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# An analytical Survey on Ant colony optimization for routing protocol antsim

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**Abstract: This paper introduces Ant Net, a new routing algorithm for communications networks. Ant Net is an adaptive, distributed, mobile-agents-based algorithm which was inspired by recent work on the ant metaphor. Ant Net has been applied to a datagram network and been compared with both static and adaptative state-of-the-art routing algorithm. In Ant Net, each artificial ant builds a path from its source to its destination node. While building the path, it collects explicit information about the time length of the path components and implicit information about the load status of the network. This information is back-propagated by another and moving in the opposite direction and is used to modify the routing tables of visited nodes. Ant Net show extraordinary results for heavy traffic situation and score absolute performance when internal parameters have been tuned. However, the effectiveness is very sensitive to these parameters. The purpose of this project is to provide a clear understanting of the Ants-based algorithm, by giving a formal and comprehensive systematization of the subject. The simulation developed in matlab and antsim will be a support of a deeper analysis of the factors of the algorithm, its potentialities and its limitations. Then the state-of-the-arts utilisation of this algorithm and its implementations in routing algorithms, mostly for mobile ad hoc networks, will be explained. Results of recent studies will be given and resume the current employments of this great algorithm inspired by the Nature**

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

## I. INTRODUCTION

Ant as a single individual has a very limited effectiveness. But as a part of a well-organised colony, it becomes one powerful agent, working for the development of the colony. The ant lives for the colony and exists only as a part of it. Ant colonies are sometimes described as superorganism because it appears to operate as a unified entity. Each ant is able to communicate, learn, cooperate, and all together they are capable of develop themselves and colonise a large area. They manage such great successes by increasing the number of individuals and being exceptionally well organised. The self organising principles they are using allow a highly coordinated behaviour of the colony, furthermore bring them to accomplish complex tasks, whose difficulty far exceed the individual capabilities of a single ant. Pierre Paul Grassé, a French entomologist, was one of the first researchers who investigate the social behaviour of insects. He discovered[i] that these insects are capable to react to what he called “significant stimuli," signals that activate a genetically encoded reaction. He observed that the effects of these reactions can act as new significant stimuli for both the insect that produced them and for the other insects in the colony. Grassé used the term stigmergy to describe this particular type of indirect communication in which “the workers are stimulated by the performance they have achieved”. Stigmergy is defined as a method of indirect communication in a self-organizing emergent system where its individual parts communicate with one another by modifying their local environment.

Ants communicate to one another by laying down pheromones along their trails, so where ants go within and around their ant colony is a stigmergic system. Similar phenomena can be observed for some animals, such as termites, which use pheromones to build their very complex nests by following a simple decentralized rule set. Each insect scoops up a 'mudball' or similar material from its environment, invests the ball with pheromones, and deposits it on the ground. Termites are attracted to their nestmates' pheromones and are therefore more likely to drop their own mudballs near their neighbors'. Over time this leads to the construction of pillars, arches, tunnels and chambers.

In many ant species, ants walking from or to a food source, deposit on the ground a substance called pheromone. Other ants are able to smell this pheromone, and its presence influences the choice of their path, that is, they tend to follow strong pheromone concentrations. The pheromone deposited on the ground forms a pheromone trail, which allows the ants to find good sources of food that have been previously identified by other ants. Using random walks and pheromones within a ground containing one nest and one food source, the ants will leave the nest, find the food and come back to the nest. After some time, the way being used by the ants will converge to the shortest path

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## II. THE DOUBLE BRIDGE EXPERIMENT

The ants begin by walking randomly. They cannot see the ground and have a very limited view of what is around them. Therefore, if the ground has not been explored yet, they will just wander and take random decision at each crossroads. After a while, the places around the nest will be all explored. The ants will get to know that by the marking done by the previous ants. Indeed, they will leave behind them the famous pheromones and inform the other ants that the way is already explored.

