ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A NOVEL ACO ALGORITHM BASED ON AVERAGE ENTROPY FOR REAL ESTATE PORTFOLIO OPTIMIZATION

YANCANG LI, BEIBEI HENG, SHUJING ZHOU, RONG CHEN, SUFANG LIU

Hebei Engineering Institute, Handan 056038, China

ABSTRACT

Portfolio is an import measure of risk distribution in real estate development. In order to provide a more effective algorithm and overcome the shortcomings of the common portfolio optimization algorithms, an improved ant colony optimization algorithm based on average entropy was proposed. The average entropy can adjust the parameters of the algorithm adaptively. After the establishment of the portfolio optimization model, the improved algorithm is introduced into the real estate portfolio optimization. Application results show its efficiency and robustness in solving the real estate portfolio optimization problems.

Keywords: *Real Estate, Portfolio, ACO, Ant Colony Algorithm, Average Entropy*

1 INTRODUCTION

The real estate circle is a filed with high potential rewards and high risks. How to control the investment risk and improve the cash flow and profitability of the project are urgent questions for the investors and the real estate development companies. Real estate portfolio is an effective strategy of risk management [1]. The meaning of this method is “Don’t put your eggs into one basket”. But, in practice, it is difficult to decide the proportion of every type. The portfolio theory is mature in stock market, yet they cannot be directly used in real estate portfolio. The common real estate portfolio models and algorithms have much deficiency, especially their calculations are complicated and results are not the best solution [2, 3]. This has signifies the study of the optimization algorithms.

The Ant Colony Optimization (ACO) Algorithm, proposed by Italy scholars Dorigo M., Mahiezzo V. and Colorni A. in 1991 and first investigated systematically in Dorigo’s dissertation, is a new kind of mode-based evolutionary meta-heuristic bionic algorithm, and a swarm intelligent algorithm for complex optimization, especially for the discrete NP-hard complicated combinatorial optimization, e.g. TSP (Traveling Salesman Problem), JSP (Job-shop Scheduling Problem), FSP (Flow shop Scheduling Problem), QAP(Quadratic Assignment Problem), SOP(Sequential Ordering Problem), QOS multicast routing and little has been done for the search in continuous-space problems[4-7].Yet because of the short development history, the basic ant colony algorithms have much deficiency, especially its premature.

To break through the limitations described above, an improved ant colony algorithm based on the average entropy is proposed here. By controlling the average entropy, we realize the self adaptively adjusting of the algorithm. And the improved algorithm can be employed in solving the real estate portfolio problems effectively.

The paper is structured as follows. First, the basic knowledge of the ant colony algorithm was briefly introduced. Then, the improved ACO was proposed and was employed to the real estate portfolio optimization. Engineering practice shows its efficiency.

2 THEORY AND MODE OF BASIC ANT COLONY ALGORITHM

The ant colony algorithm is a kind of stochastic explorative algorithms. As the other kinds of stimulated evolutionary algorithms, it finds the best solution of optimization problem by making uses of the evolutionary procedure of a set of cooperating agents of candidate solutions. It is demonstrated that in the nature, the ant colony can finally find the shortest way from the food to their home. The reason is that ants can communicate through the pheromone. The ant can leave his own pheromone and feel the other’s and use it to direct his way ahead. So the action of the ant colony is a positive feedback behavior: to a route, the more ants pass, the more pheromone it has, and the more probability for other ants to select it. At last the shortest route will be found by the ant colony, this process is called the ant’s autocatalysis behavior [8].

Journal of Theoretical and Applied Information Technology
30th November 2012. Vol. 45 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The ant colony algorithm stimulates the process through artificial ants. As distribute agents, the artificial ants' action can be described as: under the direction of artificial pheromone trails and the problem-based heuristic average, a colony of stochastic artificial ants move in the solution construction graph corresponding to formulate the solution of the problem [9]. As a long-term memory, the function of pheromone is a media for the communication. Positive feedback makes the ants find the high quality solution. In this sense, the ant colony algorithm is an auto catalytic reinforcement learning algorithm based on Monte Carlo, and it is also a constructive algorithm based on pheromone parameterized probabilistic mode.

The basic ant colony algorithm has many advantages: (1) using the positive feedback and distribution calculation, the algorithm can easily realize the parallel computation. (2) It has strong robustness and is easy to realize the combination with other improvement algorithms. (3) Compared with the GA, the ACO can more easily to tackle the constraint. Yet, basic ACO has the following shortcomings: (1) It is easy to fall into stagnation. (2) The calculation is complicated. (3) It has low efficiency in solving the continuous-space problem. Many learners have done a lot to overcome these defeats[9]. In some degree, all the improvements above have done much good for the development of the ant colony algorithm, yet we still have a long way to go.

