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Energy Efficient Routing in Wireless Sensor Network Using Ant Colony Optimization and Firefly Algorithm

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***Abstract*—Energy conservation in Wireless Sensor Networks (WSN) is a crucial venture as their miniaturize nature limits their power capabilities. An effective way of energy conservation is the adoption of efficient routing of data from source to sink. This work investigates the performance of two meta-heuristic algorithms, Ant Colony Optimization (ACO) and Firefly Algorithm (FA) on optimal route detection in a WSN routing management system. An adapted ACO was used to search for optimal routes between selected source and sink nodes, after which a developed Discrete FA ran same search. Performance of both were tested on sensor networks deployed randomly, in a clustered pattern and finally randomly-clustered. Evaluators used were energy budget of reported routes. Results show that FA was able detect routes with less cost than those detected by ACO for short routes while ACO performed better with longer routes. Considering the enhanced speed of performance of ACO in comparison to FA and the local search nature of FA, it would be beneficial for future work to explore a hybridized FA-ACO algorithm.**

***Keywords*—WSN, Firefly Algorithm, Ant Colony Optimization,**

I. Introduction

Wireless Sensor Networks (WSN) are a collection of small devices working together to capture/monitor a particular phenomenon of interest. They find useful applications in home automation, disasters and environmental monitoring, military operations, multiple target tracking, security surveillance, health services and other commercial purposes [1], [2]. Energy management in WSN is crucial as their usefulness is dependent on how long they are alive and replacement is difficult as deployment area usually is not easily accessible. As such a lot of techniques are employed to prolong their lifespan, these include topology management schemes (can be location-driven or connection driven), power management (sleep/wakeup protocols and MAC protocols), data reduction schemes (data compression and in-network processing), energy efficient data acquisition and sending (adaptive sampling, hierarchical sampling and efficient routing) and mobility based schemes (such as mobile sink and mobile relay) [3]. This work presents an investigation of efficient routing in WSN.

Routing in WSN is handled differently from what is obtainable in traditional wireless networks. This is because of the limited resources available in sensors, and as such any routing technique deployed in WSNs should minimize energy consumption and ultimately maximize network lifetime [4]. Generally the many WSN efficient routing schemes can be categorized into network structure, communication models, topology based and reliable routing schemes. The network structure protocols on which this paper is based takes into consideration how the nodes are interconnected and routes used to send data to destination from source. They are further classed into flat protocols, hierarchical protocols and location based protocols [5]. This paper investigates energy optimization of a location based routing protocol using meta-heuristic algorithms.

Meta-heuristic algorithms are designed to mimic natural phenomena as they randomly search through a space for the optimum solution subject to preconfigured constraints. In this paper we use two of such algorithms, Firefly algorithm and the Ant Colony algorithm, to find the optimal path that minimizes the total energy expended in sending a data packet from source to sink. First, a review of related works is presented in section II. A description of the optimization problem and detailed report of two methods of route optimization based on each algorithm is outlined in section III. A Vehicle Routing Problem with Time Windows (VRPTW) dataset was used to test and evaluate the performance of the algorithms, after which comparison is made between the two algorithms in section IV. Section V presents the conclusions of the investigation

II. Related Works

A. Related Work on Routing Protocol in WSN

A wireless sensor network (WSN) consists of sensor nodes which are distributed around a given location. These sensors have limited energy capability to stay alive for a long period of time [4]. Although, over the years, sensors have improved in their computational capabilities, the batteries are still highly inefficient in comparison. Consequently, in an effort to extend the life of a sensor node, research has been pointed towards reducing the energy demand of the nodes. This is obviously because the core design aspects in a WSN are Energy Efficiency and Reliability [6]. Energy Efficient (EE) Routing has been mentioned in the literature as a means of extending the life of a sensor node[7]. Since energy is expended during transmission, the most energyefficient route during transmission will consume the least energy. This has engendered EE routing protocol for WSNs.

Basically, routing protocols for WSN are classified into flat protocol, hierarchical protocol and location based Protocol [5]. In Flat protocol routing scheme, nodes are distributed uniformly; with none performing a leading role; to transmit data in a cooperative manner i.e. transmitting to the next neighbor. In the case of the hierarchical scheme, nodes are given varying roles and groups known as clusters [8]. Each cluster must have a Cluster Head (CH) which is a node that has higher capabilities than other nodes and is used to relay data to the sink node. Within a distribution of nodes, there may be many possible routes to get to a particular destination. Mathematical models were developed in [9] to determine the most energy efficient route to use in a WSN under resource restriction. The task of determining the most energy efficient route is a hard optimization problem [10]. Consequently, many meta-heuristic techniques have been developed to find the most optimal energy efficient route.