**Figure 1 : Picture of ants**

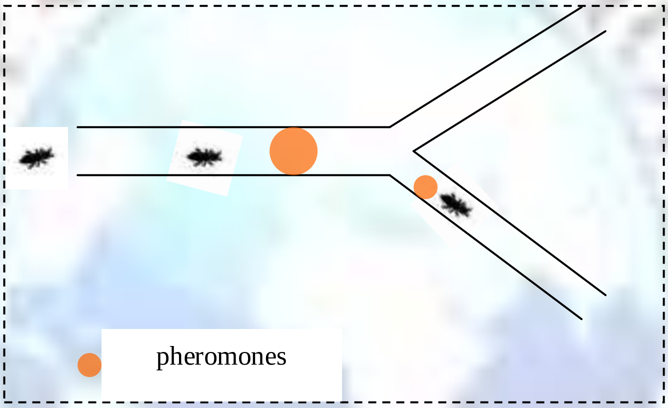


**Figure 2: Ants and pheromones**

The concentration of pheromones depends on the number of ants who took the way, the more ants taking the way, the more pheromones. Deneubourg et al. verified the pheromones marking of ants by the experience known as "double bridge experiment"[ii]. The configuration is as shown in figure 1.2: the nest of a colony of ants is connected to the food via two bridges of the same length. In such a setting, ants start to explore the surroundings of the nest and eventually reach the food source. Along their path between food source and nest, ants deposit pheromones. Initially, each ant randomly chooses one of the two bridges. However, due to random fluctuations, after some time one of the two bridges presents a higher concentration of pheromones than the other and, therefore, attracts more ants. This brings a further amount of pheromone on that bridge making it more attractive with the result that after some time the whole colony converges toward the use of the same bridge.

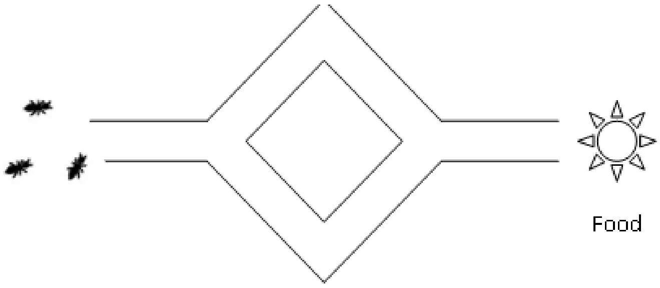


**Figure 3: The Double Bridge Experiment**

The second experimentation, figure 3 gives also two paths to the food source, but one of them is twice longer than the other one. Here again the ants will start to move randomly and explore the ground. Probabilistically, 50% of the ants will take the short way while the 50% others will take the long way, as they have no clue about the ground configuration. The ants taking the shorter path will reach the food source before the others, and leave behind them the trail of pheromones. After reaching the food, they will turn back and try to find the nest. At the cross, one of the paths will contain pheromones although the other one will be not explored. Hence the ant which carries the food will take the path already explored, as it means it is the way to the nest.

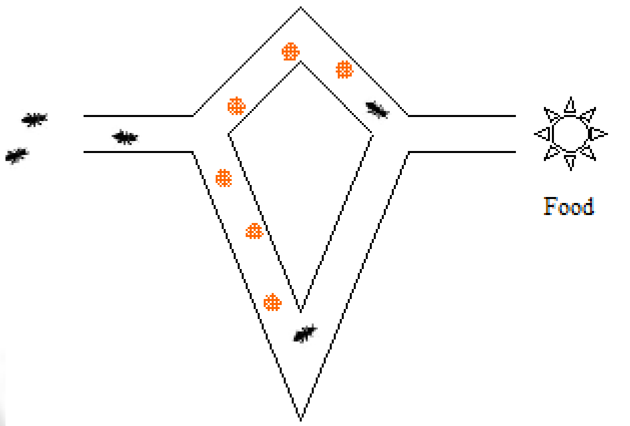


**Figure 4 : Ants exploring the double bridge**

As the ant is choosing the shortest way and will continue to deposit pheromones, the path will therefore become more attractive for others. The ants who took the long way will have more probability to come back using the shortest way, and after some time, they will all converge toward using it. Consequently, the ants will find the shortest path by themselves, without having a global view of the ground. By taking decision at each cross according to the pheromones amount, they will manage to explore, find the food, and bring it back to the nest, in an optimized way.

