International Journal of Computer Science
Scholarly Peer Reviewed Research Journal - PRESS - OPEN ACCESS
ISSN: 2348-6600

http://www.ijcsjournal.com Volume 5, Issue 1, No 12, 2017 ISSN: 2348-6600
Reference ID: IJCS-211 PAGE NO: 1317-1320

Sri Vasavi College, Erode Self-Finance Wing 3rd February 2017
National Conference on Computer and Communication NCCC'17
http://www.srivasavi.ac.in/ nccc2017@gmail.com

ANT COLONY SYSTEM WITH STATE TRANSITION

Mrs. K. Sathya Sundari
(Ph. D., Part time Category – B
Research & Development Centre,
Bharathiar University, Coimbatore)
Tamil Nadu, India
E-Mail : selvisathika@gmail.com

ABSTRACT- Ant Colony System (AS) is a first member of algorithms inspired by behavior of real ants. Ant System (AS) is being the prototype of a number of ant algorithms, which collectively implement ACO paradigm. ACS makes (i) State transition, (ii) Pheromone updating .

Key Word : AS, ACO

Introduction :AS was initially applied to solve traveling salesman problem. However, it was not able to compete against the state-of-the art algorithms in the field. Authors of AS, on the other hand, have the merit to introduce ACO algorithms and show the potentiality of using artificial pheromone and artificial ants to search of better solutions for complex optimization problems. Then research on AS was carried out in order to achieve the following goals:

- To improve the performance of the algorithm.
- To investigate and better explain the behavior of the algorithm.

Gambardella and Dorigo (1995) proposed an extension of AS called Ant-Q algorithm, which integrates several ideas from Q-learning (Watkins and Dayan 1992). They also proposed Ant Colony System (ACS) (Gambardella and Dorigo 1996, Dorigo and Gambardella 1997b), which is a simplified version of Ant-Q. ACS maintains the same level of performance as Ant-Q algorithm in terms of the complexity and the computational results. The following aspects make ACS to differ from AS: (i) State transition, (ii) Pheromone updating

State transition rule

Ants use state transition rule to select the next state that is to be added to partial solution. ACS employs a transition rule called pseudo-random-proportional, which is a balance between pseudo-random state choice rule used in Q-learning (Watkins and Dayan 1992) and random-proportional action choice rule used in AS. In ACS, an ant selects a state using the biased random choice as in AS during some of the time, whereas the best state is selected during the rest of the time based on the heuristic information and the

International Journal of Computer Science
Scholarly Peer Reviewed Research Journal - PRESS - OPEN ACCESS
ISSN: 2348-6600
http://www.ijcsjournal.com Volume 5, Issue 1, No 12, 2017 ISSN: 2348-6600
Reference ID: IJCS-211 PAGE NO: 1317-1320
Sri Vasavi College, Erode Self-Finance Wing 3rd February 2017
National Conference on Computer and Communication NCCC'17
http://www.srivasavi.ac.in/ nccc2017@gmail.com

pheromone level. Pseudo-random-proportional rule selects the best state with a probability q_0 and selects a random state with a probability $1-q_0$ where q_0 is a constant given as input ranging from 0 to 1. However, all the time, random-proportional rule used in AS selects the next state randomly with a probability distribution, which depends on the heuristic information and the pheromone level. Pseudo-random-proportional state transition rule in ACS provides a way to compromise between exploration of new states and exploitation of the heuristic information and the pheromone level. Hence, pseudo-random-proportional rule uses a state transition rule given in Equation.

$$s = \begin{cases} \underset{j \in S}{Max}\{[\tau(i,j)]^{\alpha}.[\eta(j)]^{\beta}\} & \text{if } q \le q_0 \\ r & \text{otherwise} \end{cases}$$

where $q \in [0,1]$ is a uniform random number and r is a component, which is chosen randomly according to the probability distribution defined by Equation (4.1). The random number q is selected each time an ant moves from a state i to another state j. If the value of q is less than or equal to the value of q_0, the ant will select the best state. Otherwise, the ant will select a biased random state.

