Proceedings of the Eastern Asia Society for Transportation Studies, Vol. 5, pp. 581 - 591, 2005

THE ACO ALGORITHM FOR CONTAINER TRANSPORTATION NETWORK OF SEAPORTS

Zijian GUO
Associate Professor
School of Civil and Hydraulic Engineering
Dalian University of Technology
2 Linggong Road, Ganjingzi District,
Dalian 116024, Liaoning, P. R. China
Fax: 86-411-8467-4141
E-mail: zjguo@dlut.edu.cn

Xiangqun SONG
Associate Professor
School of Civil and Hydraulic Engineering
Dalian University of Technology
2 Linggong Road, Ganjingzi District,
Dalian 116024, Liaoning, P. R. China
Fax: 86-411-8467-4141
E-mail: songxiangqun@hotmail.com

Peng ZHANG
Graduate
School of Civil and Hydraulic Engineering
Dalian University of Technology
2 Linggong Road, Ganjingzi District,
Dalian 116024, Liaoning, P. R. China
Fax: 86-411-8467-4141
E-mail: rocbirds@163.com

Abstract: The rapid growth of international container handling in recent years has led to an increased utilization of mega-containerships and the rebuilt of container network. This paper, focusing on the computing complexity dealing with hub and spoke system, proposes a new reliable combination optimization method, named ACO (ant colony optimization) algorithm, to solve the container transportation network problem for marine transport system. To prove its utility, we compare the proposed method with the result by Dijkstra algorithm through a simple example. The result shows ACO algorithms is of a credible and excellent probability accumulation searching method.

Key Words: Optimization, Ant Colony Optimization, Container transportation

1. INTRODUCTION

On the impact of the trend of global container transportation, worldwide freights capacity centralized to the large hinge ports. The competition among the seaport groups or among the seaports belongs will become even vehement. The companies, who hanker for maximizing their profits, will choose a strategic decision for their investment and management. Their target is to make sure of the lowest conveyance cost and the fastest speed as well as keeping mutually harmony. The carriers for international containers compel all shippers have to depend on the flawless transportation chain; the goods stream inclines to choose transportation chain, not a certain individual port. In this way, the competition among the seaports has not been the point to point, but the competition in the whole logistics system and the supply chain. The advantage should be whether or not has competition in the center that provides extended service to distributed information management system and the transportation network in the area which the port belong to. The challenge that the port is facing to is how to bring oneself coming into the main line of the transportation chain.

The research about the methods of optimizing the transportation network has a rapid development and there has brought forth many methods. The researches on optimization theory are becoming more and more mature in the international academic circle. The related methods of optimization in container transportation network such as Simulated Annealing, Genetic Algorithms, Artificial Neural Network, Chaos Optimization, Taboo Search, have been developed by simulating or revealing some natural phenomenon or process (Ding, 2003).

Here, we, focusing on the computing complexity dealing with hub and spoke system, propose a new reliable combination optimization method, named ACO (ant colony optimization) algorithm, to solve the container transportation network problem for marine transport system.

In this paper, we built a simulated model based on ACO algorithm and got the optimal solution by a simple example. In addition, compared with the traditional algorithm, this model has verified its correctness, validity and superiority of the new algorithm by applying them to the optimization of container transportation network.

2. THE ACO ALGORITHM FOR CONTAINER TRANSPORTATION NETWORK SYSTEM

2.1 The Description of the Container Transportation Network

In general, it's known that there exist four factors in an optimization problem of container transportation, namely economical efficiency, speediness, security and inventory cost. Economical efficiency means the total cost of transportation was lowest. Speediness express the time on the way was shortest. Security presents the level of freight damage. Inventory cost is given by the time in the stock and lay-days. These four valuation items are hardly attain superior at the same time in a certain transport project, so they are usually calculated in synthesize cost which include transport cost in the process of transportation, cost of time loss in the transport process, goods expenses on the way, cost in the stock, environment depletion expense in the transport process, cost of ships transfer and any other cost that the paper make no mention of. The purpose of optimization of the container transportation network system is obtaining the lowest cost as mentioned above. It's an arduous mission because it belongs to combination explode problem which was hard to solve. Even though, it will decrease unnecessary economic expend and obtain more economic interest.

In a marine transport system, each port is a node and the waterway between any two nodes is the link. All nodes are brought into an integrated transportation system then oriented graphs with significance are formed. The transportation cost should be lowest from the start node arranged to the end-point and the whole transportation cost of the transportation network including all nodes should be lowest. This is a typical combinatorial optimization problem.