### A. Biological Ants to Ants-Agents

The transposition of the ants into an algorithm is made with the help of agents. These ants-agents will have the responsibility to locally and autonomously take decisions. The algorithm is shared between a large number of agents which will perform tasks simultaneously instead of having one decision-maker for the whole colony. The decisions are based on a random choice, whose factors are the amounts of pheromones. Thus the macroscopic development of the colony comes from microscopic decisions, using ground-marking process. This algorithm is shared among all the agents and made the evolutions very fast. In a computer-based simulation, the ants are replaced by agents which will explore the ground, let pheromones and once the goal reached try to come back. Goss et al., developed a model to explain the behavior observed in the double bridge experiment. Assuming that after t time units since the start of the experiment, m1 ants had used the first bridge and m2 the second one, the probability p1 for the (m + 1)th ant to choose the first bridge can be given by:

$$p_{1(m+1)} = \frac{(m_1 + k)^h}{(m_1 + k)^h + (m_2 + k)^h}$$

where parameters k and h are needed to fit the model to the experimental data. The probability that the same (m+1)th ant chooses the second bridge is p2(m+1) = 1 -p1(m+1). Monte Carlo simulations, run to test whether the model corresponds to the real data, showed very good fit for k=20 and h=2. This basic model, which explains the behaviour of real ants, may be used as an inspiration to design artificial ants that solve optimization problems defined in a similar way. In the above described experiment, stigmergic communication happens via the pheromone that ants deposit on the ground. Analogously, artificial ants may simulate pheromone laying by modifying appropriate pheromone variables associated with problem states they visit while building solutions to the optimization problem. Also, according to the stigmergic communication model, the artificial ants would have only local access to these pheromone variables. Therefore, the main characteristics of stigmergy mentioned in the previous section can be extended to artificial agents by:

- Associating state variables with different problem states
- Giving the agents only local access to these variables.

Another important aspect of real ants' foraging behaviour that may be exploited by artificial ants is the coupling between the convergence mechanism and the implicit evaluation of solutions. By implicit solution evaluation, we mean the fact that shorter paths (which correspond to lower cost solutions in the case of artificial ants) are completed earlier than longer ones, and therefore they receive pheromone reinforcement quicker. Implicit solution evaluation coupled with autocatalysis can be very effective: the shorter th the shorter the path, the sooner the pheromone is deposited, and the more ants use the shorter path. Stigmergy, together with implicit solution evaluation and autocatalytic behaviour, gave rise to Ants-based algorithms. The basic idea of Ants-based algorithms follows very closely the biological inspiration. Therefore, there are many similarities between real and artificial ants. Both real and artificial ant colonies are composed of a population of individuals that work together to achieve a certain goal. A colony is a population of simple, independent, asynchronous agents that cooperate to find a good solution to the problem at hand. In the case of real ants, the problem is to find the food, while in the case of artificial ants, it is to find a good solution to a given optimization problem. A single ant (either a real or an artificial one) is able to find a solution to its problem, but only cooperation among many individuals through stigmergy enables them to find good solutions.

In the case of real ants, they deposit and react to a chemical substance called pheromone. Real ants simply deposit it on the ground while walking. Artificial ants live in a virtual world, hence they only modify numeric values (called for analogy artificial pheromones) associated with different problem states. A sequence of pheromone values associated with problem states is called artificial pheromone trail. In Ants-based algorithms, the artificial pheromone trails are the sole means of communication among the ants. Just like real ants, artificial ants create their solutions sequentially by moving from one problem state to another. Real ants simply walk, choosing a direction based on local pheromone concentrations and a stochastic decision policy. Artificial ants also create solutions step by step, moving through available problem states and making stochastic decisions at each step. There are however some important differences between real and artificial ants:

- Artificial ants live in a discrete world: they move sequentially through a finite set of problem states.
- The pheromone update is not accomplished in exactly the same way by artificial ants as by real ones. Sometimes the pheromone update is done only by some of the artificial ants, and often only after a solution has been constructed.

Some implementations of artificial ants use additional mechanisms that do not exist in the case of real ants. Examples include look-ahead, local search, backtracking, etc.

### B. The Pheromones

Pheromones represent in some ways the common memory. The fact that it is external and not a part of the ants / agents, confers to it an easy access for everyone. The memory is saved in without regarding the configuration of the ground, the number of ants, etc. It is totally independent, and still remains extremely simple. Pheromones are just values stored in a 2-dimensional array, in reality like in algorithm, in a discrete way though. In our implementation we will see that two different types of pheromones are used. The first one is represented in red and is let by the ants which do not carry the food. We will call it the Away pheromone, as it means that the ant is going away from the nest. Oppositely, the ants which carry the food to bring it back to the nest let a blue trace behind them, the Back pheromone. Pheromones just proceed to one task: nature will take care of it in the real life, although it is a simple process in algorithms. In course of time, a global reduction of the pheromones by a certain factor is applied, simulating the evaporation process. Thus the non-succeeding path will see their concentration of pheromones reduced, although good solutions will stay full of pheromones as the ants keep using it. The convergence is very influenced by the factor of evaporation, and we will see how important it is in the simulation.

