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Ant colony optimization: Artificial Ants as a technique of intelligence computation

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Abstract: Ant colonies, and more generally social insect societies, are distributed systems that, in spite of the simplicity of their individuals, present a highly structured social organization. As a result of this organization, ant colonies can accomplish complex tasks that in some cases far exceed the individual capabilities of a single ant. The field of ''ant algorithms'' studies models derived from the observation of real ants' behaviour, and uses these models as a source of inspiration for the design of novel algorithms for the solution of optimization and distributed control problems. The main idea is that the self-organizing principles which allow the highly coordinated behaviour of real ants can be exploited to coordinate populations of artificial agents that collaborate to solve computational problems. Several different aspects of the behaviour of ant colonies have inspired different kinds of ant algorithms. Examples are foraging, division of labour, brood sorting, and cooperative transport. In all these examples, ants coordinate their activities via stigmergy, a form of indirect communication mediated by modifications of the environment. For example, a foraging ant deposits a chemical on the ground which increases the probability that other ants will follow the same path. Biologists have shown that many colony-level behaviours observed in social insects can be explained via rather simple models in which only stigmergic communication is present. In other words, biologists have shown that it is often sufficient to consider stigmergic, indirect communication to explain how social insects can achieve self-organization. The idea behind ant algorithms is then to use a form of artificial stigmergy to coordinate societies of artificial agents. One of the most successful examples of ant algorithms is known as ''ant colony optimization,'' or ACO, and is the subject of this work. ACO is inspired by the foraging behaviour of ant colonies, and targets discrete optimization problems. This work describes how real ants have inspired the definition of artificial ants that can solve discrete optimization problems.

Keywords: Antnet; routing algorithm; antsim; Ants-based algorithm.

1 INTRODUCTION

The visual perceptive faculty of many ant species is only rudimentarily developed and there are ant species that are completely blind. In fact, an important insight of early research on ants' behavior was that most of the communication among individuals, or between individuals and the environment, is based on the use of chemicals produced by the ants. These chemicals are called pheromones. This is different from, for example, what happens in humans and in other higher species, whose most important senses are visual or acoustic. Particularly important for the social life of some ant species is the trail pheromone. Trail pheromone is a specific type of pheromone that some ant species, such as Lasius niger or the Argentine ant Iridomyrmex humilis (Goss, Aron, Deneubourg, & Pasteels, 1989), use for marking paths on the ground, for example, paths from food sources to the nest. By sensing pheromone trails foragers can follow the path to food discovered by other ants. This collective trail-laying and trail-following behavior whereby an ant is influenced by a chemical trail left by other ants is the inspiring source of ACO. This chapter presents an overview of ant colony optimization (ACO) {a metaheuristic inspired by the behavior of real ants. ACO was proposed by Dorigo and colleagues as a method for solving hard combinatorial optimization problems. ACO algorithms may be considered to be part of swarm intelligence, that is, the research field that studies algorithms inspired by the observation of the behavior of swarms. Swarm intelligence algorithms are made up of simple individuals that cooperate through self-organization, that is, without any form of central control over the swarm members. A detailed overview of the self-organization principles exploited by these algorithms, as well as examples from biology. Many swarm intelligence algorithms have been proposed in the literature

II. ANT COLONY OPTIMIZATION

Some of the combinatorial optimization problems are difficult to solve optimally in polynomial computational time. Metaheuristic is an alternative to solve this kind of problems by using approximate methods that try to improve a candidate solution with problem-specific heuristic. Metaheuristics give a reasonably good solution in a short time, although they do not guarantee an optimal solution is ever found. Many metaheuristic implement some stochastic optimization. For example, greedy heuristic can be used to build the solution, which is constructed by taking the best action that improves the partial solution under construction. However, these heuristic methods produce a very limited variety of solutions, and they can easily get trapped in local optima. There are metaheuristic methods proposed to solve these problems; e.g. simulate annealing that guides local search heuristic to escape local optima (Dorigo & Stützle, 2004). A metaheuristic is a general framework that guides a problem specific heuristic.