2.2 The Optimization Objective Function of the Container Transportation System

In the theory of transportation network, Beckmann (1965) has proposed the fundamental mathematical formulation with the concept of static equilibrium. And lots of further researches have been done then. Here we focus on the computing complexity of this kind of transportation network and extend the basic idea of ACO (ant colony optimization) algorithm to the container transport network for marine system. As a matter of fact, marine transportation network is only a part of worldwide supply chain. In order to simply the problem, we assume that the container cargo is transported from port to port. It is acceptable when we make a master plan of a hub port with hub and spoke system.

The optimization objective function of the model can descript as follows:

$$\min TC = \sum_{i=0}^{n}\sum_{j=0}^{m} P_{ij} Q_{ij} v_{ij} d_{ij} \tag{1}$$

$$\textbf{\textit{s.t.}} \quad P_{ij} = f(Q_{ij})$$

$$v_{ij} = \begin{cases} 1 & i \neq j \\ 0 & \text{other} \end{cases}$$

Where

TC ——total cost in transport process, unit: 0.01million \$;

P_{ij} ——unit cost of container transport; unit: 0.01million\$/(0.01millionTEU·sea mile), it imply the decision variable which will change according to the carrying volume of a vessel;

Q_{ij} ——numbers of container transported from port i to port j, unit: 0.01millionTEU;

v_{ij} ——the connection of node i and j;

d_{ij} ——distance between port i and port j, unit: sea mile;

n,m ——numbers of start and end node.

2.3 Ant Colony Optimization Algorithms Approach for Network Optimization

Ant Colony Optimization (ACO) is a new intelligent optimization algorithm. It has been successfully applied to much NP-hard combinatorial optimization problems (Xin, 2002). As the name suggests, this algorithm was inspired by the ant colony's searching food behavior in the real world. The main idea of this algorithm is ants search food by colony and they communicate with each other with trail of a chemical substance, which in the algorithm we called pheromone. The pheromone is a kind of distributed numeric information, which can reflect the behavior of ants, increase or decrease their experience accumulated. Recently, many researchers studied and developed the ACO algorithm, and the application domain of the algorithms was extended gradually.

2.3.1 Description of ACO Algorithm

Initially, all m ants are placed on start point S. Ant i starts the tour from node S based on the probabilistic decision, and chooses a line joint to S. Then ant i starts the next tour from the other point a on this line. In addition, chooses another line joint to a, and the like until find the endpoint T. whereupon, ant i gets a solution from S to T. The pheromone updated after each ant chooses a line (local updating). Ant j starts tour from S with the same method after ant i finished the searching. Moreover, it gets a solution from S to T. After obtaining all m solution, the local search algorithms adopted to find the local optimal solution, on the base of which the global optimal solution is calculated out. Then the iteration continued until the stopping criterion is met, namely the maximum iteration is satisfied. At this point, the project of the network is optimal.

