \frac{1}{\min Z_i + R \times M_i} \tag{11}$$

$\min Z_i$ is the total objective for cost-sensitive multi-logistics center and R is the punishment weigh for infeasible path.

The earlier evolution of the affinity function is easy to fall into the local optimal solution, so it is annealed by the following equation:

$$\text{affinity}'(X) = \exp\left(\frac{-(\text{affinity}_{max}(X) - \text{affinity}(X))}{T_i}\right) \tag{12}$$

$$T = T_0 R^{(g-1)} \tag{13}$$

affinity'(X) is value after the annealing and $f_{max}(X)$ is the maximum value for the affinity function. T is the annealing temperature and g is the immune algebra. After transformation, the difference value of the affinity function is small while the temperature is high in early genetic algorithm. While the temperature declines, the tensile effect strengthens. The value of the affinity function increases gradually.

Key steps of the immune clone algorithm: The immune clone algorithm produces the new solution and expands continuously the search range according to the affinity and it can search the local and global optimal solution. The key steps is to clone, antibodies mutation and selection (Rao and Vaisakh, 2013; Tavakkoli-Moghaddam *et al*., 2007)

Antibodies clone: A = (a_1, a_2,..., a_m) is the initial antibody group and the scale $C(a_i)$ of each antibody after clone is as follows:

$$C(a_i) = \left\lceil M \times \frac{f(a_i)}{\sum_{i=1}^{m} f(a_i)} \right\rceil \tag{14}$$

M is the population scale after the clone and $f(a_i)$ is the affinity function between antibody and antigen. After the clone, A' = {A'_1, A'_2,..., A'_1,..., A'_m}, A'_1 = {a_{i1}, a_{i2},..., a_{in}}, $a_{i1} = a_{i2} = \ldots\ a_{in} = a_i$.

Antibodies mutation: The antibodies increase the diversity by the mutation. The clone mutation is as follows Eq. 19:

$$v' = v+P_m\times\exp(-f)\times N(0, 1) \quad (15)$$

v is parent antibody and v' is son antibody. N(0, 1) is the Gaussian variable with mean value 0 and its variance σ = 1. Calculate the fitness f(V), f(V'). If min{1, exp(-f(V')-f(V)/T_k)}>random[0, 1], accept the new solution according to annealing rule. Otherwise, abandon the mutated antibody V'. T_k is the temperature.

Antibody selection: $A'_i = \{a_{i1}, a_{i2},\ldots, a_{in}\}$ is the antibody after mutation and a_{ij} has the best affinity. If the antibody $f(a_{ij})$ is more than father $f(a_i)$, the new a_{ij} replaces a_i.

Antibody crossover: The crossover is to recombine partial structure of two parent antibodies for generating the new antibody. The provisional antibody population C_r. r_c = random[0, 1]. If $r_c<P_c$, the crossover is as follows:

$$V'_1 = r_c\times V_1+(1-r_c)\times V_2 \quad (16)$$

$$V'_2 = r_c\times V_2+(1-r_c)\times V_1 \quad (17)$$

V_1 and V_2 are parent antibodies and V^c_1, V^c_2 is their sons. P_c is the crossover probability.

The probability of acceptance is as follows:

$$P_a = \begin{cases} 1 & f_{new} \geq f_{old} \\ \dfrac{1}{\exp\left(\dfrac{f_{old}-f_{new}}{T}\right)} & f_{new} \prec f_{old} \end{cases} \quad (18)$$

f_{old} is the fitness value of the parents and f_{new} is the offspring after the mutation [25]. T is the annealing temperature. When the new solution is worse, it is accepted by the probability P_a. P_a decreases gradually with the lower temperature. The acceptance mode increases the diversity of every generation and improves the local search ability, so the search is the optimal.

Realization of the algorithm: The annealing immune clone algorithm is applied to the optimization of the multiple depots vehicle routing and the concrete steps are as follows.

Step 1: **Initialization:** Initialize the antibodies scale N in random solution space, the maximum iteration K_{max}, iteration times k = 0. Generate $A = \{A_1, A_2, A_3,\ldots, A_n\}$ as the initial antibody population. P_c is the crossover probability. P_m is the mutation probability. T_0 is the initializing temperature

Step 2: Calculate the affinity affinity(A_i), i = 1, 2,…, N

Step 3: Clone the antibody group and acquire the antibody group A^c with the scale N_c

Step 4: Restructure A^c to get the new antibodies with the scale N_c and calculate the antibody groups A^c and A with the scale $2N_c$. Delete the antibodies with lower affinity, get the antibody group $A^{c'}$ with the scale N_c

Step 5: Mutate the antibodies A^c, $A^{c'}$ according to the Eq. 11-12 and get the mutated antibody population

Step 6: Generate the new antibody population by crossover

Step 7: Merge the antibodies A^c, $A^{c'}$ after crossover. Select antibodies with high affinity and get the new antibody population with the scale N_c

Step 8: Calculate the optimal route in the current population

Step 9: If T_k = 0, the annealing process end. Otherwise:

$$T_{k+1} = T_k \times \left(1-\frac{K}{N_c}\right)$$

k = k+1, return step 2

SIMULATION RESULTS

Effectiveness of the algorithm: Use VC+ + 6.0 to design the program and select the standard testing dataset of Cordeau. All examples can get from http://neo.lcc.uma.es/radi-aeb/webvrp/. Each dataset includes the number of the distribution centers, the clients, the vehicles number and the runtime. The measure for the length adopts the Euclidean distance. The data of standard database of Cordeau is shown in Table 1.

