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Swarm Intelligence: An Application of Ant Colony Optimization

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Abstract: *Swarm intelligence, a branch of artificial intelligence is a part which discusses the collective behaviour of social animals such as ants, fishes, termites, birds, bacteria. The collective behaviour of animals to achieve target can be used in practical applications. One of the applications is ant colony optimization. Ongoing research of ACO, there are diverse applications namely data mining, image processing, power electronic circuit design etc. One of that is network routing. By using ACO, we can find the shortest path in network routing.*

Keywords: *Swarm intelligence, Artificial Intelligence, Ant colony optimization, Network routing.*

I. Introduction

Swarm intelligence is an area of Artificial Intelligence which is, in part, influenced by the collective behaviour of decentralized, self-organized system as social insects. The expression was introduced by Gerardo Beni and Jing Wang in 1989, in the context of cellular robotic systems. SI systems consist typically of a population of simple agents or bodies interacting locally with one another and with their environment. The inspiration often comes from nature, especially biological systems. The agents follow very simple rules, and although there is no centralized control structure dictating how individual agents should behave, local, and to a certain degree random, interactions between such agents lead to the emergence of "intelligent" global behaviour, unknown to the individual agents. Examples in natural systems of SI include ant colonies, bird flocking, animal herding, bacterial growth, and fish schooling. The definition of swarm intelligence is still not quite clear. In principle, it should be a multi-agent system that has self-organized behavior that shows some intelligent actions. The application of swarm principles to robots is called swarm robotics, while 'swarm intelligence' refers to the more general set of algorithms and also used to forecasting problems.

1.1 Applications of Swarm Intelligence

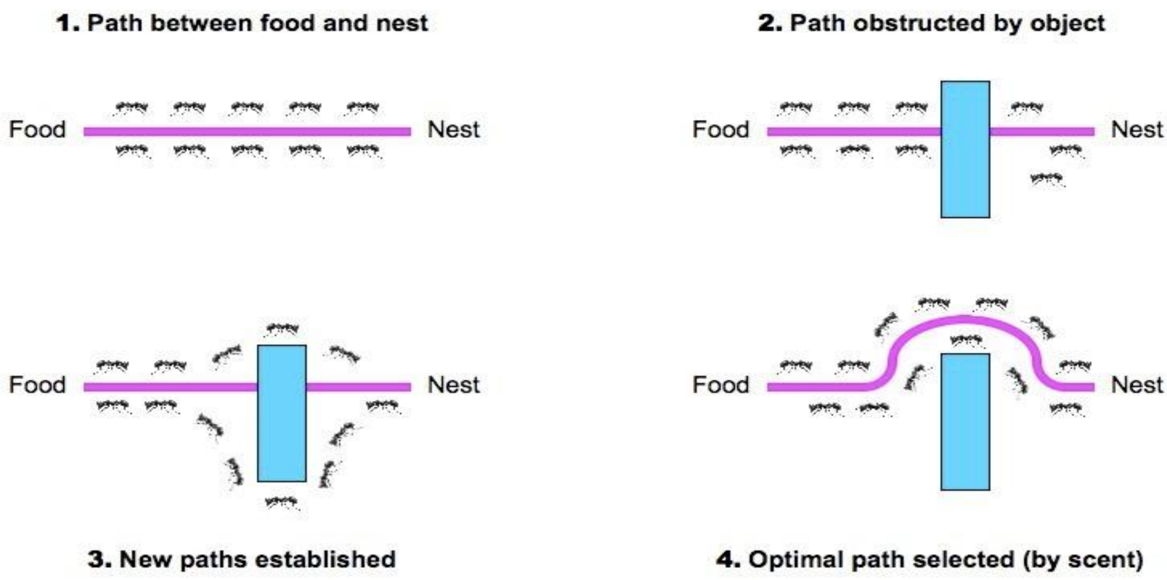
- Ant colony optimization
- Particle swarm optimization
- Artificial bee colony algorithm
- Differential evolution
- The bees algorithm
- Artificial immune systems
- Grey wolf optimizer
- Bat algorithm
- Gravitational search algorithm
- Self-propelled particles
- Stochastic diffusion search
- Multi-swarm optimization

Individual social insects, do not possess very much cognitive abilities by themselves. In a colony of social insects, such as ants, bees, wasps and termites, each insect usually performs its own tasks independently from other members of the colony. However, the tasks performed by different insects are related to each other in such a way that the colony as a capability of solving complex problems through cooperation. Important, survival-related problems such as selecting and picking up materials, finding and storing food, which require sophisticated planning, are solved by insects colonies without any supervisor or centralized controller. This collective behaviour which emerges from a group of insects has been called “swarm intelligence”.

