

Application of Ant Colony Algorithm Based on Optimization Parameters in Equipment Material Transport

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Abstract—In order to solve the path selection problem in the transport of equipment and materials, while improving the quality of solutions, this paper uses ant colony algorithm based on optimization parameters to achieve. Through genetic algorithm to solve the parameters of ant colony algorithm, resulting in a better performance parameters. The experimental results show that ant colony algorithm based on optimization parameters has been improved on path length and computation time than the traditional ant colony algorithm.

Keywords—Ant colony algorithm; Parameters adjustment; Genetic algorithm

I. INTRODUCTION

Accurately and intelligent protection supported by Information technology is the objective requirements of the security mission of the war, but also the future development of equipment support. In modern warfare, because of the large number of equipment, high degree of mechanization, losses and consumption of weaponry, ammunition and equipment, plus a wide range of battlefield, troop movement frequently, resulting in protection task is very heavy and dependence on transportation is quite serious, which put forward higher requirements for transport security program development. At the same time, the degree of today's transportation network-intensive is high, the environment of battlefield transport is complex, many decision factors should be considered when developing programs, the commander's experience and traditional labor estimates can no longer meet the needs of modern warfare. These issues are typical VRP(Vehicle Routing Problem)^[1]. The emergence of the ant colony algorithm^[2-4] provides a good way for the solution of such problems. In this paper, an improved ant colony algorithm is adopted to determine the optimal equipment and materials transport routes, and provided a solution for path optimization and decision-making problems in peacetime and wartime transportation security programs.

II. VRP MATHEMATICAL MODEL IN TRANSPORT EQUIPMENT AND MATERIALS

Assuming a rear warehouse yard have m car, they will provide transportation services for n points. Demand for each protection point is d_i ($i=1, 2, \dots, n$).The maximum loading

capacity of the vehicle is Q . From the point of view of graph theory, the problem can be expressed as a complete graph $G=(V, E)$, $V=\{0, 1, 2, \dots, n\}$ represents the set of vertices, node 0 indicates yard; $V'=\{1, 2, \dots, n\}$ represents the set of protection points $E=\{(i, j) \mid i, j \in V, i \neq j\}$ represents the set of arc(or side). Given a non-negative weights c_{ij} for each arc(i, j), c_{ij} represents the path cost of point i to point j , The value for its comprehensive benefits $Value_C$ minimum; Meanwhile, for the arc to define the following variables:

$$X_{ijv} = \begin{cases} 1, & \text{if the vehicle } v \text{ travels from the point } i \text{ to point } j \\ 0, & \text{else} \end{cases} \quad (1)$$

$$Y_{iv} = \begin{cases} 1, & \text{if the vehicle } v \text{ meet the need of protection point } i \\ 0, & \text{else} \end{cases} \quad (2)$$

$$\min F(x) = \sum_{i=0}^n \sum_{j=0}^n \sum_{v=1}^m x_{ijv} c_{ij} \quad (3)$$

$$s.t. \quad \sum_{i=1}^n \sum_{v=1}^m x_{ijv} \geq 1, \quad \forall j \in V' \quad (4)$$

$$\sum_{i=0}^n x_{ipv} - \sum_{j=0}^n x_{jpv} = 0, \quad \forall p \in V', v \in \{1, 2, \dots, m\} \quad (5)$$

$$\sum_{v=1}^m y_{iv} = 1, \quad \forall i \in V' \quad (6)$$

$$\sum_{i=1}^n d_i y_{iv} \leq Q, \quad v \in \{1, 2, \dots, m\} \quad (7)$$

$$y_{jv} = \sum_{i=1}^n x_{ijv}, \quad \forall j \in V', v \in \{1, 2, \dots, m\} \quad (8)$$

The above model, $F(x)$ represents the objective function; Formula (4) represents each support point being services by vehicle at least once; Formula (5) is vehicle constraint, it requires one car to reach one support point must leave to the yard after the completion of the service; Formula (6) represents support point i can be serviced by one car. Formula (7) represents vehicle capacity constraints, which represents the sum of the needs of all support points serviced by vehicle v and cannot be greater than the loading capacity of the vehicle Q . Formula (8) represents the support point j can only be service by a vehicle from the support point i .

III. TRADITIONAL ANT COLONY ALGORITHM ANALYSIS

Inspired by the collective behavior of real ant colony in natural world, the Italian scholar Dorigo M in 1991 for the

first time systematically put forward optimization algorithm based on the ant populations, which called the colony algorithm, and applied it solve a series of combinatorial optimization problems. The ant colony algorithm achieved better experimental results in solving such problems^[5]. John E Bell^[6] applied optimized sub-heuristic method from ant system to solve the VRP problem. Silvia^[7] discussed VRP under the vehicle capacity restrictions; proposed CVRP of the ant colony algorithm based on the sub-heuristic algorithm and achieved better results. The reason why ants could find the shortest path from the lair to a food source, dependent on the substances called pheromones which released during ants foraging. The substance provides implicit communication media between ants, and become the basis for other ants selection path. Ant colony algorithm has three elements:

- Ants can perceive the situation in a small area, and could judge whether there are food or pheromone released by other ants;
- Each ant can release its own pheromone;
- The pheromone concentration legacy on the path will be gradually reduced over time.

