A HETEROGENEOUS ANT COLONY OPTIMIZATION WITH TRAVELING SALESMAN PROBLEM

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ABSTRACT

The **Ant colony optimization algorithm (ACO)** is a probabilistic technique for solving computational problems which can be reduced to solve finding good paths through graphs. The majority of research in ACO focuses on homogeneous ants although animal behaviour research suggests that heterogeneity in behaviour improves the overall efficiency of ant colonies.This algorithm is a member of the ant colony algorithms family, in swarm intelligence methods, and it constitutes some metaheuristic optimizations. Initially proposed by Marco Dorigo in 1992 in his PhD thesis, the first algorithm was aiming to search for an optimal path in a graph, based on the behavior of ants seeking a path between their colony and a source of food.

Ant colony optimization (ACO) has been widely used for different combinatorial optimization problems. In this paper, we investigate Heterogeneous ACO with respect to their runtime behavior for the Min Max Ant System Algorithm. Here we present MAX –MIN Ant System (MMAS), an Ant Colony Optimization algorithm derived from Ant System. MMAS differs from Ant System in several important aspects, whose usefulness we demonstrate by means of an experimental study. Our computational results show that MMAS is currently among the best performing algorithms for path problems.

KEYWORDS

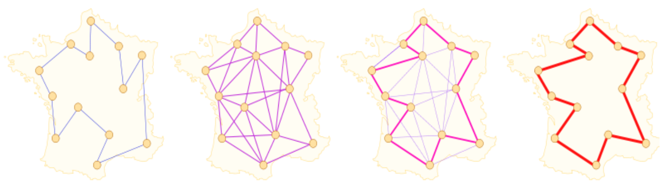
Ant Colony Optimization (ACO), Heterogeneous ACO, Networks Routing, Optimal Path.

1. INTRODUCTION

Heterogeneous Ant Colony Optimization Approach:

Heterogeneity in swarm intelligence was firstly described in Particle Swarm Optimization (PSO) by Engel brecht in who proposed that introduction of heterogeneity in a search algorithm can improve the performance. This concept can also be adopted in ACO where artificial ants with different traits of behaviour can help to improve the performance of the ACO algorithm. This mimics the actual behaviour of real ants in a colony in terms of diversity and division of labour. Heterogeneity in ACO can be grouped into individual and colony level. Artificial ants with different behaviours among them is said to be heterogeneous at the individual level while colonies of ants that differ in behaviour between the colonies is said to be the latter. Heterogeneous individual ants in ACO were first introduced by where the authors used modified ACO with heterogeneity for path planning in mobile robots in order to find obstacle-free path in a certain environment.

The author deployed ants with different sight, speed and function behaviours and found that the performance of Heterogeneous ACO (HACO) is better in terms of path planning when compared to conventional ACO. Chira et al. discussed the different sensitivity of the artificial ants to the pheromone trail level in. Ants with higher pheromone sensitivity strongly follow the pheromone trail while ants with lower pheromone sensitivity are more inclined towards random search. In the meantime, Hara et al. proposed the use of classic and exploratory ants where each ant constructs a partial solution which is then combined to produce one single solution. Yoshikawa et al. introduces a cranky ant approach to tackle the exploration-exploitation problem which appears to prevent the algorithm from being stuck in local optima.



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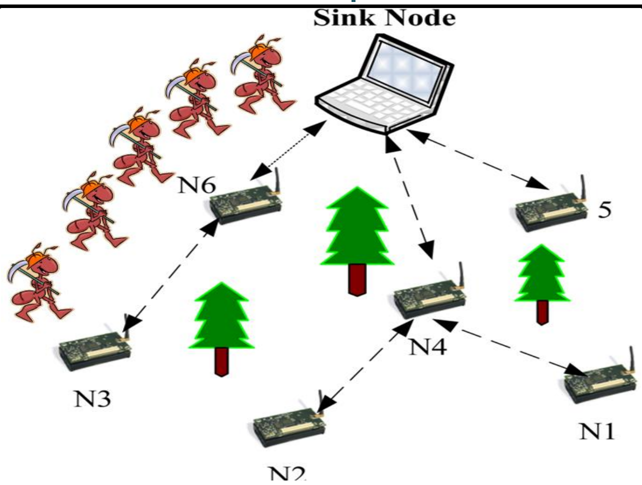

Fig.1.1 scheduling problem need ACO

The cranky ants will explore paths with low pheromone level which is the opposite of the behaviour of standard artificial ant. Meanwhile, Zhang et al. Proposed colony level heterogeneity where ant colonies have different pheromone updating rules in order to balance exploration and exploitation in the search process. The authors proposed two colonies where each exhibits behaviour of Elitist Ant System (EAS) and Ant Colony System (ACS) characteristics respectively. They discussed that the algorithm overcomes stagnation and the early suboptimal H-ACO: A Heterogeneous ACO for TSP 147 path convergence problem. Melo et al. Proposed a multi-caste ant colony in Ant Colony System (ACS) where ants with different preference towards q0, parameter that controls the degree of exploration or exploitation in ACS.