## III. IMPLEMENTATION OF THE ANTS-BASED ALGORITHM

A modeling language is any artificial language that can be used to express information or knowledge or systems in a structure that is defined by a consistent set of rules. The rules are used for interpretation of the meaning of components in the structure. In order to develop an application which really suits to the definitions, the first action is to give a complete modeling of the specifications. First the problem will be divided into classes, linked to one another and resuming the simulated world.

We can easily define 3 main classes:

- Ant. Agent which can smell the pheromones and make a move on the ground
- .Ground. Here we will call it Playground; it is the 2-dimension space which contains the ants and the pheromones.
- Pheromones. Or traces, they are the trails which partially lead the ants.

### A. The factors

The factors that really modified the ants' behaviour and the probability for them to converge toward the best solution are:

- The number of ants: it should depend on the size of the playground and the number of nodes.
- Their endurance: if the food is far away from the nest, the ants need to have enough endurance to go to the nest. If not, they will always come back to the nest without finding the food's source.
- The traces evaporation speed: the pheromones reduce as the time passes, however it should not be too fast or too slow. The convergence's speed depends a lot on this factor.
- The factor of away and back attractiveness: the ants privilege the away pheromone to come back to the nest, but it should also take in consideration the amount of back pheromones. The factor will play an important role in the decision process when an ant reaches a node.

### B. Comparison with existing implementation of the ants-based algorithm

The most famous implementation on the internet is called AntSim 1.0, and has been developed in VB by nightlab. It requires the .net framework

- In this application, the ants will move very quickly and as soon as they discover the food, a solution is analysed. There is an evaluation of the path, which does not exist in our implementation, and which the ants are not capable of.

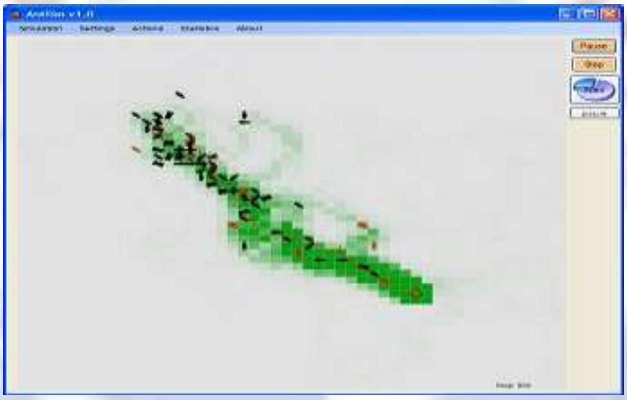

**Figure 5: The Ant Sim v1.0 application**

- The application has been released in January 2007 and is famous for its settings capability and the statistics provided while the ants are moving, as shown in figures 5 and 6
- The original ants-based algorithm has been fully implemented. However, it has been noticed that one nice improvement would be to vary the amount of pheromones that an ant let on its way, according to its proximity with the nest or the food. The closer it is to the goal, the more pheromones it should let.
- This way and with the help of the evaporation process, the amount of pheromones will be more valuable and will give more information.

## IV. ANALYSIS OF THE STATE-OF-THE-ART ADAPTATIONS OF THE ANTS-BASED ALGORITHMS TO ROUTING PROTOCOLS

In the following, we will often talk about the ACO. The full form is Ant Colony Optimization metaheuristic. The ACO metaheuristic is a multi-agent framework for combinatorial optimization whose main components are: a set of ant-like agents, the use of memory and of stochastic decisions, and strategies of collective and distributed learning. The networks become nowadays more and more complicated, with moving nodes, varying loads, etc. The users however expect more quality and more services despite the growing complexity of the networks. The theses which will be analysed in the following study some adaptations of the Ant Colony Optimization to routing protocols, and often compare its efficacy to the current routing algorithms. Most of the papers see in the ACO a great tool for wireless Ad Hoc networks as it has a strong capacity to adapt to changes. However, some new algorithms based on ACO are also analysed for wired networks and are giving encouraging results.