Artificial Bee Colony meta-heuristics algorithm [11] and improved harmony search algorithm [12] were used to determine the optimal energy efficient route in a WSN. An Improved Genetic Algorithm was developed to eliminate the possibility of choosing an invalid note for routing in a WSN [13]. Parameters used in the node selection include nodes position in relation to sink, neighboring nodes, remaining energy and energy requirement. Since this research work was based on using Firefly and Ant Colony optimization algorithms for route optimization, the literature will be based on them.

B. Review of Firefly Related Work

Firefly optimization algorithm, which is presented in more detail in section III have been used to solve several research optimizations in literature. These work include, but not limited to a wide range of issues in the field of engineering design problems, image processing, identification and clustering, and software testing [14]. A review of some of its application is hereby presented.

In [15], the authors modified the original firefly algorithm by discretizing it and applying several novel route operators to solve the Vehicle Routing Problem with Time Windows (VRPTW). Results presented showed that the developed Evolutionary Discrete Firefly Algorithm (EDFA) is promising compared to other versions of EDFAs. Another discrete firefly algorithm, using the sigmoidal logistic function is presented in [16], is used to find the optimal solution to permutation flow shop minimizing the makespan. The problem is NP-hard and formulated as a mixed integer programming. Results revealed superior performance to the ant colony. This same discrete algorithm was also applied by the authors to solve the manufacturing cell formation problem [17].

Firefly algorithm was used for routing optimization in WSN in [18]. A novel fitness function depending on residual energy, node degree and distance was proposed, and then optimized. Results showed superior performance to some stated existing routing algorithms.

Another interesting work combined firefly algorithm with the gossip algorithm and applied it to WSN to investigate time of sensor synchronization and data convergence rate [18]. The impact of hybrid algorithm was investigated on a live network to find out how simulation results correlate with live field applications. Conclusion drawn from results obtained indicate that assumptions such as fireflies communicating at the speed of light and the low latency due to fast processing speed is not applicable in a live networks where much higher latency is expected. A wide range of application in diverse fields are presented in [14], [19].

C. Review of Ant Colony Optimization Related Work

An Adaptive Ant Colony Optimization (ACO) algorithm is proposed in [20] for clustering based dynamic routing in a WSN. This was designed to take into consideration the unpredictable nature of a Wireless Sensor Network. Sensors nodes can be deployed in either a sparse or dense nature. The ACO finds the optimal network setting in order to improve data aggregation thereby reducing data redundancy. An adaptive routing scheme based on ACO was also developed in [10]. Route selection is based on the residue energy inn the nodes as well as the location of nodes. In this case, clusters were not used in the grouping of nodes.

Fuzzy logic was used in addition to ACO in [21] in a cross-layer WSN protocol stack to optimize routing in a WSN. To improve EE of the routing protocol, a multilayer approach was adopted. Nodes were grouped into clusters with cluster heads which are closest to the sink. Fuzzy logic was used in the cluster head selection using metrics such as residual energy, number of neighbors and quality of communication link for the selection. However, ACO was used for reliable and energy efficient inter-cluster routing from cluster heads to sinks.

ACO was further used to determine a multi-objective optimization i.e. energy efficiency and security of transmitted data [22] in a WSN. The factors used to carry out this include the time delay, bandwidth and the energy consumption. Neural Network was used together with ACO to for the purpose of routing in [23]. The neural network is used to select the cluster head while ACO was used to determine best route. An ACO was used to develop an enhanced routing protocol for WSN [24] with mobility as the metric.

III. Methodology

This section presents details about how the Firefly algorithm (FA) and Ant Colony optimization (ACO) algorithms are used to optimize the selection of energy efficient route between two nodes. The objective function used for optimization was derived from [9]. It requires finding the route with the least energy consumption and maintaining the energy limitation of the nodes. Consequently, the next section provides details about the input parameters for the developed algorithm i.e. the objective function and defined constraints. When a node wants to transmit, it searches for the most optimal route to use for the transmission. Fig. 1 shows an overview of the link between source and sink nodes. Subsequent sections provide details on the FA and the ACO techniques adopted.

