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## Comparing Ant Colony Optimization & Genetic Algorithm for Solving Energy Efficient Coverage in WSNs

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**Abstract:** The popularity of Wireless Sensor Networks (WSN) has increased tremendously in recent time due to growth in Micro-Electro-Mechanical Systems (MEMS) technology. Wireless sensor networks (WSNs) with hundreds to thousands of sensor node can gather information from the environment and, based on some local decision process, they can transmit the sensed data to the user terminal. These sensor nodes have some constraint due to their limited energy, storage capacity, and computing power. Generally, it needs a fixed amount of energy to receive one bit of information and an additional amount of energy to transmit the same. Many solutions has been proposed where energy awareness is essential consideration for routing. The LEACH, PEGASIS, GROUP, Particle Swarm optimization etc has provided elegant solutions and has shown very effective results. In this paper, we have proposed a Ant Colony Optimization based Routing protocol (ACOR) where we have taken energy efficiency as major criteria for performing routing and deriving optimized path for data forwarding and processing to base node. The ACOR generates a whole new path of routing by taking energy as fitness value to judge different path and choose best optimized path whose energy consumption is less as compared to other routing paths. We concluded with the result obtained by performing experiment on our proposed algorithm ACOR and comparing its result with Genetic Algorithm which shows better result as compared to Genetic Algorithm and the experiments performed are done using Matlab software.

**Keywords:** Ant Colony Optimization, Routing, Energy Optimization, Genetic Algorithm, Wireless Sensor Network.

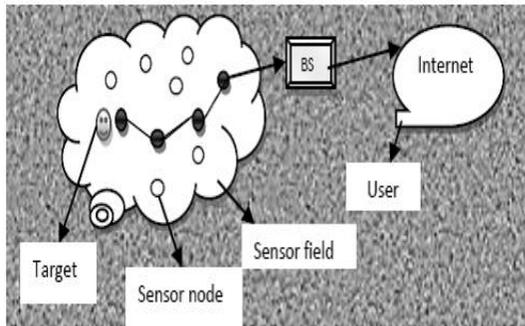
### 1. INTRODUCTION

The popularity of Wireless Sensor Networks (WSN) are increasing day-by-day in recent years due to the advances in low power wireless communications, information technologies and electronics field. The wireless sensor networks are based on the cooperation of a number of tiny sensors and which are depending upon four parts: sensor (motes), processor, transceiver, and battery. The Sensor get information from surrounding area and processor change the analog information into digital information. Then transceiver transmits the converted data to the base- station directly, or through

neighboring sensor. The development of low-cost, low-power, a multifunctional sensor has received increasing attention from various industries. Sensor nodes or motes in WSNs are small in size and are sensing capability, connecting and processing data while communicating with other nodes connected in the network, via radio frequency (RF) channel. [1-2].

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**Figure 1:** Wireless Sensor Network

In sensor networks, minimization of energy consumption is considered a major performance criterion to provide maximum network lifetime. When considering energy conservation, routing protocols should also be designed to achieve fault tolerance in communications. The WSNs can be divided in two classes: structured and unstructured. In a structured WSN, all or some of the sensor node are deployed in a pre-planned manner at fixed locations. The advantage of a structured WSN is that fewer devices can be deployed with lower network maintenance and management costs. An unstructured WSN contains a dense collection of sensor nodes, which are randomly placed into the field.

The Ant Colony Optimization (ACO) is a family member of the Swarm Intelligence based approaches applied for optimization problems. The ant colony optimization algorithm (ACO) is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs. A multi-path data transfer is also accomplished to provide reliable network operations, while considering the energy levels of the nodes. The Genetic algorithm (GA) is a family of evolutionary algorithms based approaches applied for optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, the more fit individuals are stochastically selected from the current population, and each individual's genome is modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been

reached for the population. a genetic algorithm(GA) is used to create energy efficient coverage. For a chromosome, the gene index determines a node and the gene's value identifies the parent node. The single-point crossover and mutation operators are used to create future generations. A repair function is used to avoid invalid chromosomes, which would contain cycles (loops). The chromosome fitness is determined by residual energy, transmission and receives load, and the distribution of load. The population size and the number of generations are based on the network size.