The comparison between ACO and traditional routing algorithms is done with analysing:

- The routing information;
- The routing overhead;
- The adaptively

### A. Routing Information

The routing information consists of what is exchanged to get to know the architecture of the network, hence forward the data packets to the best path. For RIP, the nodes exchange the distance-vector information, each node giving to the other their neighbors and so on. In OSPF, the nodes tables need on the link-state information of all the links in every path to compute the shortest path. In ACO, the paths from a source to a destination are explored independently and in parallel. The figure 6 shows a simple configuration of 6 nodes.

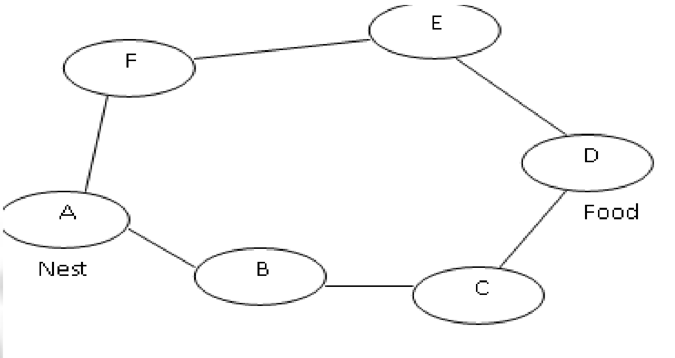


**Fig 6: Nodes**

For RIP, the nest A depends on routing tables sent by B and F, as well as the Food depends on C and E's routing tables. In OSPF, A needs to know all the link-state between itself and the food to find the shortest path. In ACO, the paths from the source to the food are explored by using n number of ants, the ants leaving the nest at the same time and taking a random first path. n/2 ants will go through B while the other half will take the way to F. The ants which reach the first the food indicates which way is the shortest without having to wait for the second half of ants to reach. As soon as an ant arrives at a node, the corresponding pheromones value for a path is updated. Hence, each entry of the pheromone table in a node can be updated independently. In the figure 6, the Food point, node D, can immediately use the information in its pheromone table to route data packets to the nest when any ant from either path arrives (and updates its pheromone table).

### B. Routing protocols presented in this paper

- DSDV, Destination-Sequenced Distance Vector algorithm
- OLSR, Optimized Link State Routing algorithm
- AODV, Ad Hoc On Demand Distant Vector
- DSR, Dynamic Source routing
- ZRP, Zone Routing Protocol
- GPSR, Greedy Perimeter Stateless Routing
- TRP, Terminode Routing Protocol
- ABC, Ant Based Control System, for wired networks
- AntNet, for MANET ASGA,
- Ant System with Generic Algorithm Synth
- ECA, Synthetic Ecology of Chemical Agent Termite
- AntHocNet for MANET
- MARA, Multi-agent Ants-based Routing Algorithm

### C. Information overhead

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. This is because ants are generally very simple agents. The following table summarizes the differences between ACO and traditional routing algorithms.

| | RIP / OSPF | ACO algorithm |
|---|---|---|
| Routing preference | Based on transmission time / delay | Based on pheromones concentration |
| Exchange of routing information | Routing information and data packet transmitted separately | Can be attached to data packets |
| Adapting to topology change | Transmit routing table / Flood LSPs at regular interval | Frequent transmission of ants |
| Routing overhead | High | Low |
| Routing update | Update entire routing table | Update an entry in a pheromone table independently |

**D. Adaptivity**

In dynamic networks, transmitting large routing table (in RIP) or flooding multiple copies of LSPs (in OSPF) in short or regular intervals may incur large routing overhead. However, flooding LSPs and transmitting routing table in longer intervals may result in slower responses to changes in network topology. Since ants are relatively small they can be piggybacked in data packets, more frequent transmission of ants to provide updates of routing information may be possible. Hence, using ACO for routing in dynamic network seems to be appropriate. Related to the issue of adaptively is stagnation. Stagnation occurs when a network reaches its convergence; an optimal path ρ is chosen by all ants and this recursively increases an ant's preference for ρ. This may lead to: 1) congestion of ρ, 2) dramatic reduction of the probability of selecting other paths. The two are undesirable for a dynamic network since:

1) ρ may become nonoptimal if it is congested;
2) ρ may be disconnected due to network failure;
3) other nonoptimal paths may become optimal due to changes in network topology, and iv) new or better paths may be discovered.