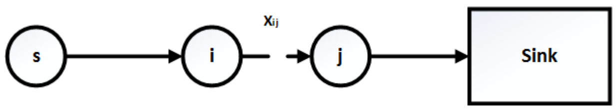

Figure 1. Schematic of WSN

A. Input Parameters

The model considers multi-period transmissions from nodes and aims at prolonging the lifetime of the WSN. It is assumed that there are n number of nodes distributed randomly around an area with each node having a limited energy with an initial value of e_{i0}. The equation for the optimization process is represented in equation 1 where e_j is the energy at the next hop node.

$$min(\sum e_{i0} - \sum e_j) \quad (1)$$

Equation 2 is used to determine the amount of energy consumed during transmission from source to destination node. Where cw is the energy used to wake nodes for transmission and ct is the energy expended by a node to transmit to the next hop node i.e. a node directly linked. This direct transmission is constrained by a a linking distance which is a maximum distance (ld) within which nodes can transmit. Therefore, two nodes i and j that are d_{ij} distance away from each other can only communicate directly if $d_{ij}<ld$. Such nodes will be considered to be linked where X_{ij} represents the connect between node i and j. X_{ij}= 1 means there is a link between i and j otherwise, $X_{ij} = 0$ this is shown in equations 3 and 4.

$$E_{it} - E_{it-1} + cw \sum X_{ijt} + ct \sum d_{ij} X_{ijt} = 0 \quad (2)$$

$$d_{ij} = \sqrt{(Dx[i] - Dx[j])^2 - (Dy[i] - Dy[j])^2} \quad (3)$$

where Dx is the x coordinate of the node (i or j) while Dy is the y coordinate of the node (i or j).

$$X_{ij} = \begin{cases} 1 & d_{ij} < ld \\ 0 & Otherwise \end{cases} \quad (4)$$

Furthermore, nodes are required to have enough energy for transmission to the next hop neighbor $E_i < E_{ij}$ where E_i is the remaining energy in node i and E_{ij} is the energy required to transmit from node i to next hop node j.

B. Ant Colony Optimization Algorithm

In this section, we present the use of ant colony optimization (ACO) algorithm for the selection of the optimal energy efficient route. The pheromone secreted along the selected path is based on the equation (5) which shows the inverse relationship between the deposited pheromone and the cost.

$$\varphi(i,j) = \varphi(i,j) + \frac{Q}{cost(k)} \quad (5)$$

Where φ is the deposited pheromone, i= source node, j = destination node, k = selected ant and Q is a constant. Subsequent ants are most likely going to select the path with the most pheromone along its trail. This is represented in the equation (6)

$$P(i,j) = \frac{[\varphi_{(i,j)}]^\alpha}{[\varphi_{(i,j)}]^\alpha + [\varphi_{(i,k)}]^\alpha} \quad (6)$$

A colony of ants (P) is generated to find possible solutions subject to the condition of least energy consumption along a selected path. The decision at each node on which path to select next is made using a Roulette Wheel Selection algorithm. The pseudocode for the ACO is shown in Algorithm 1.

Algorithm 1 Ant Colony Optimization Algorithm

```
While termination condition is not met
  For each ant k=1 to P,
          Move ant(k) until it gets to destination
           Compute the cost of the route using the objective
function
          Compare cost with best route
                 If lower,
                    overwrite best route with new route,
                 Else
                    maintain best route
                 End If
  End For
Use best route to transmit data
Update pheromone trail
Perform evaporation
End While
```

C. Firefly Related Algorithm

The firefly algorithm is a highly efficient algorithm that mimics the social behavior of fireflies and was introduced in 2009 [25]. The original algorithm was formulated to solve continuous optimization problems and works based on three assumptions of the behaviors of the fireflies stated in [14]. A population of fireflies is randomly generated and each generation evaluates its fitness based on a set objective function. The fitter fireflies attract other less fit in close proximity to it. The movement of each firefly towards the fitter fly is guided by equation 7.

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2}(x_j^t - x_i^t) + \alpha \epsilon_i^t \quad (7)$$

The first term is the position of the firefly in the subsequent round, the second term (due to attraction) is the movement towards a better firefly dependent on the distance, r_{ij} , of firefly x_i to x_j, the coefficient of absorption, β_0 and the attraction coefficient γ. The last term is the randomization parameter which determines the degree of exploitation of the search space. Detailed explanation of each parameter and setting is presented in [26].