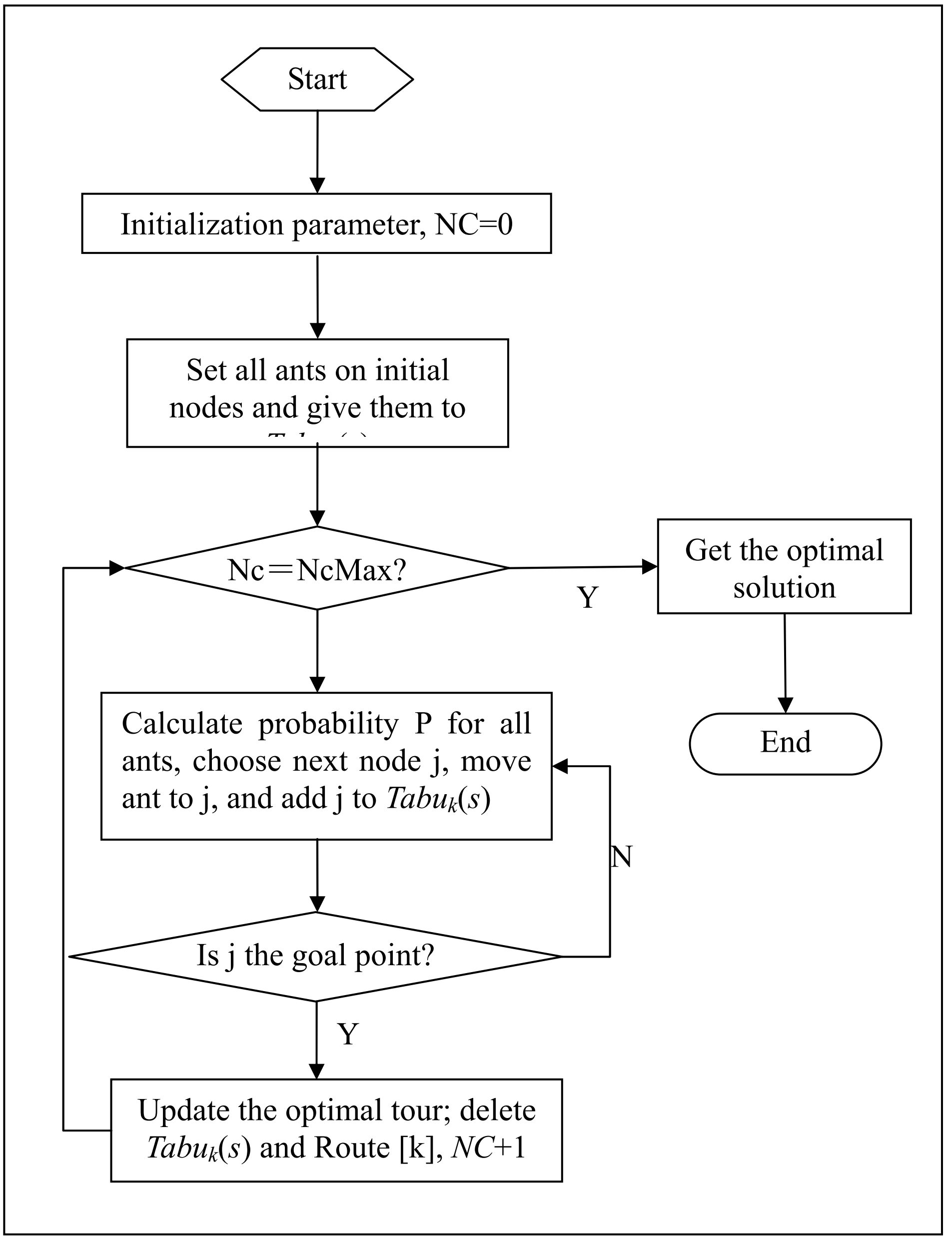

Fig.1 Algorithm Flowchart of the Model

The pseudo code of the algorithm is given as follows:

```
While (ant has not found the object node and the stopping criterion is not met)
  Deposit all ants on the start node S;
  For (the number of ants)
        For (each node)
        Choose the next node to visit according to the probabilistic decision;
        If the object node is met, break;
        Continue;
        End For;
        For (each node)
        Update the pheromone on each edge according to local updating decision;
        End For;
  For (each ant)
        Calculate the cost solution from Route [k];
```

End For;
If the best tour from this iteration is better than the globally best tour, then set this is the globally best tour;
Reinforce the pheromone of the edges belonging to the globally best tour according to global updating decision;
End While;
Output the globally best tour and cost;

2.3.2 Formulation of Basic Algorithm Model

Initially, creating n port nodes randomly (1≤m≤n) (Zhang, 2002), m ants are placed on the first node. Then, each ant moves and chooses a next node. Each ant tends to visit the path whose pheromone is higher, and finally find the goal node. After all ants have done the search process, the global pheromone update mechanism and pheromone volatilization mechanism were started-up immediately. Each ant releases pheromone inverse to the path's length it has found in the path it has went across. After that, each ant begins new search until the condition was satisfied.

(1) State Transition Rule

Ant i selects the node connected with high pheromone, the probability is calculated by the formulation as follows (Dorigo, 1991; Dorigo, 1992; Colorni, 1991):

$$P_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} * [\eta_{ij}]^{\beta}}{\sum\limits_{u \in J_k(i)} [\tau_{iu}(t)]^{\alpha} * [\eta_{iu}]^{\beta}} & if \quad j \in J_k(i) \\ 0 & \text{other} \end{cases} \tag{2}$$

Where
α and β mean heuristic information and importance of the pheromone that can affect the choice of the ants;
$\tau_{ij}(t)$ means the pheromone trail;
$\eta_{ij}(t)$ means a locally available heuristic information, generally, $\eta_{ij}(t)=1/d_{ij}(t)$;
$J_k(i)$ means the nodes gather ant has not visited.