In the Ant Colony Optimization, ants use heuristic information, which is available in many problems, and pheromone that they deposit along paths which guides them towards the most promising solutions. The most important feature of the ACO metaheuristic is that the ants search experience can be used by the colony as the collective experience in the form of pheromone trails on the paths, and a better solution will emerge as a result of cooperation.

The basic principle of the ACO algorithm is graphically shown in Figure 1. The principle works as follows: first, a finite set of solution components has to be derived to construct solutions to the combinatorial optimization (CO) problem. Secondly, the pheromone model, which is a set of pheromone values, has to be defined. This set of values is used to parameterize the probabilistic model. The pheromone values ∈ are usually associated with solution components. The ACO approach solves iteratively the optimization problems in two steps:

- candidate solutions are constructed using probability distribution from a pheromone model;
- the candidate solutions are used to bias the sampling by modifying the pheromone value in order to obtain high-quality solutions.

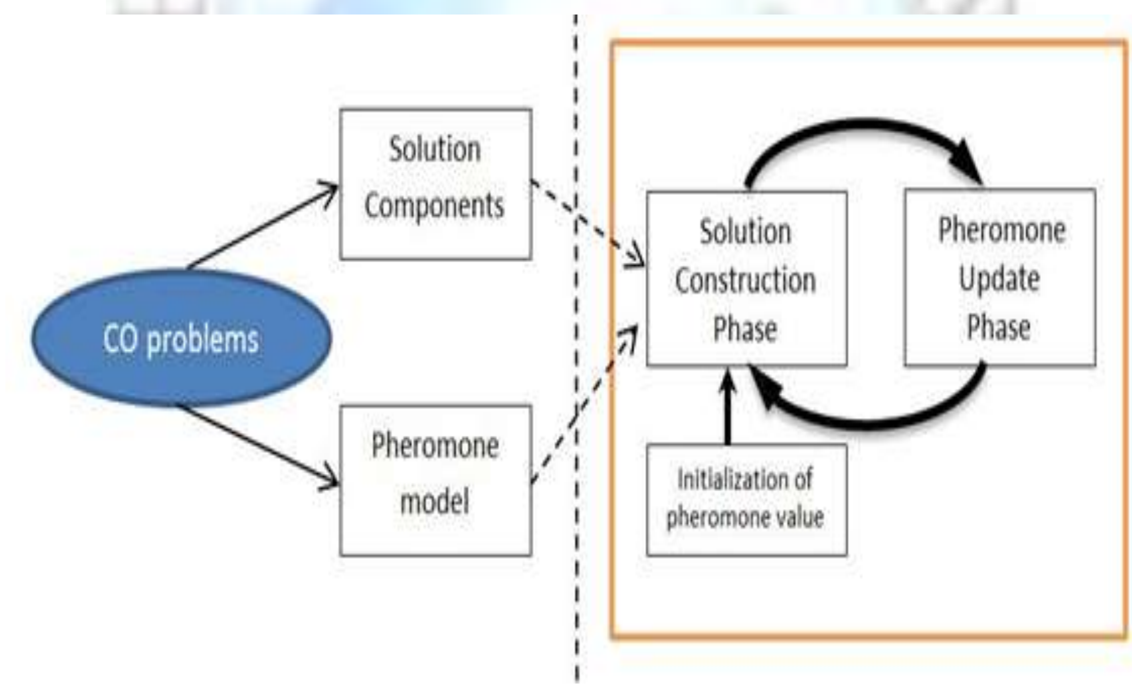

Figure 1: Basic principle of AC

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III ARTIFICIAL ANT

Construction Phase

Artificial ants construct solutions from a sequence of solution components taken from a finite set of available solution components = c= { c_1, c_2, … , c_n }. A solution construction starts with an empty partial solution $s^p = \emptyset$. Then, at each construction step, the current partial solution is extended by adding a feasible solution component from the set $(Sp) \in C \backslash Sp$, which is defined by the solution construction mechanism. The process of constructing graph = GC = $(\boldsymbol{V}, \boldsymbol{E})$ the set of solution C components may be associated either with the set V of vertices of the graph GC, or with the set $\boldsymbol{E}$ of its edges. The allowed paths GC are implicitly defined by a solution construction mechanism that defines the set (Sp) with respect to a partial solution. The choice of solution component from (Sp) is done probabilistically at each construction step. The exact rules for probabilistic choice of solution components vary across different variants of ACO.