The focuses of our work in this paper is a novel GA-ACO algorithm for solving the energy efficient coverage and prolong its network lifetime. It considers the energy efficient coverage in wireless sensor network between genetic algorithm and ant colony optimization to achieve the network lifetime of all two algorithms adaptively. The rest of the paper is organized as follows. Section 2 introduces the ACO algorithm. Section 3 presents the genetic algorithm. Section 4 represents the simulation of Ant Colony Optimization and Genetic Algorithm which is based on Matlab. At last we conclude this paper.

## 2. ANT COLONY OPTIMIZATION ALGORITHM

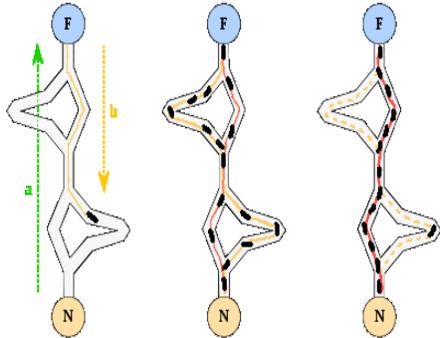
Ant colony optimization (ACO) [6] is one of the most popular meta-heuristics used for combinatorial optimization (CO) in which an optimal solution is sought over a discrete search space. The well-known CO's example is the traveling salesman problem (TSP) [1] where the search-space of candidate solutions grows more than exponentially as the size of the problem increase, which makes an exhaustive search for optimal solution infeasible.

The first ACO algorithm –Ant System (AS)- has been introduced by Marco Dorigo in the early 1990's [2,3,4], and since then several improvement of the AS have been devised (Gambardella & Dorigo, 1995[5]; Stützle & Hoos, 1997[6]). The ACO algorithm is based on a computational paradigm inspired by real ant colonies and the way they function. The underlying idea was to use several constructive computational agents (simulating real ants) [7]. Ant's behavior is governed by the goal of colony survival rather than being focused on the survival of individuals. The behavior that provided the inspiration for ACO is the ants' foraging behavior (see Figure 1), and in particular, how ants can find shortest paths between food sources and their nest. When searching for food, ants initially explore the

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area surrounding their nest in a random manner. While moving, ants leave a chemical pheromone trail on the ground. Ants can smell pheromone.

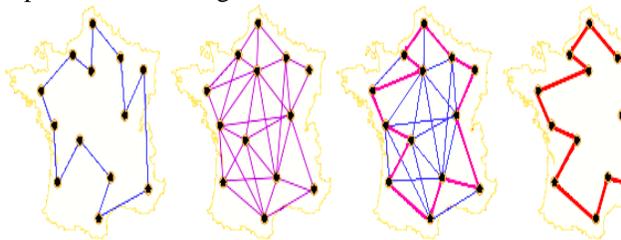


**Figure 2:** Ants use pheromone as indirect communication to build best tour

When choosing their way, they tend to choose, in probability, paths marked by strong pheromone concentrations. As soon as an ant finds a food source, it evaluates the quantity and the quality of the food and carries some of it back to the nest. During the return trip, the quantity of pheromone that an ant leaves on the ground may depend on the quantity and quality of the food. The pheromone trails will guide other ants to the food source. It has been shown in [8] that the indirect communication between the ants via pheromone trails enables them to find shortest paths between their nest and food sources. In this paper I'll view the relations between ACO parameters and how the number of iterations is increased as the number of ants decreased or as the evaporation coefficient increased.

## a. Ant System (AS)

The first ACO algorithm was called the Ant system [5], the objective of AS is to solve the travelling salesman problem (TSP), in which the goal is to find the shortest round-trip to link a series of cities. The general algorithm is relatively simple and based on a set of ants, each making one of the possible round-trips along the cities.