(2) Global Updating Rule

The pheromone trails are updated after ants have completed the tour construction. That is done by the remained pheromone trails after evaporating and the pheromone the ant deposit on the line when they played the visit.
As has been noded, the update follows this rule (Dorigo, 1992; Colorni, 1991):

$$\tau_{ij}(t+1) = \rho * \tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \tag{3}$$

Where
1-ρ means the degree of pheromone evaporation, $\rho \in (0,1)$.
This evaporation mechanism helps to avoid unlimited accumulation of the pheromone, and give ants the opportunity to choose other lines.
$\sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t)$ is the amount of pheromone ant k deposit on the line it has visited. It can calculate

with the method as follows (Stützle, 2000):

$$\sum \Delta \tau_{ij}^{\ k}(t) = \begin{cases} Q/C_{ij}^{\ k}(t) & \text{if ant k viseted line r(i, j)} \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

Where

$C_{ij}(t)$ means the cost, length, or other function consume in line(i,j);

Q is the initial constant in each line.

(3) Local Updating Rule

The pheromone updated simultaneously in the process each ant formatted the solution. This updating process fell into step with rule as follows (Stützle, 2000; Fu, 2003):

$$\tau_{ij} = \alpha * \tau_{ij} \quad (5)$$

Where α is a constant that belongs to (0,1).

2.3.3 The Probabilistic Decision Research of ACO Algorithms

According as the traditional ACO algorithms, ants choose the next node j whose probability is biggest. If at certain iteration, most ants choose the same line that is just not the best tour, then because of the accumulation of the pheromone, all ants will tend to choose this line and cannot to judge whether there has a better choice. The problem always exists in the optimization of traffic field. Therefore, we make some improvement at the time the ants choose node, in order to slower down the speed the ants choose line otherwise they will give up the line that may be better. The random selection we use is just like the Roulette Wheel Selection in the Genetic Algorithms.

This strategy choice can achieve as follows:

Create a random number "drand" belong to [0,1], if

$$P_{i,0}^k + P_{i,1}^k + \cdots + P_{i,j-1}^k \le drand \le P_{i,1}^k + P_{i,2}^k + \cdots + P_{i,j}^k \quad (6)$$

Where P^k_{ij} means the probability choice of individual; apparently, this strategy choice is just very like the wheel in roulette wheel selection.

Calculate the probability $P_{ij}^k = \dfrac{([\tau_{ij}]^\alpha \cdot [\eta_{ij}]^\beta)}{\sum_{j \in J_k} [\tau_{ij}]^\alpha \cdot [\eta_{ij}]^\beta}$;

Create a random number "drand" belong to [0,1];

```
j=1;
    if tabu[k][j]==0
        if Σ_{i=0}^{j} P_ij^k ≥ drand ;
            add j to tabu[k][j];
            tabu[k][j]=1;
        else
            j=j+1;
        end
end
```

3. EXAMPLE

3.1 Input Data

The paper uses this model to analyze a real port transportation network. First, select several port nodes, joint every two nodes with lines, and then combine all nodes to an integer transportation system. This has become a directed graph with weight. The cost is lowest from the required start point to the required endpoint, and also the cost of the whole transportation network is lowest---this is a typical combination optimization problem. Select the node element in the network as follows:

Table 1. Node of the System

1	2	3	4	5	6	7	8	9
DL	*TJ*	*QD*	*BS*	*HK*	*HY*	*SP*	*LA*	*RD*

Input the forecast foreign trade data in Table 2 into the model that has been established and run the routine of the algorithm.

Tabel 2. OD Distribution

		DESTINATION					
		BS	*HK*	*HY*	*SP*	*LA*	*RD*
ORIGIN	*DL*	32.9	49.63	19.11	50.22	70.53	76.6
	TJ	11.83	24.81	9.45	26.93	22.81	19.22
	QD	23.78	95.38	9.03	7.06	2.79	10.06
	BS	0	86.13	24.51	38.07	25.93	22.13
	HK	0	0	67.28	9.32	5.43	11.86
	HY	0	0	0	13.32	7.11	38.96
	SP	0	0	0	0	125.94	160.39

(10thousand TEU)