Many more approaches implement heterogeneity at the colony level, but as this paper study and implementation at individual level, thus colony level heterogeneity will not be discussed in detail here. Each of these algorithms approach the principle of heterogeneity from a different standpoint, either using different ant roles or through the implementation of problem specific heterogeneity. The approach taken in this paper is one of biological plausibility for ants with similar roles, but differing behavioural traits, which would normally be expressed through genetic differences, but here are drawn from a distribution.

The majority of research in ACO focuses on homogeneous ants although animal behaviour research suggests that heterogeneity in behaviour improves the overall efficiency of ant colonies. This introduces and analyses the effects of Heterogeneity of behavioural traits in ACO to solve hard optimisation problems by introducing unique biases towards the pheromone trail and local heuristics for each ant. The well-known Ant System (AS) and Max-Min Ant System (MMAS) are used as the base algorithms to implement heterogeneity and experiments show that this method improves the performance when applied on Travelling Salesman Problem (TSP) instances particularly for larger instances.

In this research project, we investigate the influence of each ant having different behavioural characteristics or traits in contrast to standard ACO where all ants have the same behavioural traits. In the proposed **Heterogeneous approach**, each ant has individual pheromone (α) and heuristics coefficients (β) where both α and β are parameters that control the relative importance of the pheromone trail and local heuristics used in transition probability. It is known that too much emphasis on pheromone trail or local heuristics may hinder the performance of the algorithm through over exploration or exploitation. Hence the proposed method can overcome the exploration-exploitation problem thus improving the performance of ACO. The heterogeneous approach implemented in this study stems from the actual behaviour of social insects which are heterogeneous in nature, displaying different traits and in some circumstances behavioural roles within a colony. The optimal solution for choosing the best shortest path is to select the one with the smallest total cost (i.e., distances, time-spent) [8].

The first ant algorithm was introduced by Dorigo et al. [1] in 1991 and was called the Ant System (AS) [1] [2]. Dorigo and Gambardella proposed the Ant Colony System (ACS) [4][5] later in 1996, while Stützle and Hoos proposed the MAX -MIN Ant System (MMAS) [3]. ACO has drawn much research attention and various extended versions of the ACO paradigm were proposed, such as the Best-Worst Ant System (BWAS) [8], the Rank based Ant System (RAS) [7] etc..

The main novel idea of ants with memory algorithm, to be discussed in the remainder of the paper, is the synergistic use of the previous best solution constructed by ants.

This paper is organized as follows: In section 2, we introduce the background knowledge of the TSP, AS and ACS. In section 3, we provide definition of the parameters and environment of the experiments. In section 4, we explain what ants with memory are and simulated them in ACS. In section 5 we amend the ants with memory, and then we show the results of the experiments which were generated by amended ants and compare the performance of each algorithm. Finally, in section 6, we are dedicated to discuss the main characters of ants with memory and suggesting directions for further research.

2. BACKGROUND

2.1 TRAVELING SALESMAN PROBLEM

TSP is one of the most widely known NP-hard problems. In the TSP we are given a set of cities ci,cj,…cN and the distances d(ci,cj) for each pair of distinct cities (ci,c j). The salesman has to visit every city once and only once, and return to the starting city in the end. Our goal is to find a closed tour with minimal cost. In this paper, we concentrate on the symmetric TSP, where d(ci,cj)= d(cj,ci) for 1≤i,j≤N.

Fig.2.1 The Traveling Salesman Problem

2.2 ANT SYSTEM

In origin AS [1] [2], all the m ants which have constructed a solution in the loop can update the pheromone. The value of pheromone τ_{ij} which

Contacted with the edge ij between city i and city j updated with the following formula:

$$\tau_{ij} = (1-\rho)\tau_{ij} + \sum_{k=1}^{M} \tau_{ij}^{k} \qquad (1)$$

The parameter ρ is the pheromone evaporate rate，m is the number of ants, τ_{ij}^{k} is the quantity of the pheromone left on edge (i,j) by ant k：

$$\tau_{ij}^{k} = \begin{cases} Q/L_k & \text{edge (i,j) in ant k`s tour} \\ 0 & \text{Otherwise} \end{cases} \qquad (2)$$

Where Q is a constantly is the length of the tour which constructed by ant k in the current loop.