**Figure 3:** Undirected graph show nodes and the edges between the nodes, the Figure show the four stages of ACO to reach shortest closed path.

At each stage, the ant chooses to move from one city to another according to some rules:

- i. It must visit each city exactly once.
- ii. A distant city has less chance of being chosen (the visibility).
- iii. The more intense the pheromone trail laid out on an edge between two cities, the greater the probability that that edge will be chosen.
- iv. Having completed its journey, the ant deposits more pheromones on all edges it traversed, if the journey is short.
- v. After each iteration, trails of pheromones evaporate.

## 2.2 ACS (Ant Colony System):

ACS was the first algorithm inspired by real ant's behavior. The merit is used to introduce the ACO algorithms and to show the potentiality of using artificial pheromone and artificial ants to drive the search of always better solutions for complex optimization problems. In ACS once all ants have computed their tour (i.e. at the end of each iteration) AS updates the pheromone trail using all the solutions produced by the ant colony. Each edge belonging to one of the computed solutions is modified by an amount of pheromone proportional to its solution value. At the end of this phase the pheromone of the entire system evaporates and the process of construction and update is iterated. On the contrary, in ACS only the best solution computed since the beginning of the computation is used to globally update the pheromone. As was the case in AS, global updating is intended to increase the attractiveness of promising route but ACS mechanism is more effective since it avoids long convergence time by directly concentrate the search in a neighborhoods of the best tour found up to the current iteration of the algorithm. ANTS algorithm within the ACO frame-work has two mechanisms:

- i. *Attractiveness*: -The attractiveness of a move can be effectively estimated by means of lower bounds (upper bounds in the case of maximization problems) on the cost of the completion of a partial solution. In fact, if a state  $\tau$  corresponds to a partial problem solution it is possible to compute a lower bound on the cost of a complete solution containing.
- ii. *Trail update*: -A good trail updating mechanism avoids stagnation, the undesirable situation in which all ants repeatedly construct the same solutions making any further exploration in the

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search process impossible. Stagnation derives from an excessive trail level on the moves of one solution, and can be observed in advanced phases of the search process, if parameters are not well tuned to the problem.

## 2.3 Pseudocode for an ACO procedure

```

Begin;
Initialize the pheromone trails and parameters;
Generate population of m solutions (ants);
For each individual ant k2m: calculate fitness (k);
For each ant determine its best position;
Determine the best global ant;
Update the pheromone trail;
Check if termination Z true;
End;

```

Figure 4: ACO

## 3. GENETIC ALGORITHM

According to Goldberg et al., 1989, GA is commonly used in applications where search space is huge and the precise results are not very important. The advantage of a GA is that the process is completely automatic and avoids local minima. The main components of GA are: crossover, mutation, and a fitness function. A chromosome represents a solution in GA. The crossover operation is used to generate a new chromosome from a set of parents while the mutation operator adds variation. The fitness function evaluates a chromosome based on predefined criteria. A better fitness value of a chromosome increases its survival chance. A population is a collection of chromosomes. A new population is obtained using standard genetic operations such as single-point crossover, mutation, and selection operator. As a GA is relatively computation intensive, this chapter proposes executing the algorithm only at the base station. The proposed GA is used to generate balanced and energy efficient data aggregation trees for wireless sensor networks. The following sections present the design of the proposed GA.

### 3.1. Basic Description of GA

Genetic algorithm is started with a set of solutions (represented by chromosomes) called population. Solutions from one population are taken and used to form a new population. This is motivated by a hope, that the new population will be better than the old one.

Solutions which are selected to form new solutions (offspring) are selected according to their fitness; the

more suitable they are the more chances they have to reproduce. This is repeated until some condition (for example number of populations or improvement of the best solution) is satisfied.

It is well known that problem solving can be often expressed as looking for the extreme of a function. This is exactly the case with the following problem: some function is given and GA tries to find the minimum of the function.