In the example of Ant System (AS) applied to TSP the solution construction mechanism restricted the set of traversable edges to the ones that connected the ants' current node to unvisited nodes. The choice of solution component from ( ) is at each construction step performed probabilistically with respect to the pheromone model. In most ACO algorithms the respective probabilities – also called transition probabilities.

IV ROUTING

Routing in ACO is achieved by transmitting ants rather than routing tables or by flooding LSPs. Even though it is noted that the size of an ant may vary in different systems/implementations, depending on their functions and applications, in general, the size of ants is relatively small, in the order of 6 bytes[i]. This is because ants are generally very simple agents. The following table summarizes the differences between ACO and traditional routing algorithms. In OSPF, routing is achieved by having each node transmit a link-state packet (LSP) to every other node in a network through a flooding processing. Although an LSP, which carries information about the costs to all the neighbours of a node, is generally smaller than a routing table, the flooding process ensures that every node receives a copy of the LSP. Since an LSP from a node can be disseminated via different paths to other nodes, multiple identical copies of the same LSP may be transmitted to the same node.

V RESULTS

ACO algorithms are complex systems whose behavior is determined by the interaction of many components such as parameters, macroscopic algorithm components (e.g., the form of the probabilistic rule used by ants to build solutions, or the type of pheromone update rule used), and problem characteristics. Because of this, it is very difficult to predict their performance when they are applied to the solution of a novel problem. Recently, researchers have started to try to understand ACO algorithm behavior by two typical approaches of science:

1. the study of the complex system under consideration in controlled and simplified experimental conditions, and
2. The study of the conditions under which the performance of the studied system degrades. Contributions along these two lines of research are briefly discussed in the following.

- Study of ACO in Controlled and Simplified Experimental Conditions
- The analysis of ACO algorithm behavior on simple problems is interesting because the behavior of the algorithm is not obscured by factors due to the complexity of the problem itself.

A first such analysis was presented in chapter 1 (see also Dorigo & Stufftzle, 2001), where Simple-ACO was applied to the problem of finding the shortest path in a graph. The experimental results show that many algorithm components, which are essential to more advanced ACO models applied to challenging tasks, are also important for efficiently finding shortest paths. In a similar vein, Merkle & Middendorf (2003b) apply ACO to the linear assignment problem, a permutation problem that is solvable in polynomial time (Papadimitriou & Steiglitz, 1982). By varying the cost matrix, they are able to generate classes of instances that dier in the number and structure of the optimal solutions.