We have pointed out that the success of ants in collectively locating the shortest path is only statistical. If by chance, many of the ants initially choose a non-optimal, other ants are more likely to select leading to further reinforcement of the pheromone concentration alongρ. This is undesirable for static networks since it is inefficient ants always choose a stagnant path that is non-optimal.

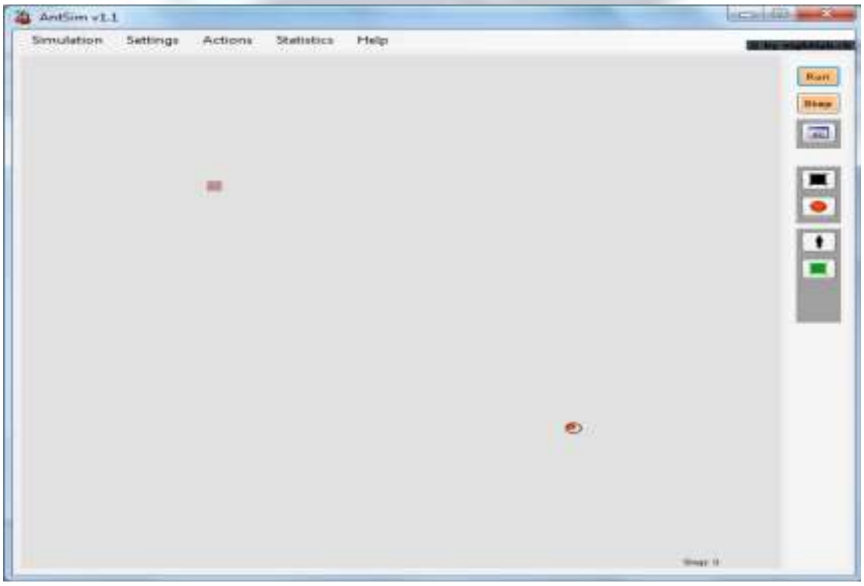


**Figure 7: simulator main Screen**

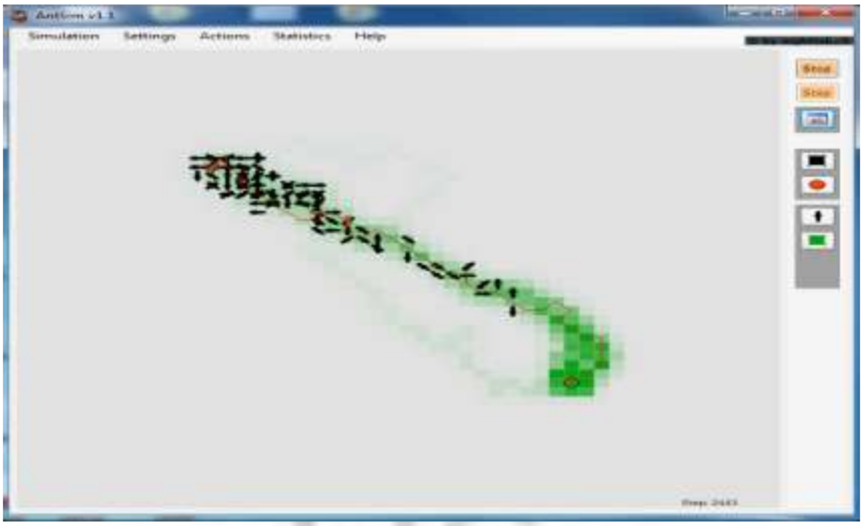

**Figure 8: ACO working Scenario**

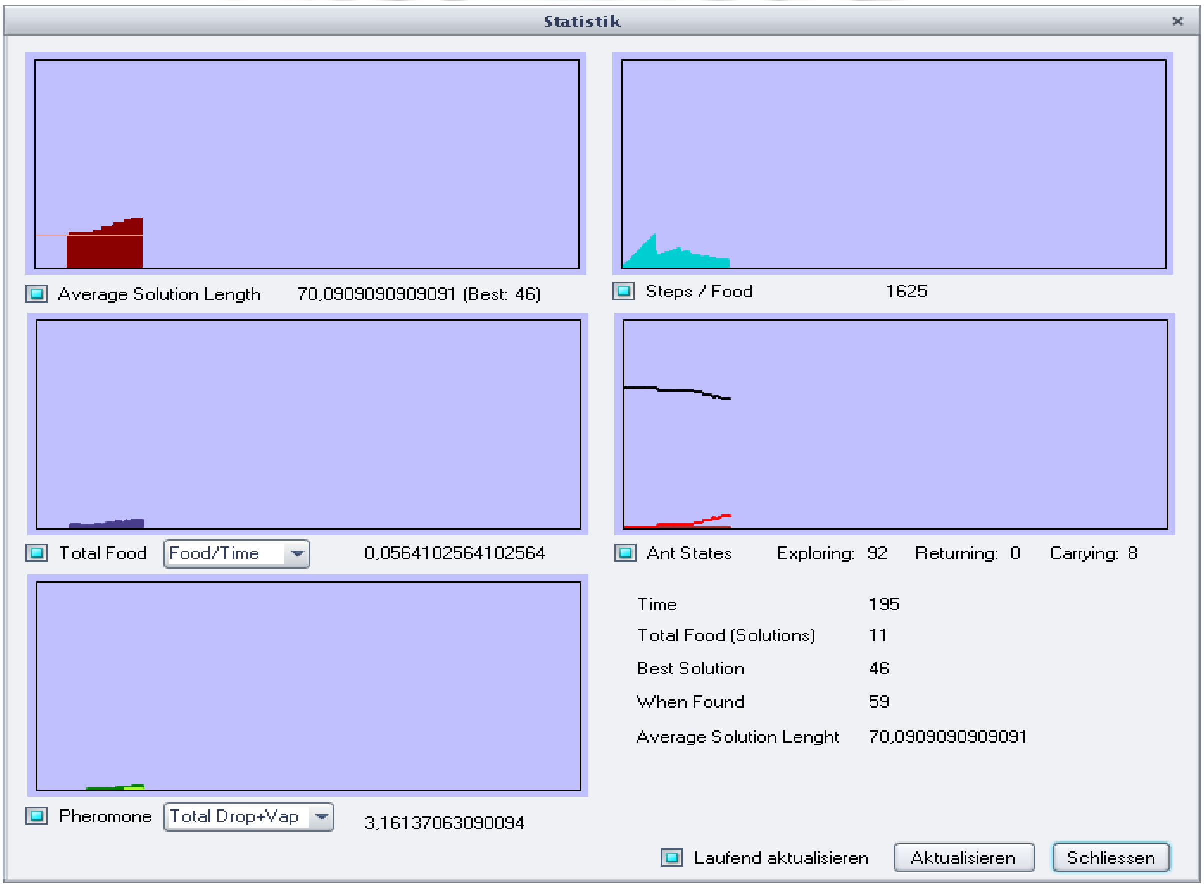


**Figure 9: simulator analysis tool**

## CONCLUSION AND FUTURE SCOPE

This work tried to cover the state-of-the-art studies about Ant Colony Optimization (ACO) algorithm and its application to routing protocols. It covers recent thesis reports and introduces the latest developed protocols based on ACO. It has been a great pleasure to study these papers. At the beginning of this project I developed my own application which simulates the ACO, which gave me the best understanding of the algorithm and its issues. Thus, the applications to the routing protocols are easier to understand since the main ideas behind them have always been inspired by the ants.