3 THE IMPROVED ALGORITHM WE PROPOSED

The basic ACO has four main parts: selection strategy, local pheromone update, local search algorithm, and global pheromone update. The positive feedback theory in the selection strategy causes the stagnation behavior. To break through this limitation, we should begin with the selection strategy which is directly related to the amount of pheromone of each route. Because the quantity of each route has uncertainty, we can introduce the average entropy, which relies on the proceeding of the algorithm into the ACO to weigh the uncertainty above. Through controlling the value of average entropy, we can control the route selection and the proportion of the stochastic local perturbation behavior and can realize the self-adaptive of the algorithm.

We define the selection probability is $p_{ij}^{k}(t)$, then, the entropy can be expressed as:

$$S = -k\sum_{i=1}^{n} p_{ij}^{k}(t)\ln p_{ij}^{k}(t) \quad (1)$$

And the average entropy $\overline{S} = \frac{S}{m}$ can be used to measure the uncertainty of selection:

$$\alpha_{(t)} = A\left|\overline{S} - S_{(t)}\right| \quad (2)$$

$$\beta_{(t)} = B - (\overline{S} - S_{(t)}) \quad (3)$$

Where A and B are constant weight respectively, and simulation experiments show that when $A = 2$, $B = 10$, the algorithm performs best.

So, we can control the entropy to ensure that in the beginning of the algorithm, $\alpha_{(t)}$ is small, and in the last, $\alpha_{(t)}$ increases. At the same time, $\beta_{(t)}$ is biggest at early stage in order to make the algorithm find the optimal route and later it becomes smaller to reinforce the function of random operation. By controlling the value of information entropy, we can control the route selection and the proportion of the stochastic local, and avoid the perturbation behavior.

The procedure of the modification we proposed is shown in Figure1.

Journal of Theoretical and Applied Information Technology
30th November 2012. Vol. 45 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

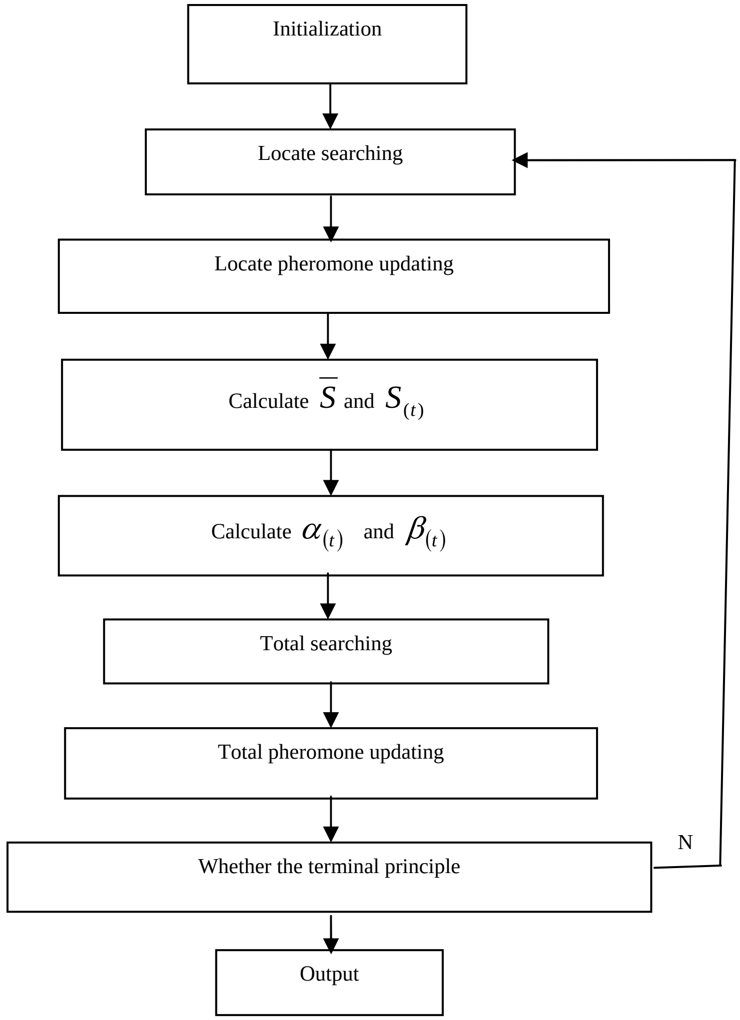

Figure 1: The Procedure Of The Modification

4 PERFORMANCE COMPARISON OF THE TWO ALGORITHMS FOR TSP

To validate the efficiency of the algorithm proposed here, we select the bayes29 (29cities, 406routes) and gr48 (48cities, 1128routes) of TSP that is the NP-hard combinatorial optimization with combinatorial explosion. Here, we define $\alpha = 1.5, \beta = 4.0, \rho = 0.6, Q = 50$, and when the average entropy is smaller than 0.01, the algorithm will terminate. To compare with the basic ant colony algorithm, we list the comparison results in Table I and Figure 2.