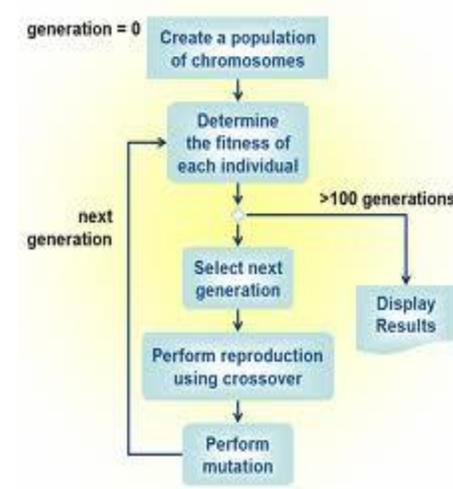


Figure 5: flow diagram of Genetic Algorithm

## 3.2 Pseudocode for a GA procedure

```

Begin;
Generate random population of P solutions
(chromosomes);
For each individual i2P: calculate fitness (i);
For iZ1 to number of generations;
Randomly select an operation (crossover or
mutation);
If crossover;
Select two parents at random ia and ib;
Generate on offspring icZcrossover (ia and ib);
Else If mutation;
Select one chromosome i at random;
Generate an offspring icZmutate (i);
End if;
Calculate the fitness of the offspring ic;
If ic is better than the worst chromosome then
replace the worst chromosome by ic;
Next i;Check if terminationZtrue;
End;

```

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## 4. SIMULATION

### 4.1 Experimental results of Ant Colony Optimization

As shown in Figure:-6a, 6b, 6c, 6d, 6e contain different number of nodes 5, 10, 15, 20, 25 and Each nodes contain different number of iteration is 100, 200, 300, 400, 500. The distance covered in 100 iteration which is covered in 5 nodes is 2.6401 and so on. The maximum iteration is 500 which contain in 25 nodes which 3.9896 distance covered. The Ants find shortest path in WSN's with optimal iteration.