The ant colony algorithm was used for TSP, QAP, NRP, VRP, MSP and achieved very good results. TSP as an example to illustrate the basic framework of the ant colony algorithm^[8]. There are n cities, d_{ij} ($i, j=1, 2, 3 \dots n$) represents the distance between city i and city j , $\tau_{ij}(t)$ represents the amount of information between city i to city j at time t , equivalent the pheromone release by ant. Suppose there are m ants, $p_{ij}^k(t)$ represents the probability of ant k moved from city i to city j at time t , then

$$p_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_{j \in allowed_k} [\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}, & (j \in allowed_k) \\ 0, & (j \notin allowed_k) \end{cases} \quad (9)$$

$allowed_k$ represents the set of city that ant k is allowed to walk next step. α (heuristic factor) represents the degree of influence that the following ants suffered by the front during the foraging process. The larger the values, the greater possibility of the following ants choose the same path, the less probability that ants search new path. Adversely, when this value is too small, the ant colony algorithm will appear local optima. η_{ij} represents expectation degree from city i to city j . β represents expectations heuristic factor, which represents relatively important degree, these heuristic information express the apriority intelligence and the determinacy factor during the ant colony optimizing process. If β is too large, the ants will choose the shortest path within the local, such will lead to a blind random search. If β is too small, it will lead to a purely random search.

The ants finish all cities, complete a circulation, the path traversed by each ant is a solution. Now renew the each path's information content in line with following formula:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}, \rho \in (0,1) \quad (10)$$

ρ is the pheromone residual coefficient, which represents the attenuation degree of the pheromone over time. $1-\rho$ is the pheromone residual factor, which represents the interactional intensity between the ants individuals. If $1-\rho$ is large, the pheromone remains on path predominant, pheromone positive feedback effect is relatively weak, the randomness of the algorithm searching become strong, thus the convergence rate is relatively slow. On the contrary, pheromone positive feedback effect is relatively strong, the randomness of the algorithm search become weak, thus the convergence rate is relatively fast, but the searching will easy to fall into the local optimal solution. Incremental $\Delta\tau_{ij}$ can be expressed as:

$$\Delta\tau_{ij} = \sum_{k=1}^m \Delta\tau_{ij}^k \quad (11)$$

$\Delta\tau_{ij}^k$ represents the information content between city i and city j that is left by ant n in this circulation, and its formula is based on the calculation model.

IV. EMPLOY GENETIC ALGORITHMS TO OPTIMIZE THE PARAMETERS OF ANT COLONY ALGORITHM

The solution character of Ant colony algorithm largely depends on the setting of the parameters, a reasonable selection of parameters critical to the application of the ant colony algorithm. This paper, combines with the actual equipment material transport, References literature^[9-10], employ the genetic algorithm^[11] to adjust the relevant parameters of the ant colony algorithm.

A. encoding

The encoding of genetic algorithms can be divided into binary coding and decimal coding (real-coded). Genetic algorithm founder Holland thought that the binary coding described much meticulous, it had greater probability to searching global optimum solution. Moreover, the binary coding is suitable for computer applications. However, the binary coding makes the Genetic Operators calculated quantity intensively and less efficient; in addition, if use a binary represent the solution of the problem requires the parameters encoding and decoding during the optimization procedure, so as to proceed the binary and decimal conversion, which exists the conversion error between the data. If the objective function value near the optimal point change rapidly that will be miss the optimal point. Thus, this paper adopts the decimal coding. Chromosome $c = (\alpha, \beta, \rho)$ represents a combination of parameters in ant colony algorithm.

B. genetic manipulation

(1) Adaptive function

In genetic algorithm, fitness function is used to indicate each chromosome's adaptation ability to its living environment. In order to take full consideration of the ant colony algorithm characteristics, from the solving problem's objective function, exploration capability of ant colony algorithm and development capability to construct the fitness function.

$$F(c) = \delta \times f(x) + \tau \times E + (1 - \tau) \times D \quad (12)$$

c represents the chromosome; δ represents the weights of objective function; $f(x)$ represents the solving problem of objective function; τ is a value between [0,1], which will affect the weight of the E and D to the fitness function; E represents exploration capability of ant colony algorithm; D represents development capability of ant colony algorithm. $E = r \times \sum (f_o(x) - f(x))^2$, $D = r \times \sum (f_p(x) - f(x))^2$; r is random number between [0,1]; $f_o(x)$ represents the optimal objective function in the iterative process; $f_p(x)$ represents the optimal objective function in the current iterative process.