From the comparison shown above, we can conclude that the basic ant colony algorithm is easy to fall into stagnation yet the algorithm we proposed break through this limitation and it can help the ants step out of the stagnation and the heuristic average is very effective and its result is more optimal than the basic ant colony algorithm.

Table I: Performance Comparison Of Two Algorithms For TSP

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

TSP	Basic ant colony algorithm		Algorithm we proposed	
	Time(s)	Optimal solution	Time(s)	Optimal solution
29	8	2180	5	2062
48	52	5494	33	5256
1577	182	26063.7	68	22257.3

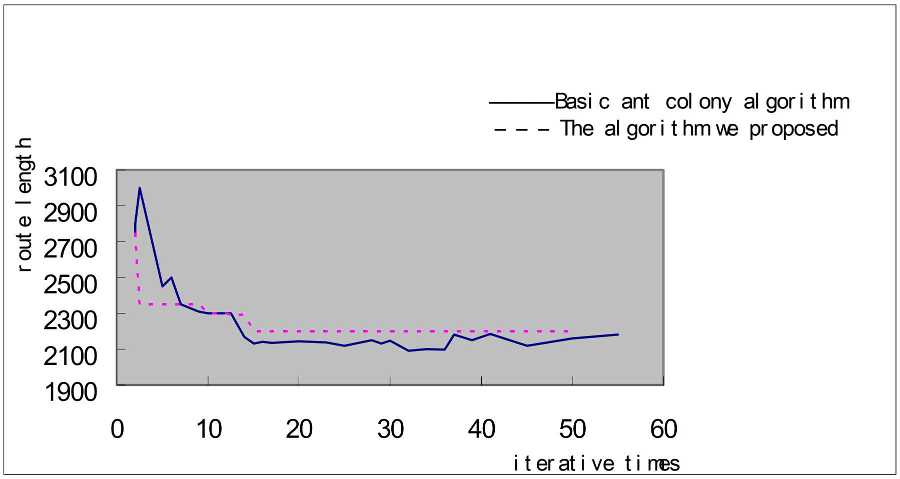

Figure 2: Comparison Of Convergence Of Two Algorithms

Table 2: Economic Indexes Of Every Type In Every Location

	High level dwelling			General resident,			Mansion			Commercial apartments			Manufacturing housing		
	N	I	P	N	I	P	N	I	P	N	I	P	N	I	P
A	44.4	34.7	7.5	15.1	57.0	5.3	70.5	42.0	3.1	43.3	70.0	3.2	6.5	26.0	5.0
B	52.6	67	3.7	6.2	62.0	3.2	44.7	45.0	2.9	52.8	56.0	4.5	12.2	12.0	4.6
C	13.8	40.0	5.6	20.3	39.0	4.5	5.6	27.0	4.6	15.5	48.0	3.9	11.3	37.0	5.2
D	35.6	31.0	6.3	8.7	70.0	5.0	33.9	19.0	5.7	41.3	52.0	3.7	4.4	25.0	3.7
E	25	55	5.1	30.3	57.0	5.3	51.7	36.0	4.8	57.5	18.0	3.0	7.9	40.0	4.3
F	55	47	7.0	12.7	62.0	4.8	53.3	34.0	4.2	62.7	58.0	3.8	17.4	47.0	3.8

5 APPLICATION IN REAL ESTATE PORTFOLIO OPTIMIZATION

The improved algorithm can be employed to solve the real estate portfolio optimization problems. See the example: A real estate development company has six locations (A. B. C. D. E. F) to select in a city. The selectable types are as follows: (1) High level dwelling. (2) General resident. (3) Mansion. (4) Commercial apartments. (5) Manufacturing housing. The economic evaluation index of every type in every location is shown in Table II, suppose the company select only one type in one location and give the scheme of the portfolio.