During constructing process, ants will visit the following city through a stochastic mechanism While an ant locating in city i has constructed the partial solution, the probability of move to city j is given by(3)：

$$p_{ij}^{k} = \frac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{c_{il} \in N(s^p)} \tau_{il}^{\alpha} \cdot \eta_{il}^{\beta}} \quad \text{if } c_{ij} \in N(s^p) \qquad (3)$$

0 o therwise

The parameter $N(s^p)$ here is aset of suitable

Elements. In another word, it is a set of edges (i,l) here the parameter l means the city not visited by ant k. The parameters α and β contact with the importance between pheromone and the heuristic information which was given by (4)：

$$\eta_{ij} = 1/ d_{ij} \qquad (4)$$

Where the parameter d_{ij} shows the distance between city i and j.

2.3 ANT COLONY SYSTEM

One major difference between the ACS [4-6] and the AS is that the ACS introduces Local Pheromone Update into the algorithm at the end of each step of the construction, also known as offline pheromone update. And only when every ant explored the last edge of its tour the algorithm updates the pheromone as:

$$\tau_{ij} = (1-\phi)\cdot\tau_{ij} + \phi\cdot\tau_0 \qquad (5)$$

Here $\phi \in (0,1]$ is the parameter about the pheromone

decay rate, the τ_0, which is defined as $\tau_0 = (L_{nn})^{-1}$,

Initializes the value of pheromone [4][5].

The local pheromone update gives the algorithm a character by decreasing the pheromone values on the visited edges, subsequent ants can be encouraged to explore other edges so that new different solutions might be found with greater probabilities.

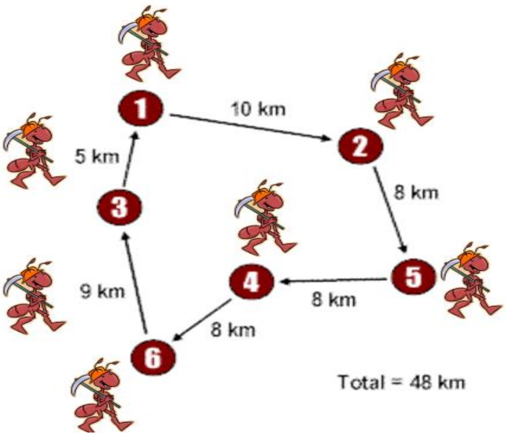

Fig2.3.1 ACO apply in TSP

The offline pheromone update only executed by the last ant at the end of each iteration, called iteration-best or best-so-far. But there still a little different between them as formula (6) shows:

$(1-\rho)\cdot\tau_{ij} + \rho\ \Delta\tau_{ij}$ (i,j)

belongs to best tour,

$\tau_{ij} = \{$

τ_{ij} otherwise. (6)

Here $\tau_{ij} = 1 / L_{best}$, L best could be Lib

There is another important difference between the ACS and the AS while using decision rule by ants. In the ACS, ants use so called pseudorandom proportional rule [4][5], the probability of an ant move from the city i to the city j was determined by a parameter q_0 and a random variable q which is uniformly distributed over[0,1]:

$$j = \begin{cases} \arg\max_{c_{il}\in N(s^p)} \{\tau_{il}\eta_{il}^{\beta}\} & \text{if } q \le q_0 \text{ (Exploitation)} \\ \text{use formular (3)} & \text{otherwise(Exploration)} \end{cases} \quad (7)$$

3 ACO ALGORITHMS FOR SOLVING NETWORKS ROUTING PROBLEM

The proposed H-ACO approach technique for shortest path routing is illustrated in the block diagram shown in Figure (1), which describes the main procedures of the system.

4 GENERAL CHARACTERISTICS OF H-ACO FOR ROUTING

The following set of core properties characterizes ACO instances for routing problems [1], [5], [7], [9]:

[1] Provide traffic-adaptive and multipath routing.

[2] Rely on both passive and active information monitoring and gathering.

[3] Make use of stochastic components.

[4] Do not allow local estimates to have global impact.

[5] Set up paths in a less selfish way than impure shortest path schemes favoring load balancing.

5 OBJECTIVE OF RESEARCH

This research aims at: using Heterogeneous-ACO approach using MMAS and AS algorithm to find the optimal path from source node to destination node in networks.

6 TOOLS AND SCOPE OF RESEARCH

[1] Algorithm: Heterogeneous Ant Colony Optimization

[2] Software: Network Simulator 2

[3] Case study: 9 states of different size networks (10, 15, 20, 25, 30, 40, 50, 60, 75).