In this work, the Firefly Algorithm was modified to handle the discrete problem of route selection. First, the fireflies search for feasible routes by using incremental dimensions (d) until a feasible route is found. This is then used to generate three initial population C_1, C_2, and C_3 shown in equations 8, 9 and 10.

$$C_1 = \begin{pmatrix} P_i^j & P_{i+1}^j & \cdots & P_{d-2}^j \\ P_i^{j+1} & P_{i+1}^{j+1} & \cdots & P_{d-2}^{j+1} \\ \vdots & \vdots & \cdots & \vdots \\ P_i^n & P_{i+1}^n & \cdots & P_{d-2}^n \end{pmatrix} \tag{8}$$

$$C_2 = \begin{pmatrix} P_i^j & P_{i+1}^j & \cdots & P_{d-1}^j \\ P_i^{j+1} & P_{i+1}^{j+1} & \cdots & P_{d-1}^{j+1} \\ \vdots & \vdots & \cdots & \vdots \\ P_i^n & P_{i+1}^n & \cdots & P_{d-1}^n \end{pmatrix} \tag{9}$$

$$C_3 = \begin{pmatrix} P_i^j & P_{i+1}^j & \cdots & P_{d}^j \\ P_i^{j+1} & P_{i+1}^{j+1} & \cdots & P_{d}^{j+1} \\ \vdots & \vdots & \cdots & \vdots \\ P_i^n & P_{i+1}^n & \cdots & P_{d}^n \end{pmatrix} \tag{10}$$

In the matrices, n i s the number of fireflied, each value $P \in \{1,2......N\}$ and N is the number of sensors. Luster C1 and C2 search for routes shorter and longer than the feasible route while C3 searches for route of same length. The three clusters were the fed to the firefly algorithm for final test, with a retest of teh C1 and C2 for a feasible route. Two fitness functions were then used to initiate movement in fireflies and perform the search for the best firefly, f{} n(x) and g(x). See equations 11and 12.

$$f_i(x) = E(P_i \rightarrow P_{i+1}) \tag{11}$$

$$g(x) = \sum_{i=1}^{d-1} E(P_i \rightarrow P_{i+1}) \tag{12}$$

where i=1,2,......No. of iterations and is set not less than the dimension of each population

$f_{i(x)}$ is the energy expended by P_i in sending data to P_{i+1} for iteration i. and

g(x) is the total energy expended along a route.

The pseudocode of the modified firefly and parameter setting is shown in Algorithm 2.

Algorithm 2 Pseudocode for Firefly Algorithm

```
Initial population of n fireflies x(t)=[x_1,x_2........x_d]
Divide population into 3 clusters
Generate objective function fn(x),
Generate objective function g(x)
Light intensity Ii determined by g(x)
Define light absorption coefficient
For k=1:n
   While (t<MaxGeneration),
      If g(k ) = inf
        Mutate k to new_k using β0=0, and β0=1,
      for invalid and valid nodes for each x_(i ) respectively.
        Each x_(i )moves probabilistically towards the valid
nodes closest to it.
         If g(new_k) < g(best_k)
            best_k = new_k
            End If
         End If
   End While
End for k
Report best_k as final route
Post process results and visualization
```

IV. Results and Discussion

The developed algorithms were tested using VRPTW dataset with 100 nodes being considered. Source and sink nodes were selected at random and the algorithms are tasked with finding a route with the least possible energy consumption i.e. Cost. The number of iterations for the algorithm were set at 200, 150, 100 and 50. The results were observed to determine which algorithm performed best as the number of iterations increased. Furthermore, 1000 individuals were considered for both Algorithms and 3 different VRPTW datasets were considered namely: the Random (R1), Clustered (C1) and Random-Clustered (RC1). The values for the constraints of the objective function are shown in Table I. The results obtained are shown in Tables II, III and IV.

Table I
Constraints of Objective Function

Parameter	Value
e_0	10
ct	0.1
cw	1
ld	15

For the randomly distributed sensors, the results show that as the number of iterations increased, the performance of Ant Colony Optimization (ACO) increased while that of Firefly Algorithm (FA) remained same (See Table II). FA performed better than ACO in finding routes under the random dataset. It therefore can be inferred that for problems where the solutions are randomly distributed in a search space, FA would be the recommended algorithm to use.