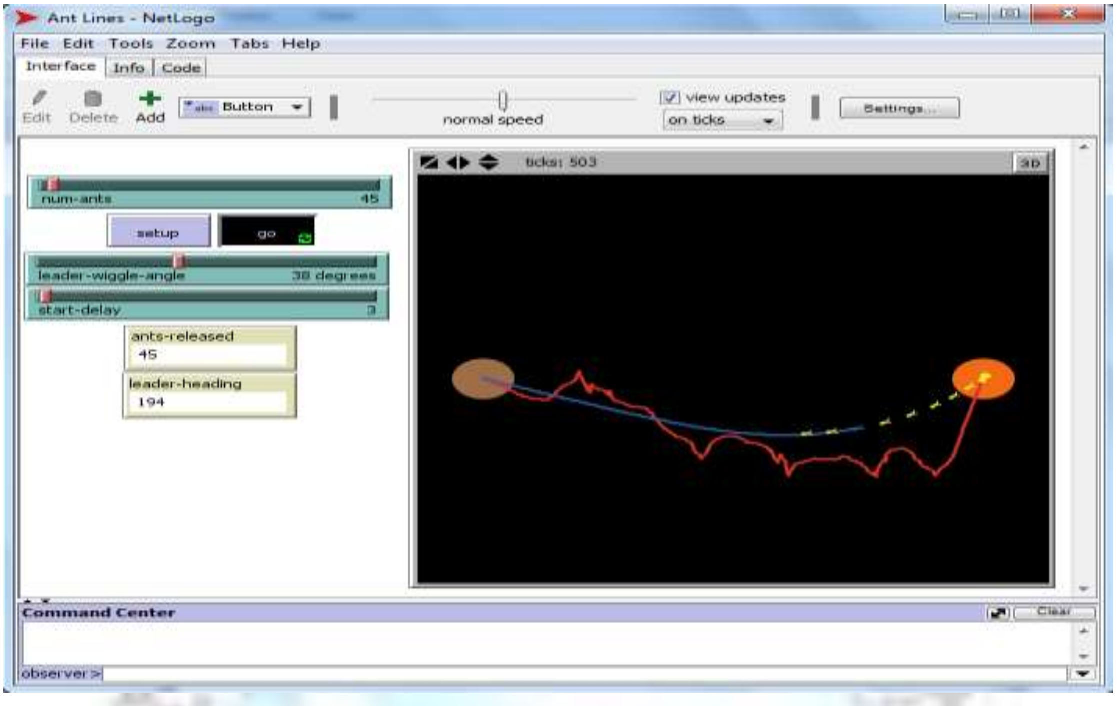

Fig. 2: Optimum path Searching by ANT in Netlogo Simulator

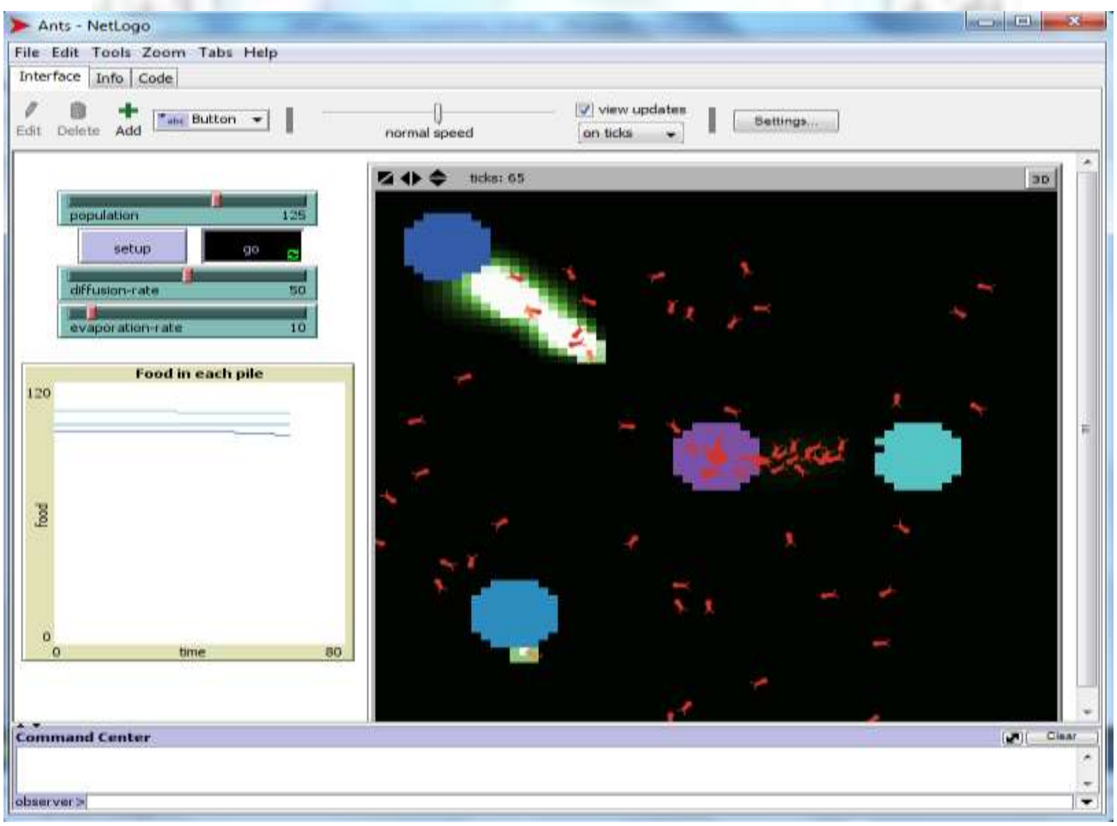

Fig. 3: Optimum path searching by ANT for food in NetLogo

A Application based ACO in shortest path searching in RIP (Routing Information Protocol) in Matlab