7 SNAP SHOTS

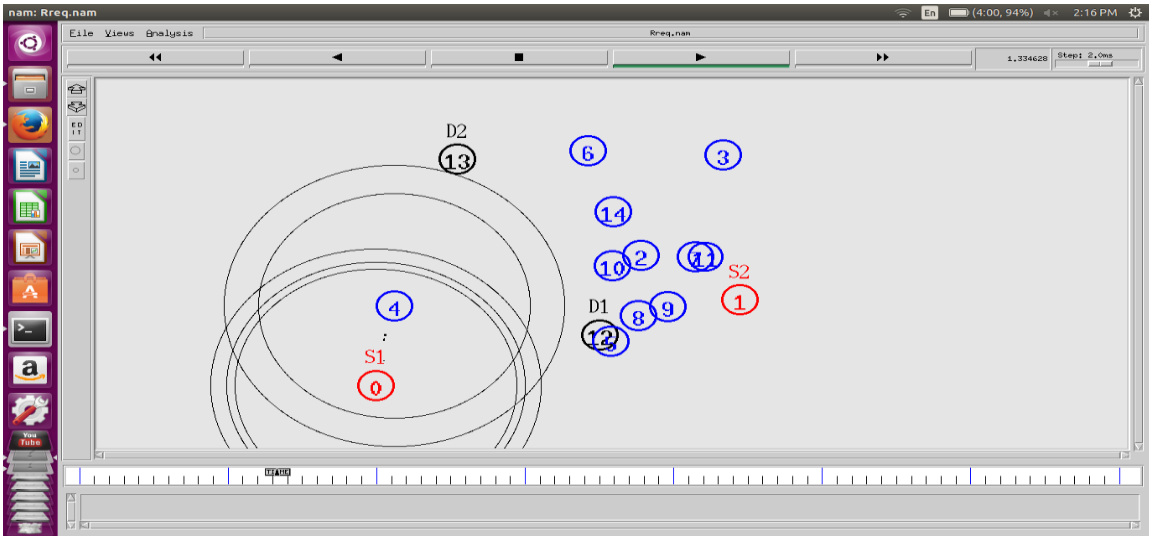

Figure No. 7.1 Establish TCP connection- Here the source nodes are establishing the TCP connection between the nodes to start transmission of packets

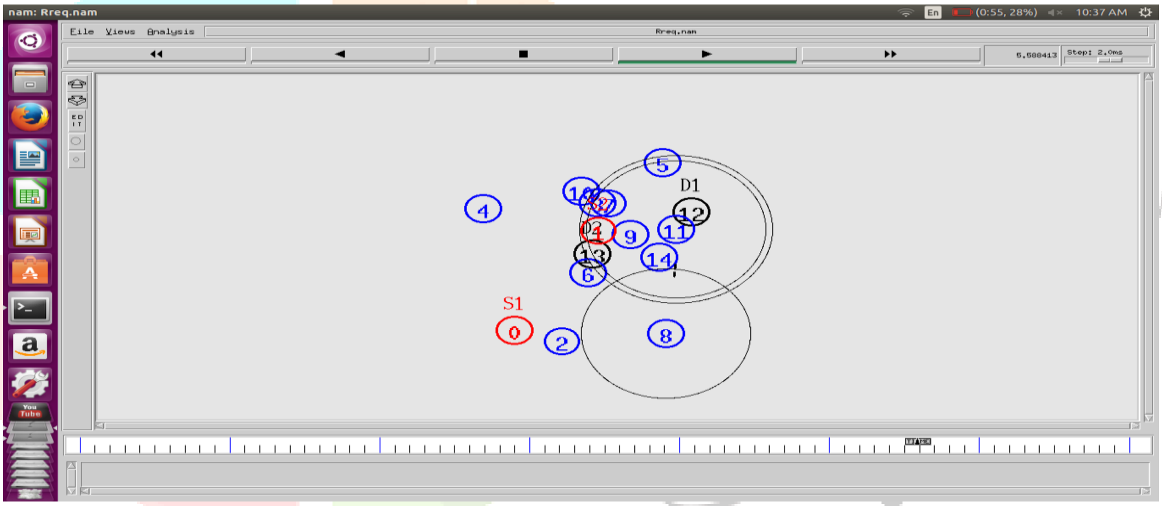

Figure No.7.2 Packet on destination- finally data packets reach to their destination before the hop count

8 CONCLUSIONS

The proposed Heterogeneous-ACO approach using MMAS and AS algorithm is presented in this work to solve the routing problem. When the size of information transmitted over the network is increased there is a need to send it via shortest path in higher speed. Therefore, H-ACO algorithm is utilized to find the optimal solution (i.e., shortest path) to send information from source to destination passing through all nodes .According to the obtained results from the case studies, the proposed algorithm prove its success fullness for solving the routing problem with least computational time.

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