In the clustered scenario, it was observed that as the number of iterations increased, FA quickly converged towards the best observed route while ACO converges slowly towards

Table II
RESULTS FROM R1 SENSOR DEPLOYMENT DATASET

Iterations	Source Node	Sink Node	ACO Route Detected	Cost of ACO Route	Firefly Route Detected	Cost of Firefly Route
200	49	65	[49,11,90,32,66,65]	10.813	[49,11,90,32,66,65]	10.8132
	71	46	[71,20,70,62,48,46]	11.18	[71,20,70,88,48,46]	11.082
	72	36	[72,26,27,88,7,19,36]	13.379	[72,58,89,18,48,36]	11.3624
	22	20	[22,21,53,28,69,70,20]	12.262	[22,21,26,76,81,20]	11.0932
	16	67	[16,91,42,15,41,23,67]	12.304	[16,37,57,41,23,67]	11.0755
150	49	65	[49,11,90,32,66,65]	10.813	[49,11,90,32,66,65]	10.8132
	71	46	[71,20,30,10,62,48,46]	12	[71,20,70,88,48,46]	11.082
	72	36	[72,21,40,58,89,18,48,36]	13.442	[72,58,89,18,48,36]	11.3624
	22	20	[22,74,21,26,76,50,51,20]	12.751	[22,21,26,76,81,20]	11.0932
	16	67	[16,100,87,57,41,23,67]	12.179	[16,37,57,41,23,67]	11.0755
100	49	65	[49,11,90,32,66,65]	10.813	[49,11,90,32,66,65]	10.8132
	71	46	[71,20,90,11,48,46]	11.416	[71,20,70,88,48,46]	11.082
	72	36	[72,73,2,13,89,18,48,36]	13.767	[72,58,89,18,48,36]	11.3624
	22	20	[22,21,53,27,31,70,20]	12.472	[22,21,26,76,81,20]	11.0932
	16	67	[16,100,42,57,41,23,67]	12.106	[16,37,57,41,23,67]	11.0755
50	49	65	[49,11,90,32,66,65]	10.813	[49,11,90,32,66,65]	10.8132
	71	46	[71,20,30,10,62,48,46]	12	[71,20,70,88,48,46]	11.082
	72	36	[72,40,53,89,83,8,46,36]	14.063	[72,58,89,18,48,36]	11.3624
	22	20	[22,4,54,68,50,51,20]	12.47	[22,73,26,76,81,20]	11.1041
	16	67	[16,91,42,57,41,23,67]	12.083	[16,37,57,41,23,67]	11.0755

Table III
RESULTS FROM C1 SENSOR DEPLOYMENT DATASET

Iterations	Source Node	Sink Node	ACO Route Detected	Cost of ACO Route	Firefly Route Detected	Cost of Firefly Route
200	64	10	[64,68,43,47,20,21,10]	11.087	[64,41,47,20,21,10]	10.085
	52	97	[52,24,23,10,2,99,97]	12.585	[52,24,23,10,2,99,97]	12.5853
	10	66	[10,21,20,47,69,66]	9.8866	[10,21,20,47,43,66]	9.8866
	32	92	[32,33,34,29,23,10,2,99,92]	16.038	[32,29,27,23,10,2,98,92]	14.4769
	35	2	[35,31,32,29,23,10,2]	11.738	[35,32,29,26,10,2]	10.3921
150	64	10	[64,68,43,47,20,21,10]	11.087	[64,41,47,20,21,10]	10.085
	52	97	[52,49,47,20,21,10,2,99,97]	14.885	[52,24,21,10,2,99,97]	12.7235
	10	66	[10,21,20,47,69,66]	9.8866	[10,21,20,47,43,66]	9.8866
	32	92	[32,29,27,24,25,23,10,1,2,99,92]	17.92	[32,29,23,10,6,2,99,92]	14.4687
	35	2	[35,32,29,23,10,3,2]	11.569	[35,32,29,26,10,2]	10.3921
100	64	10	[64,68,43,47,20,21,10]	11.087	[64,41,47,20,21,10]	10.085
	52	97	[52,24,23,10,5,75,2,99,97]	15.015	[52,24,23,10,2,99,97]	12.5853
	10	66	[10,21,20,47,69,66]	9.8866	[10,21,20,47,43,66]	9.8866
	32	92	[32,29,28,23,10,9,6,2,99,100,92]	18.149	[32,29,23,10,2,98,94,92]	14.4818
	35	2	[35,32,29,22,23,10,2]	11.627	[35,32,29,26,10,2]	10.3921
50	64	10	[64,69,47,20,21,10]	10.27	[64,41,47,20,21,10]	10.085
	52	97	[52,49,47,20,23,10,2,99,97]	15.041	[52,24,23,10,2,98,97]	12.8766
	10	66	[10,21,20,47,43,66]	9.8866	[10,21,20,47,43,66]	9.8866
	32	92	[32,33,34,29,23,10,2,98,96,94,92]	18.155	[32,29,23,10,2,98,95,92]	14.4787
	35	2	[35,34,29,21,10,2]	10.927	[35,32,29,26,10,2]	10.3921

the same route. This is shown in Table III. The performance of FA was therefore, better than ACO in finding routes in the clustered dataset.