Tour Path solved by ACO N=48

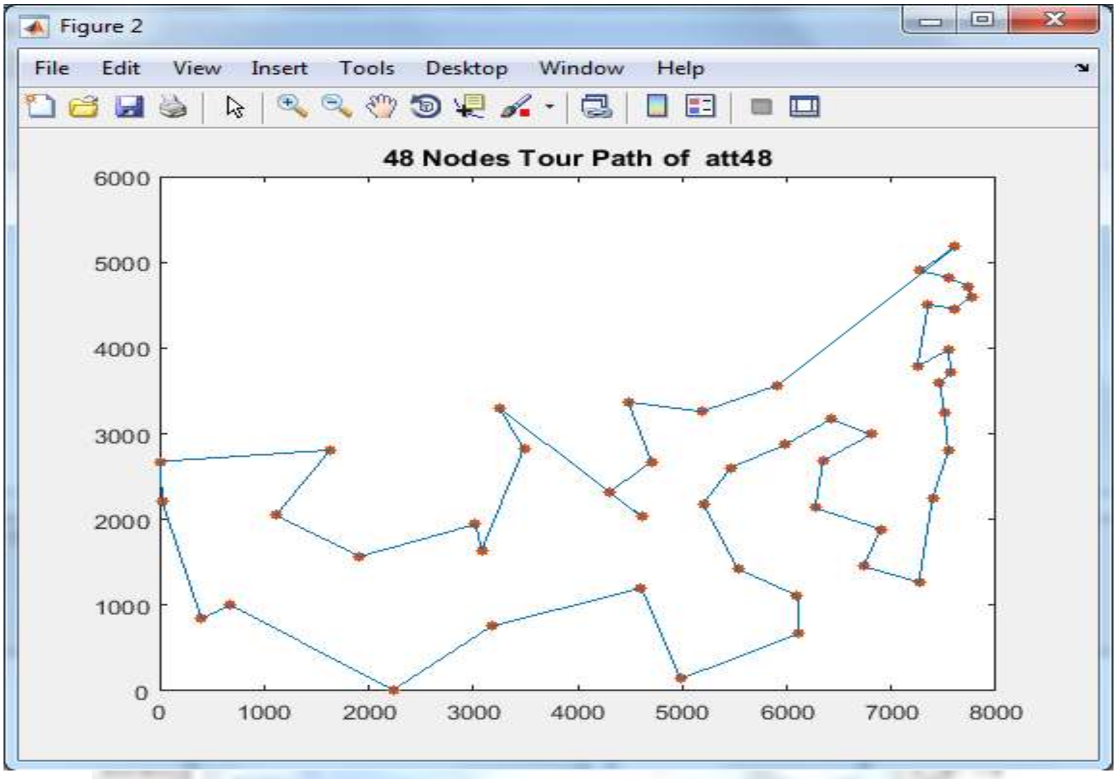

Figure 4: 48 Node tour Path

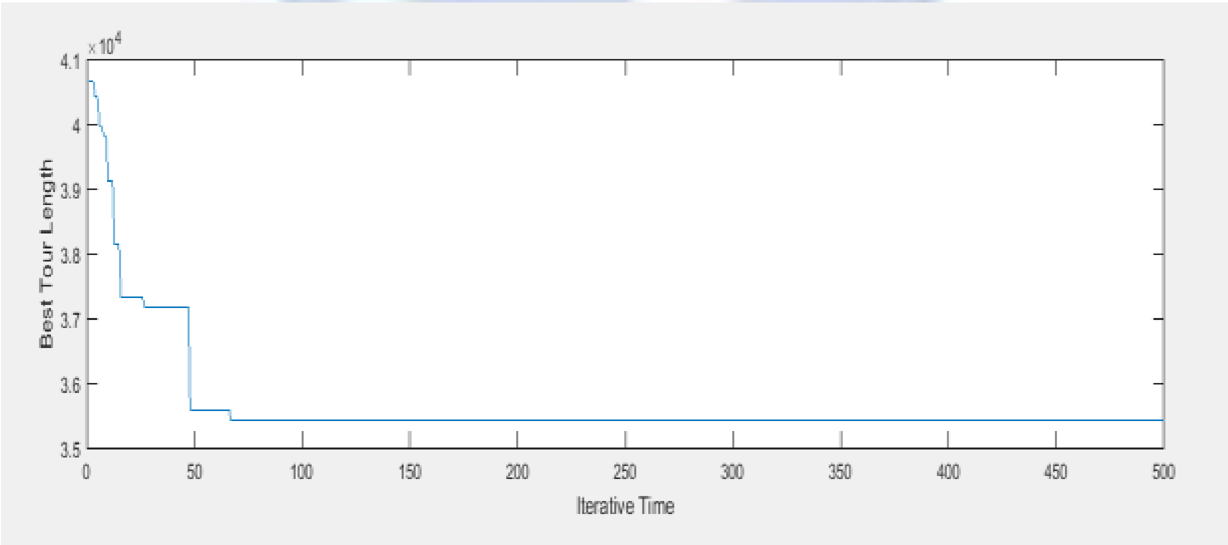

Figure 5: Best Tour Length vs Iteration Time

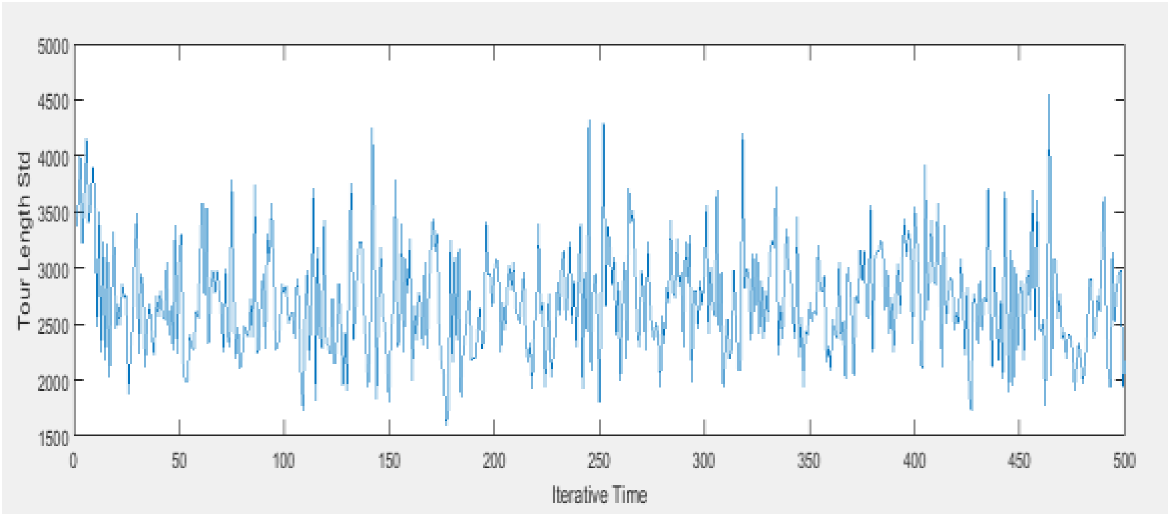

Figure 6 : Tour Length Standard vs Iteration time

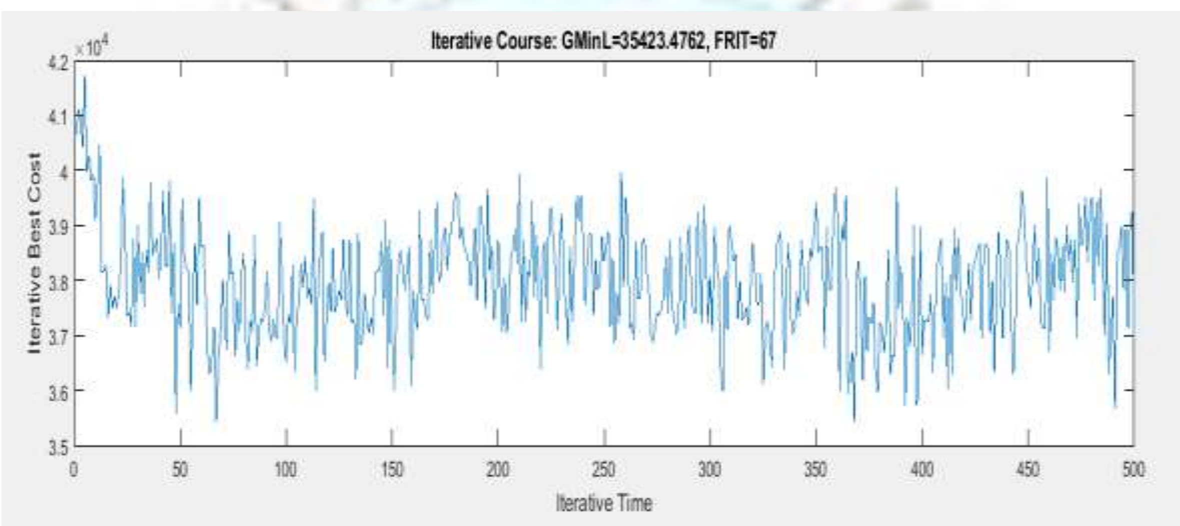

Figure 7 : Iteration Best Cost Vs Iteration Time

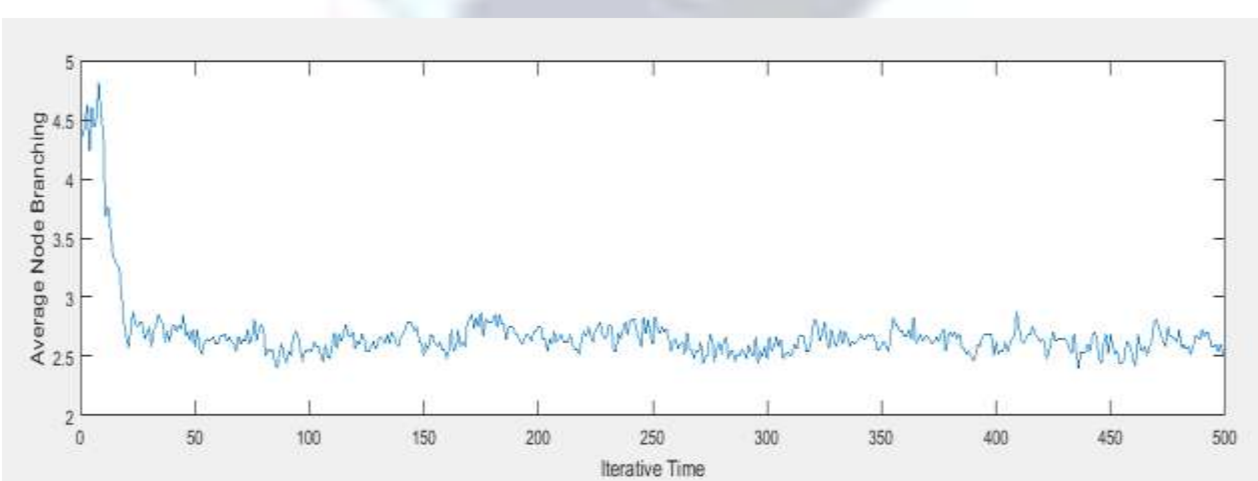

Figure 8: Average Node Branching Vs Iteration time

CONCLUSION

I hope this report gave you a good understanding of the ACO and therefore, entire satisfaction. Implementing prospect theory in the ACO for tackling continuous constrained problems can be a challenge. Also, the use of prospect theory could be investigated in the real time application of ACO in the mobile robot path planning where the robot interacts with the environment. When algorithms inspired by the behaviour of ants to solve the optimization problems were first introduced in the early 90s it seemed questionable. Since many results from ACO research have shown successful applications the perspective has changed and now they are considered one of the most promising approaches (Dorigo, Birattari & Stützle, 2006). The use of human behaviour in ACO was also questionable, so a better understanding of the theoretical properties is certainly another research direction that will be pursued in the future in order to obtain more fundamental properties of ACO-PT algorithms.

1. Ant foraging with Antsim is not the only social insect behavior that has inspired computer scientists and roboticists.

2. This project tried to cover the state-of-the-art studies about Ant Colony Optimisation (ACO) algorithm and its application to routing protocols. It covers recent thesis reports and introduces the latest developed protocols based on ACO.

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