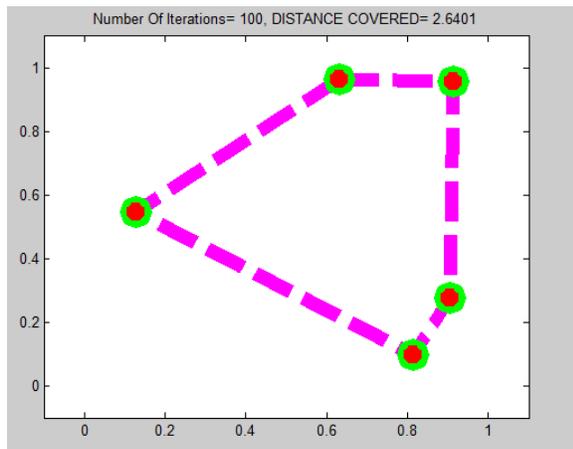


Figure 6a: Node-5 and Iteration-100

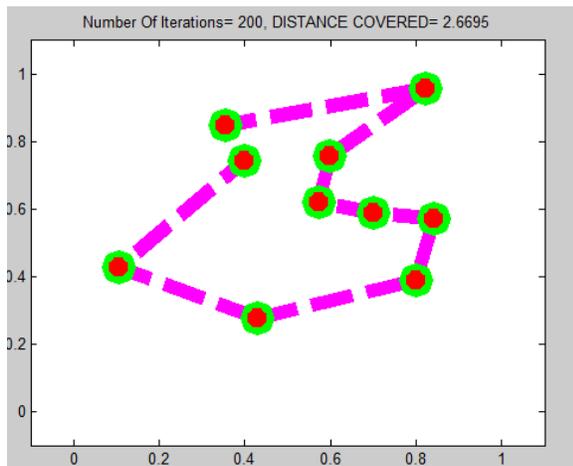


Figure 6b:- Node:-10 and Iteration:-200

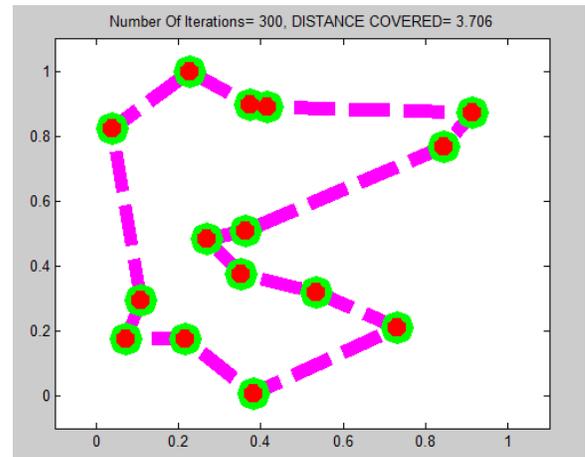


Figure 6c:- Node:-15 and Iteration:-300

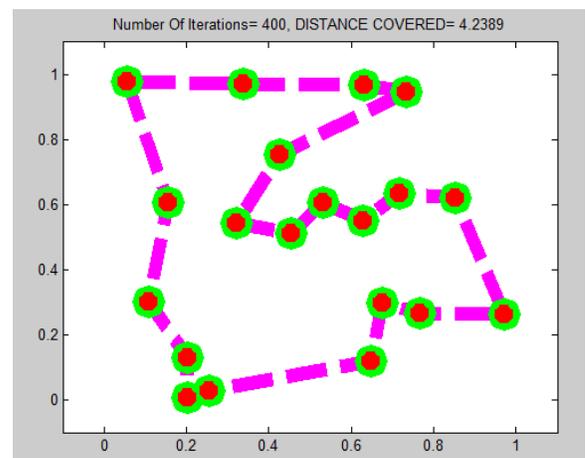


Figure 6d: - Node:-20 and Iteration:-400

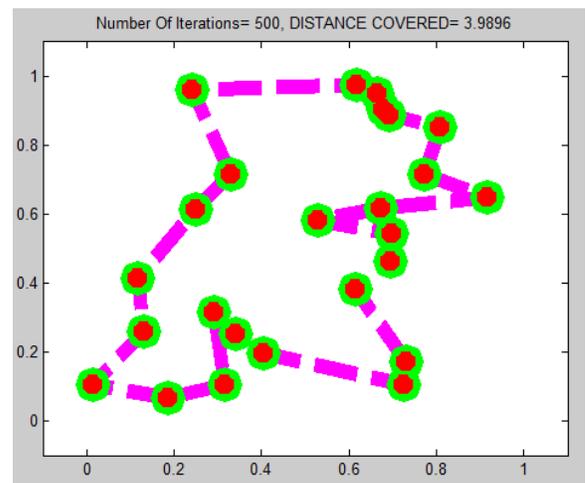


Figure 6e: - Node:-25 and Iteration:-500

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## 4.2 Experimental results of Genetic Algorithm

As shown in Figure:-7a, 7b, 7c, 7d, 7e contain different number of nodes 5, 10, 15, 20, 25 and Each nodes contain different number of iteration is 100, 200, 300, 400, 500. The distance covered in 100 iteration but it take only one iteration which is covered in 5 nodes is 26.4011 and so on. The maximum iteration is 500 but it took 319 iterations which contain in 25 nodes which 45.8288 distance covered. In the system when given iteration complete to cover the optimal path but it take less iteration than given iteration. It has a drawback in WSN's because it take less iteration to complete the path but the system consume more time to complete communication in the given iteration. The Population find shortest path in WSN's with optimal iteration.