Table 1: Dataset of Cordeau

No.	Client	Depot	Vehicle	Runtime
P01	48	4	2	500
P02	96	4	3	480
P03	144	4	4	460
P04	192	4	5	440
P05	240	4	6	420
P06	288	4	7	400
P07	72	6	2	500
P08	144	6	3	475
P09	216	6	4	450
P10	288	6	5	425
P11	48	4	1	500
P12	96	4	2	480
P13	144	4	3	460
P14	192	4	4	440
P15	240	4	5	420
P16	288	4	6	400
P17	72	6	1	500
P18	144	6	2	475
P19	216	6	3	450
P20	288	6	4	425

Table 2: Best, mean, worst and deviation

				Deviation (%)	
No.	Best	Mean	Worst	Worst	Best
P01	1074.12	1079.34	1086.72	1.17	0.00
P02	1764.35	1773.62	1780.54	1.04	0.12
P03	2373.65	2381.74	2386.52	0.54	0.00
P04	2817.62	2820.42	2842.69	0.96	0.18
P05	2965.18	2973.64	2992.32	0.92	0.00
P06	3607.24	3610.35	3632.46	0.81	0.11
P07	1418.22	1426.45	1443.76	1.80	1.80
P08	2101.74	2106.45	2116.56	0.95	0.29
P09	2720.84	2731.48	2736.46	0.42	-0.15
P10	3475.17	3482.54	3493.46	0.53	0.00
P11	1006.86	1015.56	1020.43	1.46	0.11
P12	1464.50	1471.46	1484.65	1.38	0.00
P13	2001.81	2009.32	2022.45	1.03	0.00
P14	2195.33	2204.24	2215.65	0.93	0.00
P15	2447.26	2462.41	2476.54	0.84	-0.35
P16	2845.39	2852.65	2865.32	0.70	0.00
P17	1243.65	1245.48	1249.73	1.09	0.60
P18	1788.18	1799.75	1809.64	1.20	0.00
P19	2259.42	2269.54	2284.32	0.85	-0.25
P20	2991.79	2999.48	3019.73	0.93	0.00

Table 3: SAICA and other algorithm in solving the path length in P01

Algorithm	Best	Worst	Mean
TS	1089.56	1120.43	1098.37
VNS	1081.63	1098.51	1092.86
CAVNS	1083.87	1095.96	1088.23
SAICA	1074.12	1086.72	1079.34

The parameters of the multiple depots vehicle routing optimization based on the Simulated Annealing Immune Clone Algorithm (SAICA) is as follow. M = 60, T_{max} = 500, T_0 = 10000, k = 0.95, N_{min} = 20, C_{max} = 20. Execute SAICA in 100 times for each dataset and the distribute of every solution is shown in Table 2.

The percent of deviation is that the current optimal solution deviates from SAICA's. From the Table 2, the best solutions in P09, P15 and P19 are superior to the current optimal. The best solutions in P01, P03, P5, P10, P12, P13, P14, P16, P18 and P20 are equated with the current optimal. The best solutions in P02, P04, P06, P07, P08, P11 and P17 are inferior to the current optimal, but they are close to the optimal. The deviation of the worst and average solutions is less than 2%. SAICA combines the immune clone algorithm and the annealing algorithm, so it has the better performance and stability.

The algorithms in common use have TS, VNS, CNVNS and the result SAICA and the other algorithm in solving the path length is Table 3.

From Table 3 and 4 the best, the average and the worst solution of SAICA in solving the multi-depot vehicle routing are better than the other algorithms. On the one hand, the immune clone with t the annealing algorithm is introduced which is well suited for improving the multi-depot vehicle routing problem. On the other hand, the new antibodies are accepted by the simulation annealing rule in the mutation and crossover and speed up the global searching ability. The combination with the heuristic algorithms in SAICA can achieve the optimal solution more than other algorithms.

Table 4: SAICA and other algorithm in solving the path length in P11

Algorithm	Best	Worst	Mean
TS	1021.39	1034.36	1028.63
VNS	1014.56	1028.63	1023.54
CAVNS	1009.53	1023.97	1019.57
SAICA	1006.86	1020.43	1015.56

Table 5: Performance of algorithms in P01

Alogrithm	Global times	Local times	AG	Mean length
SAA	28	32	82	1234.37
ICA	34	26	113	1096.86
SAICA	48	12	70	1079.34

Table 6: Performance of Algorithms in P11

Alogrithm	Global times	Local times	AG	Mean length
SAA	25	35	93	1124.63
ICA	30	30	122	1058.54
SAICA	52	8	69	1015.56

Influence of the immune clone and the annealing algorithm: In order to verify the influence of the immune clone and the simulation annealing algorithm in SAICA, remove the immune clone algorithm for getting the Simulation Annealing Algorithm (SAA). Remove the simulation annealing for getting the immune clone algorithm (ICA). Test the above algorithms in 60 times and iterate 180 generation. The algorithms set the same parameters and adopt the consistent data. The performance of the algorithm is Table 3.

AG is the abbreviation of average convergence algebra. The global optimal convergence of SAICA is the most times from the Table 5 and 6 and the P01 is 48 times, the P11 is 52 times. The average convergence algebra reflects the convergence speed and SAICA has the more convergence speed and the less average route for adding the annealing immune clone algorithm.

CONCLUSION

In this study, in order to improve the efficiency of the multiple depots vehicle routing, put forward the annealing immune clone algorithm. One the one hand, Accelerate the searching process by the tensile annealing of the affinity function. On the other hand, the new antibodies are accepted by the simulation annealing rule in the mutation and crossover and speed up the global searching ability. The optimal solution is got by simulated annealing regulation when the annealing temperature is tended to zero. The experimental results show that SAICA adding the adaptability and the annealing algorithm improves the speed and global convergence under the condition of the invariable convergence result.

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