To solve this problem, we set up the optimization model as follows:

$$\max\ f(x) = (1-\rho)x^T\mathbf{Q}^{+}\boldsymbol{\omega} - \rho x^T\mathbf{Q}^{-}x$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$s.t\begin{cases} Rx^T \geq R_0 \\ x^T\mathbf{I} = 1, x_i \geq 0 \\ \rho \in (0,1) \end{cases} \qquad (4)$$

Where, $f(w)$ is the expected yield of the portfolio. ρ is the risk preference coefficient, $\mathbf{Q}^+$ and $\mathbf{Q}^-$ are the half covariance matrix of profitand

$\mathbf{Q}^- = [COV^-(R_iR_j)]_{n\times n}$,

$$\mathbf{Q}^+ = [COV^+(R_iR_j)]_{n\times n}..$$

x is feature vector of the portfolio ratio $\left(0 \leq x_i \leq 1, \sum_{i=1}^{m} x_i = 1\right)$.

First we calculate the average entropy of every combination, $S_j^{/} = -p_j \ln p_j$, where $S_j^{/}$ is the average entropy of combination j, $P_j = \frac{\Pi_j R_j}{\sum_{k=1}^{m}\Pi_k R_k}$, $R_i = \sum_{j=1}^{n} x_i r_{ij}$, where m is the total number of types and n is the result numbers of profit. Π_j is the probability of profit j , R_i is the profit rate of type i $(i = 1, 2, \cdots, m)$.

Known the $S_j^{/}$, we can employ the improved algorithm proposed in the paper. The $S_j^{/}$ is used as the heuristic average (equal to the distance d_{ij} of TSP) and $\eta_{ij} = \frac{1}{S_{ij}^{/}}$. We used two ants to search and when average entropy $S(t)$ is smaller than 0.01, we stop calculate and got the result. The result is shown in Table III.

The application result demonstrates that the improved algorithm we proposed can reach the global optimal result that meets our requirement. It is effective in solving the real estate portfolio optimization and its calculation is easier.

Table 3: Calculation Results

Results	NPV	IRR	PBP	Investment proportion
Type(1)location B	52.6	67	3.7	21.0
Type(2)location E	30.3	57	5.3	13.4
Type(3)location A	70.5	42	3.1	25.2
Type(4)location F	62.7	58	3.8	21.8
Type(5)location C	11.3	37	5.2	18.6

6 CONCLUSIONS

Portfolio is an import measure of risk management in real estate development. We proposed an improved ant colony optimization algorithm based on average entropy and the simulation study demonstrates that, the strategy of using average entropy to control the route selection and evolution realizes the self adaptively adjusting and avoid the stagnation behavior. The improved algorithm presented in the paper has good convergence and stability. And it can effectively solve the real estate portfolio optimization problem.

ACKNOWLEDGEMENT

This work was supported by the Talents Program of Hebei Province (2011-33).

REFRENCES:

[1] Susan Hudson Wilson, Modern real estate portfolio management, McGraw-Hill Inc., US 2000.

[2] Siwei Cheng, Venture Capital Business in China, Beijing, 2009.

[3] Rui Liu, Xiaoya Wang, "Using elitist particle

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

swarm optimization to facilitate real estate portfolio based on information entropy," Proceedings of 2008 International Conference on Risk Management & Engineering Management, Nanjing, China, June 27-30, 2008, pp. 633-638

[4] Dorigo M., Di Caro, The ant colony optimization meta-heuristic: new ideas in optimization. McGraw-Hill, New York, 1999.

[5] Dorigo M., Maniezzo V., Colorni A., "Ant system: optimization by a colony of cooperating agents", IEEE Trans on SMC, Vol.26, No.1, 1996, pp.28-41.

[6] Fardin Ahmadizar, "A new ant colony algorithm for makespan minimization in permutation flow shops", Computers & Industrial Engineering, Vol. 63, No. 2, 2012, pp.355-361.

[7] K. Thanushkodi, K. Deeba, "Hybrid intelligent algorithm for multiprocessor job scheduling", Scientific Research and Essays, Vol. 30, 2012 pp.1935-1953.

[8] Amin Afshar, Miguel A. Mariño, "Multi-objective coverage-based ACO model for quality monitoring in large water networks", Water Resources Management, Vol. 26, No. 8, 2012, pp.2159-2176.

[9] Mostafa Mashayekhi, Eysa Salajegheh, Javad Salajegheh, Mohammad Javad Fadaee, "Reliability-based topology optimization of double layer grids using a two-stage optimization method", Structural and Multidisciplinary Optimization, Vol. 45, No. 6, 2012, pp.815-833.

[10] Li Yancang and Li Wanqing, "Adaptive ant colony optimization algorithm based on information entropy: foundation and application", Fundamenta Informaticae, Vol. 77, No. 3, 2007, pp. 229-242.