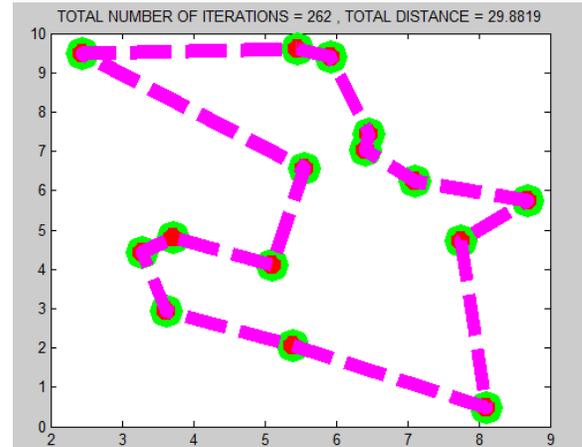


Figure 7c:- Node:-15 and Iteration:-300

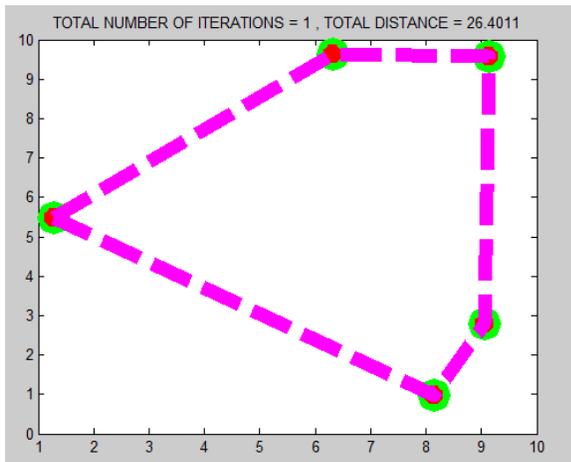


Figure 7a:- Node:-5 and Iteration:-100

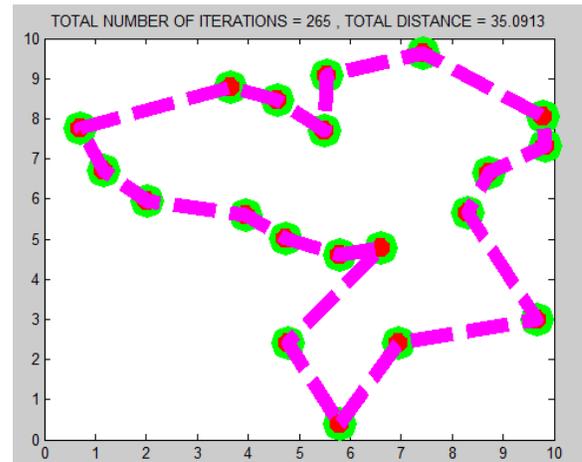


Figure.7d:- Node:-20 and Iteration:-400

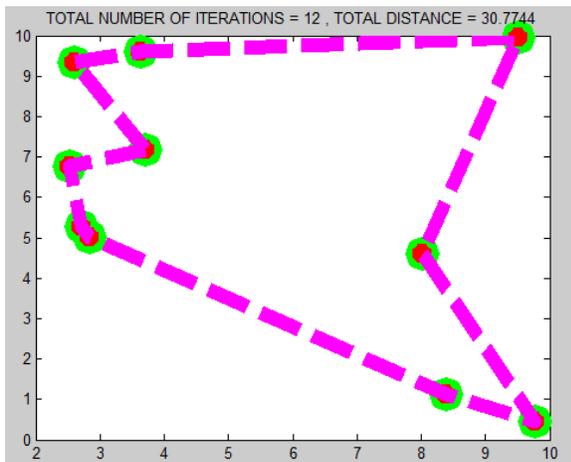


Figure 7b:- Node:-10 and Iteration:-200

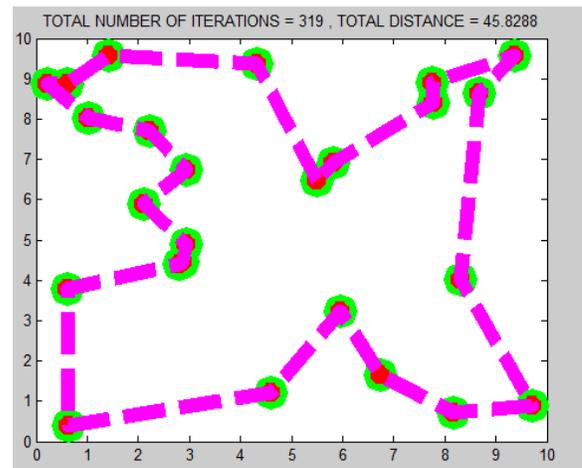


Figure 7e:- Node:-25 and Iteration:-500

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## 5. COMPARISON BETWEEN GA AND ACO FOR WSN

Both techniques (Genetic Algorithm and Ant Colony Optimization) are used to solve energy efficient coverage problem with high acceptable performance, therefore we here to compare between them and determine when we can use one as better than other.