## References

[1] http://www.nightlab.ch/antsim
[2] J Mobile Communications Group, http://www-i4.informatik.rwth-aachen.de/mcg/downloads/ants.html
[3] D. Subramanian, P. Druschel, and J. Chen, "Ants and reinforcement learning: A case study in routing in dynamic networks," in Proc. Int. Joint Conf. Artificial Intelligence, Palo Alto, CA, 1997, IJCAI-97, pp. 832–838
[4] E. Bonabeau, M. Dorigo, and G. Theraulaz, "Inspiration for optimization from social insect behavior," Nature, vol. 406, pp. 39–42, July 2000
[5] M. Roth and S. Wicker, Termite: Ad-hoc networking with stigmergy, in Proceedings of Globecom, 2003.
[6] J.S. Baras and H. Mehta, A probabilistic emergent routing algorithm for mobile ad hoc networks, in Proceedings of WiOpt03: Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks, 2003.
[7] British Telecom, Appleby & Steward, 1994
[8] http://www.rennard.org
[9] http://zool33.uni-graz.at/schmickl
[10] M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.
[11] Pasteels, J.M., Deneubourg, J.-L., and Goss, S., Self-organization mechanisms in ant societies (i): rail recruitment to newly discovered food sources, ExperientiaSupplementum, 54, 155.