(2) Selection

The common selection strategies in genetic algorithms are roulette wheel model, elitist model, expected value model etc. If the colony scale is small, using roulette wheel model will produce larger random errors, made the high fitness individuals eliminated. Elitist model easily lead to local optima genetic increasing rapidly, made the evolutionary stagnate in the local optima solution. Expected value model is the improved method for the roulette wheel model, this paper adopt this method as a selection strategy.

$$M = A_i / (\sum_{j=1}^N A_j / N) \quad (13)$$

A_i represents the fitness of individual i , N represents the colony scale.

(3) Crossover

Crossover operation in accordance with the following formula:

$$\begin{aligned} s_1 &= rc_1 + (1-r)c_2, \\ s_2 &= rc_2 + (1-r)c_1 \end{aligned} \quad (14)$$

r is random number between [0,1]; s_1 and s_2 are offspring; $c_1 = (\alpha_1, \beta_1, \rho_1)$ and $c_2 = (\alpha_2, \beta_2, \rho_2)$ are parents.

(4) Variation

Pick a gene g in chromosome c , mutate according to the following formula:

$$g' = g + \theta \quad (15)$$

(5) Stopping criterion

Apply the maximum iterations NG as a stopping criterion.

V. SIMULATION DATA AND RESULTS ANALYSIS

In this paper, we use Matlab 7.9 to simulate the improved ant colony algorithm and the traditional ant colony algorithm. Relevant parameters are set as follows: the maximum iterations about genetic algorithms $NG=30$, interlace probability $P_c=0.75$, variation probability $P_m=0.15$, the maximum iterations of ant colony algorithm $N_{max}=200$, the number of ants $m=20$, the number of guarantee points $n=40$, parameters range $1 \leq \alpha \leq 5$, $1 \leq \beta \leq 5$, $0.1 \leq \rho \leq 0.99$. The simulation results are shown in Table I.

TABLE I. COMPARISON OF THE ALGORITHM SIMULATION RESULTS

index	traditional ant	improved ant
	colony algorithm	colony algorithm
average path length (unit: km)	8.34	7.41
optimal path length (unit: km)	6.25	6.25
Average execution time (unit: s)	0.0530	0.0517
Total execution time (unit: s)	10.3621	10.2080

As can be seen from the Table I, in a specified iterations, the two algorithms found the optimal path both, but the average path length calculated by improved ant colony algorithm is shorter than the traditional ant colony algorithm, and improved ant colony algorithm is superior to the traditional ant colony algorithm in the average execution time and the total execution time.

Figure 1 shows the contrast result that the algorithm applied in one equipment support project. Path 1 is optimal.



Figure 1. The result of path optimization

VI. CONCLUSION

The ant colony algorithm showed certain advantages in solving complicated combinatorial optimization problems. Preferred parameters combinations have the better solution quality as well as the better stability, but if improper parameter selection, the ant colony algorithm will converge faster to local optima or converge slow, which have a great influence on the algorithm performance. In this paper, the genetic algorithm is used to mutate the parameters of the ant colony algorithm; experiments show that the parameters combination determined by the genetic manipulation used in ant colony algorithm has improved the path length and convergence rate compare with the traditional ant colony algorithm.

REFERENCES

[1] B. Bullnheimer, R.F Hartl, C. Strauss. An improved ant system algorithm for the vehicle routing problem[J]. Annals of Operations Research, 1999, 89:319-328

- [2] M. Dorigo, V. Maniezzo, A. Coloni. Ant system : optimization by a colony of cooperating agents[J].IEEE Transactions on Systems, Man, and Cybernetics, 1996, 26 (1) : 29-41.
- [3] L. Ma, G. Zhu, A.B. Ning. Ant Colony Optimization Algorithm[M]. Beijing: Science Press, 2008:10-30.
- [4] H.B. Duan. Ant Colony Algorithm Principle and Its Application[M]. Beijing: Science Press, 2005.
- [5] D.W. Wang, J.W. Wang, H.F. Wang. Intelligent Optimization Method[M]. Beijing: Higher Education Press, 2007.
- [6] J.E. Bell, P.R. McMullen. Ant colony optimization techniques for the vehicle routing problem[J]. Advanced Engineering Informatics, January, 2004, 18(1): 41 -48.
- [7] S. Mazzeo, I. Loiseau. An ant colony algorithm for the capacitated vehicle routing[J]. Electronic Notes in Discrete Mathematics, December1, 2004, 18, Complete: 181 -186.
- [8] S.Y. Li. Ant colony algorithm and its application[M]. Harbin: Harbin Institute of Technology Press, 2004.
- [9] S.W. Li, J.Q. Wang, J. W. Zeng. Model of ant colony algorithm parameters optimization based on genetic algorithm[J]. Computer Engineering and Design, 2011, 32(10), 3490-3493.
- [10] M. Tang, E. Ren, C. Zhao. Route Optimization of Bus Dispatching Based on GA-ACA[J]. Microcomputer Information, 2009, 11-1: 48-49
- [11] M.Q. Li, J.S. Kou, D. Lin, etc. The Basic Theory and Application of Genetic Algorithms[M]. Beijing: Science Press, 2002.