As in Figure 8, we can see the optimal path and distance between 25 sensor nodes for the same data by using both GA and ACO.

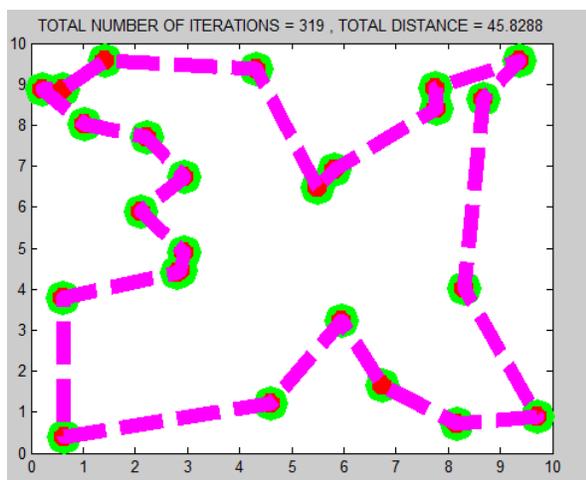
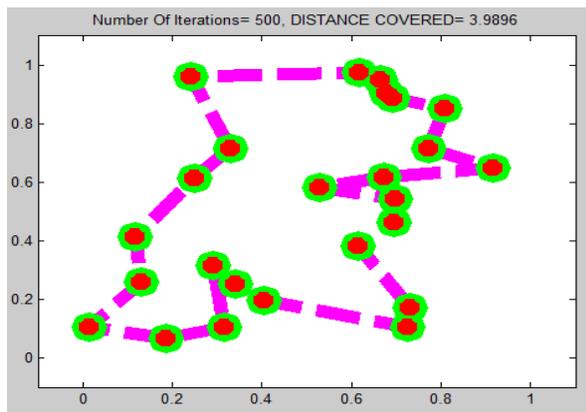


Figure 8:- the best Path of 25 nodes uses both (a) ACO and (b) GA.

For ACO, the result obtains in 25 Ants by using 500 iterations and produces the best distance as 3.9896. While for GA, the best distance is 46.8288 by using crossover and mutation probability is 0.75 and 0.009 respectively. But the first advantage for ACO is the small spent time against to the large required time by GA.

Table 1:- Comparison between GA and ACO for WSN

N	Iteration Covered In ACO	Distance Covered In ACO	Iteration Covered In GA	Distance Covered In GA
5	100	2.6401	1	26.4011
10	200	2.6695	12	30.7744
15	300	3.7060	262	29.8819
20	400	4.2389	265	35.0913
25	500	3.9896	319	45.8288

## 6. CONCLUSION

As shown by the experiment, it is difficult to select the best parameter for ACO, but we can observe the dependency of the number of iterations on both the evaporation coefficient  $p$  and the number of ants  $M$ . that if  $p=0$  that have no evaporation, the algorithm does not converge. But when  $p$  is large enough ( $p=0.9$ ), the algorithm often converged to suboptimal solutions for complex problem. This paper is the first step on determining best number iteration for ACO to have the optimal solution. It is necessary to evaluate the relation between costs,  $\alpha$ , and  $\beta$  and how these parameters effect on best number of iterations and evaporations coefficient.

Also for GA, we need to select the best value for chromosome population, crossover, and mutation probabilities. But still at this time the ACO is better than GA for Efficient Energy Coverage in Wireless Sensor Networks and prolong the lifetime of the network.

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