(**Flocking of birds**) (**Bee colony**) (**Ant colony**)

<u>Figure 1</u>

We are interested in a particular behaviour of real ants, namely the fact that they are capable of finding the shortest path between a food source and the nest without the use of visual information. The ethology discovered that Ants communicate with one another by means of pheromone (a chemical substance) trails. As an ant move, a certain amount of pheromone is dropped on the ground, marking the path with a trail of this substance. The more ants follow a given trial, the more attractive this trail becomes to be followed by other ants. This process can be described as a loop of positive feedback, in which the probability that an ant chooses a path is proportional to the number of ants that have already passed by that path. When an established path between a food source and the ant's nest is disturbed by the presence of an object, ants soon will try to go around the obstacle. Firstly, each ant can choose to go around to the left or to the right of the object with a 50%-50% probability distribution. All ants move roughly at the same speed and deposit pheromone in the trail at roughly the same rate. Therefore, the ants that (by chance) go around the obstacle by the shortest path will reach the original track faster than the others that have followed longer paths to circumvent the obstacle. As a result, pheromone accumulates faster in the shorter path around the obstacle. Since ants prefer to follow trails with larger amounts of pheromone, eventually all the ants converge to the shorter path.



<u>Figure 2</u>

II. Ant Colony Optimization

ACO, a sub-field of swarm intelligence (Blum & Dorigo, 2004; Dorigo, Di Caro, & Gambardella, 1999). It is the relatively new field of Ant Colony Optimization. Ant Colony Optimization (ACO) is a metaheuristic, originally defined by Dorigo et al, in [Dorigo et al, 1999]. A metaheuristic is a general method of defining heuristics for a wide range of problem areas which is largely influenced by the behaviour of real ants. [Dorigo and Stutzle, 2004].It is a system based on agents which simulate the natural behaviour of ants, including mechanisms of cooperation and adaptation. In the use of this kind of system as a new metaheuristic was proposed in order to solve combinatorial optimization problems.

It is one of the most advanced techniques for approximate optimization (Blum, 2005). It has been employed to solve many problems in real world situations, such as the scheduling problem (Merkle, Middendorf, & Schmeck, 2002),vehicle routing problem (Fuellerer, Doerner, Hartl, & Iori, 2009; Reimann, Doerner, & Hartl, 2004), assignment Problem (Maniezzo, Colorni, & Dorigo, 1994,Stutzle, 1997), subset problem (Leguizamo´n & Michalewicz, 1999), machine learning problem (Parpinelli, Lopes, & Freitas, 2002), Bayesian network problem (de Campos, Ga´mez, & Puerta, 2002) and industrial problem (Corry & Kozan, 2004). The inspiring source of ACO algorithms are the foraging behaviors of real ant colonies. After the observation of ant colonies, scientists discovered how ants find shortest paths between food sources and their nest. Starting from their nest, ants initially explore the lands around at random. While moving ahead, ants can leave pheromone (a kind of chemical substance) trails on the path they are going through. Other ants can smell pheromone and follow a trail. The more a trail is followed, the more pheromone will be left and the path becomes more attractive for other ants to follow. The pheromone trails are the guides helping ants find the food. The indirect communication between the ants via pheromone trails enables them to find the shortest path between their nest and food (Blum, 2005).The below Fig.3 illustrates the shortest path discovering process of ant colonies.