3.2 The Parametric Factor Research

In ACO algorithms, some parameter is concerned: ant number m, initial constant in each line Q, the parameter persistence ρ, the determine factor β of relative importance of the pheromone trail and the determine factor α of heuristic information (Chen, 2003). These factors are important in the whole algorithms, so how to choose these factors is become a new problem. According as the experience (Dorigo, 1991; Randall, 2002; Dorigo, 1996; Zhang, 2002), the following default parameter settings are used before improved. M. Dorigo (1992) $\alpha \in (0,1]$, $\beta \in (0,3]$, $\rho \in (0,1)$, $Q \in [1,100]$. We choose α=0.6, β=1.0, ρ=0.5, Q=30, $M=20$. The purpose of the test is to find the parametric sensitivity between the factor value and the optimum solution.

The test is shown as follows:

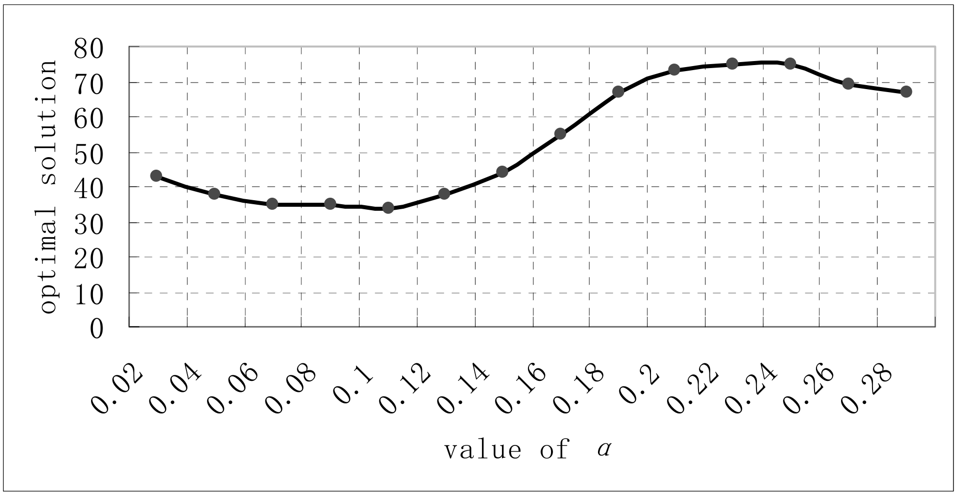

Fig 2. Parametric Sensitivity of α

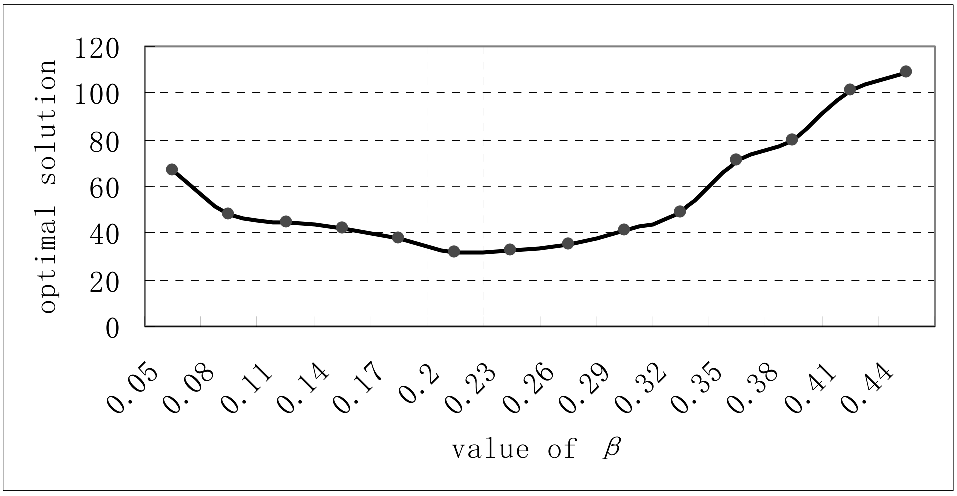

Fig 3. Parametric Sensitivity of β

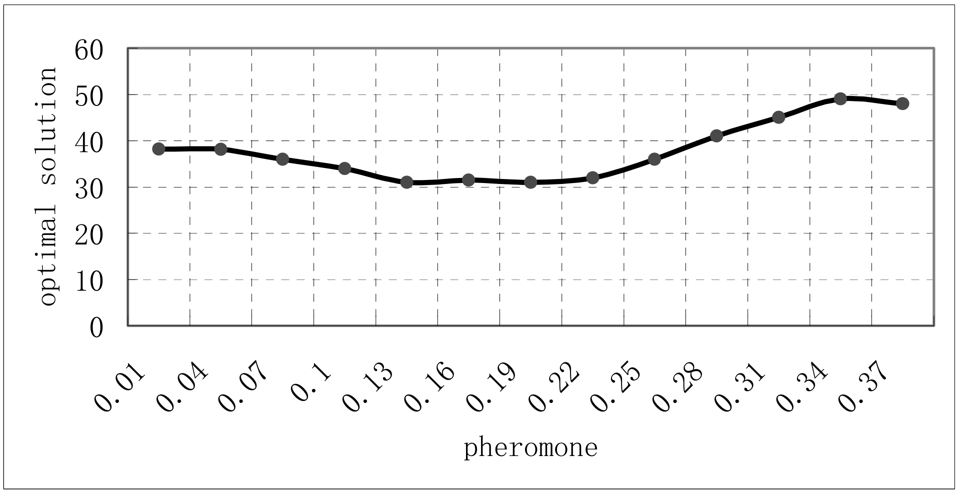

Fig 4. Parametric Sensitivity of ρ

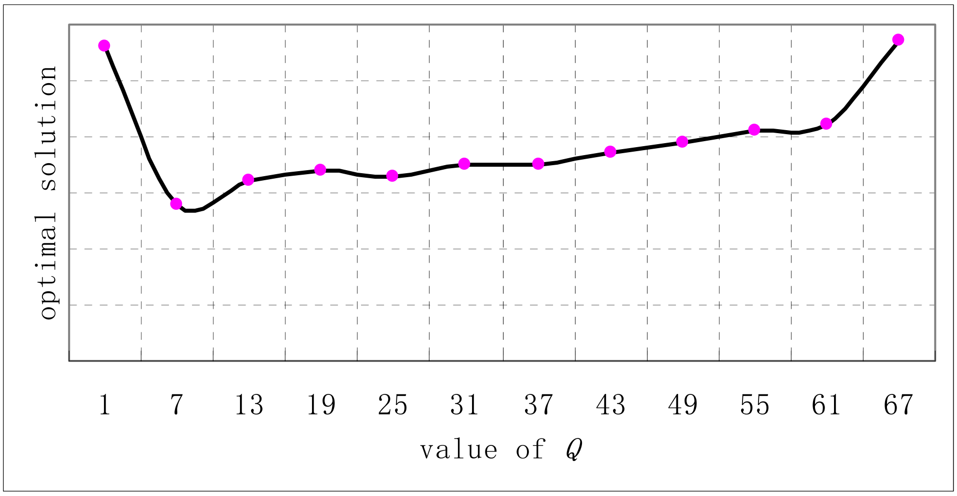

Fig 5. Parametric Sensitivity of Q

Figs 2 to Fig 5 show the change of optimal solution results from the debug of parameters at particular scope. In each test of the parameters, we firstly assume that other parameters take value in experience, and then debug the one in the debug loop. Certainly, this debugging is adjusted to pay for losing other factors' change. After debugging, we'll adjust the scope of value properly according to each parameter's sensitivity and the influence brought by other factors, and then continues the loop of debugging. The test will be end when the iterative number reaches the maximum. In Fig 2, the low-water mark of the curve is the good value for the parameter α, namely from 0.07 to 0.12. In this scope, the affect of the parameter to the optimal solution is minimal. Similarly, we can get the scope of β, ρ, Q, namely $\beta \in [0.1,0.3]$, $\rho \in [0.1,0.3]$, $Q \in [10,60]$.

As we can see from the figs, the parameters α, β, ρ, Q, have a good robustness within certain limits in which the variety of the parameter can hardly affect the optimal solution. But in case the value exceeds these limits, the parametric sensitivity changes tempestuously. The number of ants, generally, takes 0.6~1.5 times the number of nodes.