The performance of ACO improved in the Random-Clustered dataset and even performed better than FA in finding long routes. It can also be seen from Table IV that both ACO and FA have improved performance as the number of iteration increases.

Furthermore, it should be noted that both ACO and FA algorithms are statistical in nature thus they often provide different results after a number of runs. Therefore, the algorithms were subjected to multiple iterations. Even though FA performed generally better than ACO, it should be noted that there were also numerous instances where ACO performed better than FA in discovering an energy efficient route.

V. CONCLUSION

In this paper, an investigation into the performance of two meta-heuristic algorithms for energy efficient route discovery was presented. These algorithms are the Firefly Algorithm (FA) and the Ant Colony Optimization (ACO) Algorithm. VRPTW dataset was used to generate nodes to be deployed in a Wireless Sensor Network (WSN) setting and the algorithms are to find the best route that costs the least amount of energy

Table IV
RESULTS FROM RC1 SENSOR DEPLOYMENT DATASET

Iterations	Source Node	Sink Node	ACO Route Detected	Cost of ACO Route	Firefly Route Detected	Cost of Firefly Route
200	16	56	[16,12,53,69,90,66,56]	12.141	[16,13,87,52,83,56]	11.007
	6	18	[6,7,60,53,82,99,57,22,24,18]	17.572	[6,79,60,53,82,99,57,22,18]	17.0759
	96	77	[96,80,65,52,74,58,77]	13.166	[96,80,65,52,74,58,77]	13.1656
	75	31	[75,58,77,25,20,51,85,50,34,31]	18.965	[75,58,87,52,65,91,67,50,34,31]	19.973
	12	44	[12,53,69,68,54,96,72,41,44]	16.962	[12,53,69,68,54,72,41,44]	14.9452
150	16	56	[16,13,87,86,57,83,56]	12.099	[16,13,87,52,83,56]	11.007
	6	18	[6,7,60,53,82,99,52,57,24,18]	17.378	[6,79,78,53,82,52,57,22,18]	17.451
	96	77	[96,80,66,83,57,74,58,77]	14.171	[96,80,65,52,74,58,77]	13.1656
	75	31	[75,58,74,57,83,56,62,50,34,31]	18.436	[75,97,87,52,65,91,67,50,34,29,31]	21.1271
	12	44	[12,53,98,55,68,54,72,41,42,44]	17.171	[12,53,55,68,54,72,41,44]	15.0372
100	16	56	[16,13,87,52,57,83,56]	12.432	[16,13,87,52,83,56]	11.007
	6	18	[6,7,60,53,82,99,57,24,18]	16.238	[6, 7,60,98,65,64, 51,20,18]	16.9509
	96	77	[96,80,65,52,74,58,77]	13.166	[96,80,65,52,74,58,77]	13.1656
	75	31	[75,58,74,57,83,56,62,50,34,31]	18.436	[75,97,59,86,99,65,91,67,50,34,31]	20.9219
	12	44	[12,53,88,100,61,54,72,41,44]	16.69	[12,78,53,69,68,54,72,41,44]	17.0868
50	16	56	[16,15,12,53,82,65,66,56]	12.718	[16,13,87,52,83,56]	11.007
	6	18	[6,7,60,53,82,99,52,57,24,18]	17.378	[6,7,60,98,82,52,57,22,19,18]	17.5793
	96	77	[96,80,66,83,57,74,58,77]	14.171	[96,80,65,52,74,58,77]	13.1656
	75	31	[75,58,74,57,83,56,95,62,50,34,31]	19.491	[75,58,77,25,20,51,76,85,50,34,31]	21.1947
	12	44	[12,53,82,90,68,54,72,41,44]	17.024	[12,53,55,68,54,72,41,44]	15.0372

to transmit data. It can be seen from the results presented that FA performed better than ACO in discovering short routes while ACO performed better than FA in discovering long routes. Furthermore, it was observed that ACO was faster at detecting the routes in comparison to FA. This speed can be attributed to the local search nature of FA which is not applicable in the applied ACO algorithm. Consequently, it is suggested that future works should explore equipping ACO with local search functionality in order to enhance its performance. Therefore, applying a hybridized FA-ACO algorithm with a WSN deployment is proposed.

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