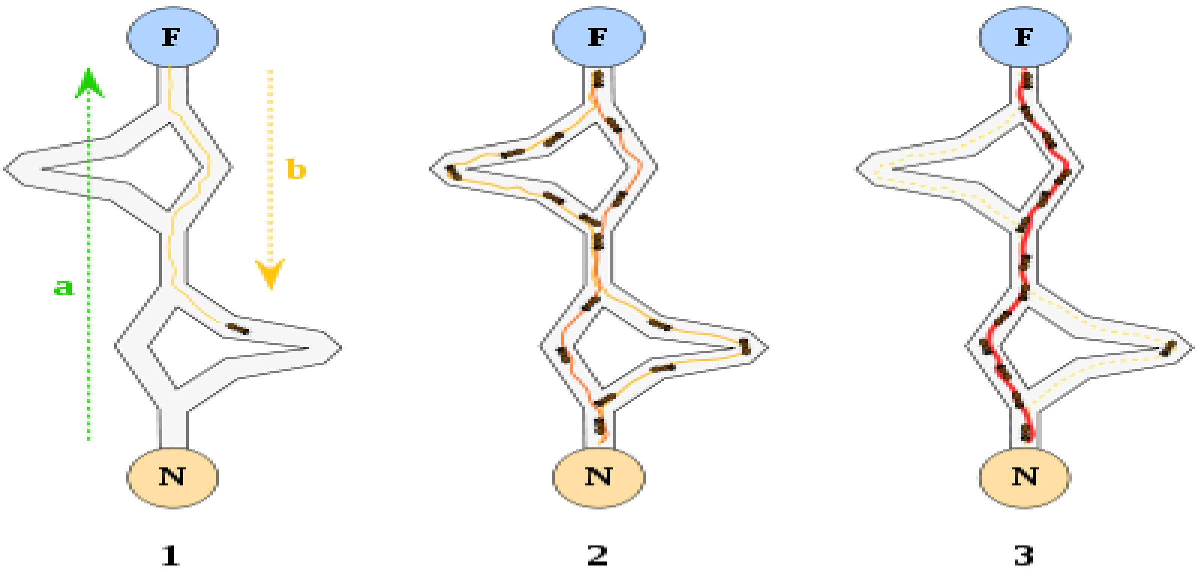


Figure 3

ACO algorithms are based on the following ideas

Each path followed by an ant is associated with a candidate solution for a given problem. When an ant follows a path, the amount of pheromone deposited on that path is proportional to the quality of the corresponding candidate solution for the target problem. When an ant has to choose between two or more paths, the path(s) with a larger amount of pheromone have a greater probability of being chosen by the ant. As a result, the ants eventually converge to a short path, hopefully the optimum or a near-optimum solution for the target problem.

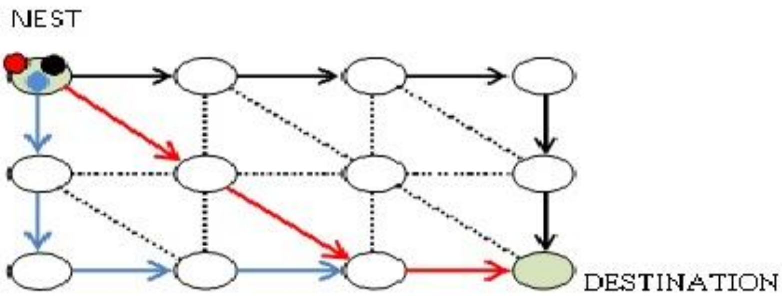


Figure 4.1

1. Ants start foraging from their nest. Initially, the selected possibility of each path is equal. So Red ant, which symbolized by red circle, go the shortest path. Other ants which symbolized by blue and black circles goes in the long path.

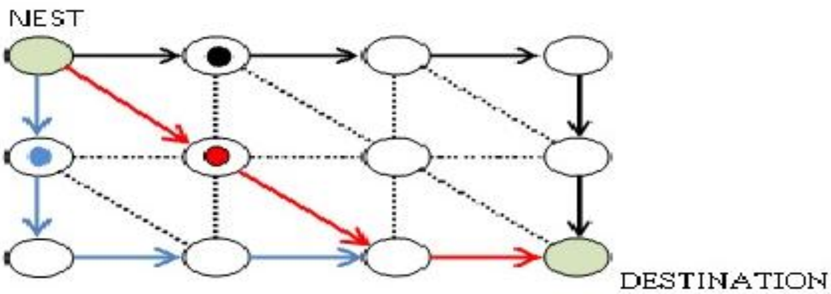


Figure 4.2

2. The ants which go the short path arrives their destination (food source) earlier. Thus, when they go back, it has higher possibility for ants to select the shortest path because the short path has stronger pheromone concentration.

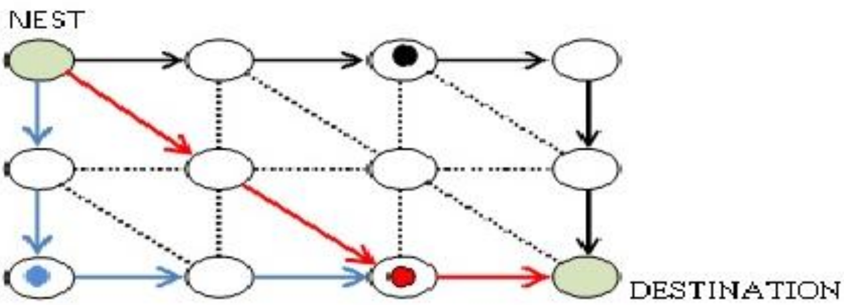


Figure 4.3

3. With more ants go the short path; the pheromone trail on it continuously increases. And with the evaporation of the pheromone on the long path, less and less ants will take it.

4.

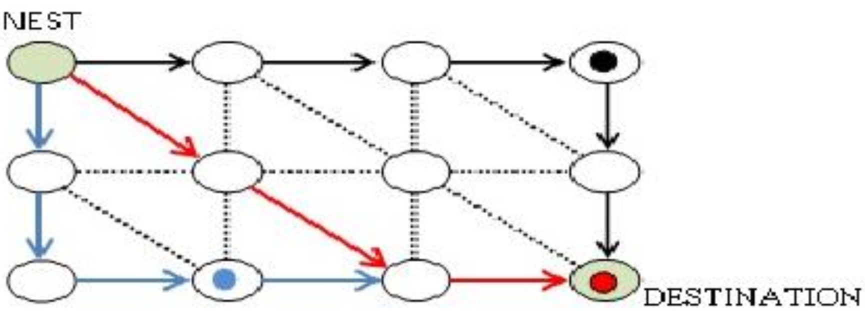


Figure 4.4

5. After sufficient round of ants' going and returning between the nest and the food source. All the ants will choose the short path .The possibility they go the long path will be 0.