3.3 Result Analysis

Table 3. Compare With the Result of Dijkstra Algorithm

	Minimum Cost	Deviance form the theoretical value	Time consumed (s)
ACO algorithm	3.23	2.5%	8
Dijkstra algorithm	3.16	0.3%	3

Seen from the result, the ACO algorithm and Dijkstra algorithm can find the optimal solution rapidly. The research speed of Dijkstra algorithm is faster when searching joint nodes than ACO algorithm due to that all ants in ACO algorithm must complete their searching loop. But with the enlargement of the problem scale, the ACO algorithm will show the advantage gradually. The reason is that Dijkstra algorithm searches the optimal solution by the manner of traversing the network that is well rated just in small-scale network. As against, ACO algorithm is a heuristic search algorithm; it can do the current search referring to the previous information and decrease the probability of blind search. The larger of the network is, the more advantage of the manner will show. Moreover, the ACO algorithm has a good parallelism; different ants can make the collaborative work that will be propitious to search speed.

4. CONCLUSIONS

This paper has studied on determining the optimal container transportation project and has considered the types of constraint condition in container transportation process. Then, the study has studied the new intelligent Ant Colony Optimization algorithms applying to transportation domain. The paper has established a model on the basis of real port transportation system and solved successfully by improved ACO algorithm.

Even though the transportation model established in this paper has taken into account finite constraint condition, in reality, the model has still possessed most character of the real transportation system. In the future research, more constraint condition in container transportation process and larger scale system should be concerned.

ACO algorithm is certainly a credible and excellent probability accumulation searching method. It can drift towards the optimal solution rapidly by firstly positive feedback iteration searching mechanism and secondly negative feedback global searching mechanism on large-scale optimization problems. In addition, the algorithm can apply to multi large-scale combination optimization problems by improve the algorithm aimed at different problems.

In ACO algorithm, the parametric sensitivity of the determined factors should be concerned. This paper has tested each factor's sensitivity in the algorithm. The result of the test shows that the factors such as $\alpha, \beta, \rho, Q, M$, have a good robustness within certain limits in which the variety of the parameter can hardly affect the optimal solution.

To sum up, it is our hope that by following these routes, the theory and application of ACO algorithm can be consummated and improved ultimately.

This work was supported by the National Natural Science Foundation of China (No. 50278011)

REFERENCES

Beckmann, M., McGuire, C.B., and Winsten C.B. (1956) **Studies in the Economics of Transportation**, Yale University Press, New Haven

Chen, L., Qin, L., Chen, H.J. and Xu, X.H. (2003) Ant Colony Algorithm with Characteristics of Sensation and Consciousness, **Journal of System Simulation, Vol.15, No. 10**, 1418-1425

Colorni, A., Dorigo, M. and Maniezzo, V. (1991) **Distributed optimization by ant colonies**, in Proc. First Europ. Conf. Artificial Life, F. Varela and P. Bourgine, Eds. Paris, France: Elsevier, 134-142

Ding, Y.L., Chen, Z.Q. and Yuan, Z.Z. (2003) A Survey of Simulating Biology Intelligent Algorithms and It's Application on Network Optimization, **Journal of Computer Engineering and Application, No. 12**, 10-15

Dorigo, M. (1992) **Optimization learning and natural algorithms**, Ph. D. Thesis, Dip. Elettronica, Politecnico di Milano, Italy.

Dorigo, M., Maniezzo, V. and Colorni, A. (1991) **Positive Feedback as a Search Strategy**, Dipartimento di Elettronica, Politecnico di Milano, Milan, Italy, Tech. Rep. 91-016.

Dorigo, M., Maniezzo, V. and Colorni, A. (1996) The ant system: optimization by a colony of cooperating agents, **IEEE Trans. Systems Man Cybernet**. **Vol. 26,** 29–42.

Fu, B.J., Zhang, M.Y. and Yu, H. (2003) An Improved Ant Colony Algorithm for the Shortest Path Problem, **Journal of Computer Engineering and Application, No. 3**, 107-109

Randall, Marcus, Lewis and Andrew, (2002) A Parallel Implementation of Ant Colony Optimization, **Journal of Parallel and Distributed Computing. Vol. 62, No. 9**, 1421-1432

Stützle, Thomas, Hoos, Holger and H. (2000) MAX–MIN Ant System, **Future Generation Computer Systems**. **Vol. 16, No. 8**, 889-914

Xin, B.J., Wang, L. and Wu, Q.D. (2002) **Research and Applications of Ant Colony System Algorithm and Its Hardware Realization**, **Vol. 30, No. 1**, 82-87

Zhang, Z.Y., Sun, J. and Tan, J.H. (2002) Application of the Improved Ant Colony Algorithm, **Journal of ShangHai JiaoTong University, Vol. 36, No. 11**, 1564-1567