Pheromone updating

Once all ants have constructed solutions, AS updates the pheromone trail using all solutions generated by the colony of ants. An amount of pheromone on each edge belonging to one of the computed solutions is modified by an amount, which is proportional to its solution value. AS then evaporates the pheromone of the entire system after construction of solutions by all ants and the process of solution construction and pheromone update are iterated. But ACS updates pheromone value for the edges belonging to the best solution computed since the beginning of the computation and this technique is called global pheromone update. Global pheromone updating technique updates the amount of pheromone on edge (i, j) belonging to the shortest path at a time t by using the pheromone on that edge at the time t-1 as given in Equation.

$$\tau(i,j)_t = \begin{cases} (1-\rho).\tau(i,j)_{t-1} + Q/L_b & \text{if } (i,j) \in \text{Global best path} \\ \tau(i,j)_{t-1} & \text{otherwise} \end{cases}$$

Where ρ is an evaporation co-efficient, Q is a constant whose value is chosen depending upon the problem size and L_b is length of the best path. Amount of pheromone deposited on each edge is inversely proportional to length of the path so as to enable shorter path to get higher amount of pheromone deposited on the edges. Global pheromone updating increases the attractiveness of promising solutions and tries to avoid long time of convergence by directly concentrating search of the best solution found up to the current iteration. ACS also employs a technique called local pheromone updating, which is intended to avoid a strong edge being chosen by all ants. While constructing its path, the local pheromone updating technique

International Journal of Computer Science
Scholarly Peer Reviewed Research Journal - PRESS - OPEN ACCESS
ISSN: 2348-6600

http://www.ijcsjournal.com Volume 5, Issue 1, No 12, 2017 ISSN: 2348-6600
Reference ID: IJCS-211 PAGE NO: 1317-1320

Sri Vasavi College, Erode Self-Finance Wing 3rd February 2017
National Conference on Computer and Communication NCCC'17
http://www.srivasavi.ac.in/ nccc2017@gmail.com

modifies amount of pheromone on the passed edge (i, j) at a time t as given in Equation.

$$\tau(i,\ j)_t = (1-\rho).\tau(i,\ j)_{t-1} + \rho.\tau_0$$

where τ_0 is the initial amount of pheromone deposited on each edge and can be defined as $(n.L_{nn})^{-1}$ (Gambardella and Dorigo 1996), where L_{nn} is length of the path produced by SPT rule. Local pheromone updating modifies pheromone trail on the edges in each time the ant travels through these edges. Local pheromone updating also represents evaporation of the pheromone in natural ants and forgets previous good paths in favor of the new best path.

Structure of basic ant colony optimization algorithm

General structure of ACO algorithm is as follows.

Initialization

Initialize parameters like α, β, ρ, q_0, and Q.

Store a maximum value to the solution.
Calculate initial pheromone value

Construction and Improvement

While termination condition not satisfied do

Construction

For each ant k do
Choose a state i with a probability and add i to partial solution
Update pheromone trial for the current move
End For
Update pheromone trail for the best ant's path
Improve the solution
EndWhile

Output

Print the best solution found.

The algorithm initializes various parameters and assigns a maximum value for the current solution. It also calculates initial pheromone value during the initialization phase. In the construction phase, the algorithm finds a solution and updates the pheromone trial, which is used to improve the solution. The algorithm repeats the construction phase until termination condition is met and finally prints the best solution found.

CONCLUSION :

Behavior of ants to find shortest path has been given. Different ant algorithms have been discussed together with local and global pheromone updating. The key to the application of ACO to a new problem is to identify an appropriate representation for the problem then the probabilistic interaction among the artificial ants mediated by the pheromone trail will generate good, and often optimal, problem solutions. Other problems solved by ACO algorithms include: graph partitioning; subset problems include knapsack problems; Quadratic assignment; graph coloring; vehicle routing; networking routing and many more.

References

1. Dorigo,M. andGambardella, L. (1997). AntColony System: A Cooperative

International Journal of Computer Science
Scholarly Peer Reviewed Research Journal - PRESS - OPEN ACCESS
ISSN: 2348-6600
http://www.ijcsjournal.com Volume 5, Issue 1, No 12, 2017 ISSN: 2348-6600
Reference ID: IJCS-211 PAGE NO: 1317-1320
Sri Vasavi College, Erode Self-Finance Wing 3rd February 2017
National Conference on Computer and Communication NCCC'17
http://www.srivasavi.ac.in/ nccc2017@gmail.com

Learning Approach to the Traveling Salesman Problem.

2. Dorigo, M., Maniezzo, V., and Colorni, A. (1996). The Ant System: Optimization by a Colony of Cooperating Agents.
3. Dorigo et al (1991). Ant Colony System: Cooperative Learning Approach to the Traveling Salesman Problem.
4. Colorni, A., Dorigo,M., Maniezzo, V., and Trubian,M. (1994). Ant System for Job-Shop Scheduling. Belgian Journal of Operations Research, Statistics and Computer Science, 34(1):39–53.
5. Watkins and Dayan 1992. Ant Colony System:Q-Learning.
6. Gambardella and Dorigo (1995), The Ant System: Optimization by a Colony of Cooperating Agents
7. Reinelt 1994. Data structure Learning Approach to the Traveling Salesman Problem.