2.1applications of ACO

On-going research of ACO in diverse engineering applications such as,

- Network routing
- Data mining
- Discounted cash flows in project scheduling
- Grid work flow scheduling problem
- Image processing
- Intelligent testing system
- System identification
- Protein folding
- Power electronic circuit design

III. ACO IN NETWORK ROUTING

Computer scientists began researching the behaviour of ants in the early 1990's to discover new routing algorithms. The result of these studies is Ant Colony Optimisation (ACO), and in the case of well implemented ACO techniques, optimal performance is comparative to existing top-performing routing algorithms.

Electronic communication networks can be categorised as either circuit-switched or packet-switched. Circuit-switched networks rely on a dedicated connection from source to destination, which is made once at start-up and remains constant until the tear-down of the connection. An example of a circuit switched network would be the British Tele coms telephone network. Packet-switched networks work quite differently, however, and all data to be transmitted is divided into segments and sent as data-packets. Data-packets can arrive out of order in a packet-switched network, with a variety of paths taken through different nodes in order to get to their destination. The internet and office local area networks are both good examples of packet-switched networks.

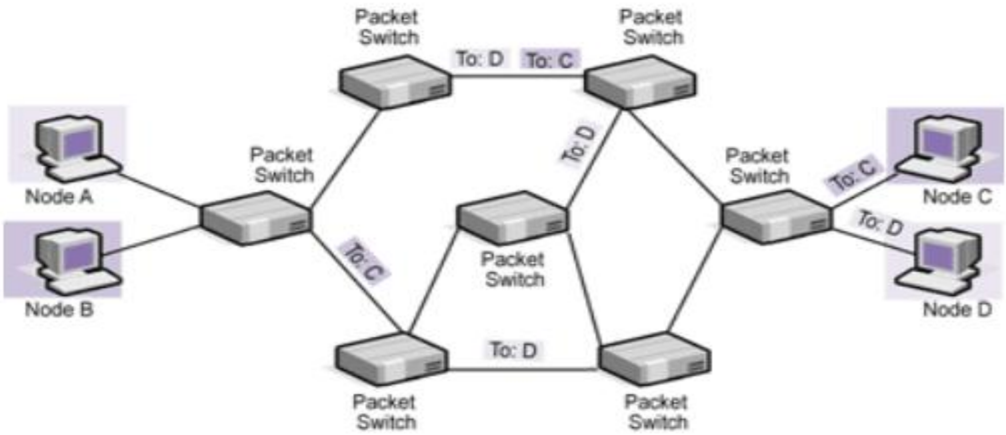


Figure 5

A number of techniques can be employed to optimize the flow of traffic around a network. Such techniques include flow and congestion control, where nodes send packet acknowledgements from destination nodes to either ramp-up or decrease packet transmission speed. The area of interest in this report concentrates on the idea of network routing and routing tables. These tables hold information used by a routing algorithm to make a local forwarding decision for the packet on the next node it will visit in order to reach its final destination.

One of the issues with network routing (especially in very large networks such as the internet) is adaptability. Not only can traffic be unpredictably high, but the structure of a network can change as old nodes are removed and new nodes added. This perhaps makes it almost impossible to find a combination of constant parameters to route a network optimally. Packet-switched networks dynamically guide packets to their destination via routing tables stored in a link state and are selected via a link state algorithm. A link state algorithm works by giving every node in the network a connectivity graph of the network. This graph depicts which nodes are directly connected. Values are stored for connected nodes in a map which represents the shortest path to other nodes. One such link state algorithm used in network routing is Dijkstra's algorithm. When a path between two nodes is found, its weight is updated in the table. Should a shorter path be found, the new optimal weight will be updated to the table, replacing the old value. The algorithm allows traffic to be routed around the network whilst connecting to the least number of nodes as possible. The system works, but doesn't take into account influx of traffic and load balancing.

IV. CONCLUSION

In this paper ACO based Routing is proposed and implemented on Network Models. The results show that the type of the variations of the ACO that should be applied on the network, obviously depends on the structure, size and the application. For example, from the reliability point of view ACO is better than other methods. This is because the number of packets destroyed during the journey is less in ACO. ACO saves the wastage of time in removing the cycles from the path of the journey of the packets and hence increases the throughput of the system. Future work on this algorithms can be carried out considering more factors that can be applied in a routing problems such a delay factor, congestion control etc.

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