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PERFORMANCE EVALUATION OF ENERGY EFFICIENT ANT COLONY OPTIMIZATION FOR WIRELESS SENSOR NETWORK

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ABSTRACT: *WSN is the collection of nodes which are capable of sensing, computing and communicating the data in the network. WSN is used in various applications such as military surveillance, application based on environmental monitoring, agriculture, structural health and smart parking. But the major challenge of this important technological trend is the limited power available for its operation, which is one of the research gaps attracting intellectual mind globally to resolve The ant colony algorithm is a type of optimization algorithm that simulates the foraging behavior of ants. Its basic principle originates from the shortest path problem encountered by ants in nature. In this research, the sensor nodes were clustered effectively using K-means technique and improved parallel Ant colony optimization (ACO) algorithm for finding the shortest path to transmit the data. The experimental result using K-means technique and parallel Ant colony optimization (ACO) algorithm for finding the shortest path to route the data performed 98% better compared with Particles Swarm Optimization (PSO). The study established that the higher the k-means cluster partition employed during clustering, the better the results obtained from ACO. The choice of ACO was necessitate due to its faster convergence compared to other existing optimization method.*

Keywords: Colony, Routing, Cluster, Node, Optimization Particle, Iteration.

I. INTRODUCTION

Wireless sensor networks (WSNs) are at the core of IoT technologies. WSN is composed of different components and technologies (Lin, Huang, & Shi, 2024). The most important is the sensor node (SN), which allows for monitoring and communicating with another SN and a base station (BS) to access the cloud/internet (Eroglu & Akcan, 2024) . Most of the research in the WSN is targeted to increase the lifetime of the network by using various methods and technology (Gulati et al., 2021). K-Means clustering algorithm is one of the most classic clustering algorithms, which uses distance as the evaluation index of similarity (Lin et al., 2024). Clustering and routing are the techniques through which the efficiency of the network is improved by increasing the lifetime of the sensor nodes (Wan, Zhang, Li, & Li, 2021). The energy of a sensor node depends on the data

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rate transferred by the sensor nodes, distance between the nodes and the sink node (Gulati et al., 2021). In WSN after the clusters are formed cluster head is to be determined. Detecting of cluster head has also placed a crucial role in WSN. Cluster head is determined in various ways in network and in maximum case it is determined by using the residual energy (Wan et al., 2021). The major role of cluster head is to collect and aggregate the data from various sensor nodes, after aggregating transfer the data to sink node which also consume energy of the network (Kulkarni and Venayagamoorthy, 2011). So it is necessary to reduce the energy consumption taken for making the cluster and aggregating the data in cluster head. Recent development in the Artificial intelligence technology leads to development in the various technologies in other fields (Redha, 2017). Using such artificial intelligence technology will also reduce the energy consumption of WSN which increases the lifetime of the complete network (Jia, Jia, & Shao, 2025). One of artificial intelligence technique is Ant Colony Optimization (ACO) which is generally used for finding the optimal path (Jia et al., 2025). By using this technique energy consumption of the sensor node can be reduced and lifetime can be increased (Oluwadu & Oyedeji, 2025).

For time critical application, detection of optimal path should be faster enough to make the application efficient. This research work focus on detecting of optimal path by using parallel ant colony optimization algorithm. K-Mean clustering approach is used for grouping of sensor nodes because it is faster than other hierarchical clustering algorithm. Rotating the cluster head while implementing algorithm based on free space propagation model, increases the lifetime of the network. The specific objectives are

i. Ant colony optimization to obtain shortest path
ii. K-means algorithm for shortest path
iii. Performance evaluation of combined algorithm of k-means and ant colony optimization

II. MATERIALS AND METHODS

The materials needed for the research are discussed below.

2.1 Materials

Both ACO and k-means algorithm will be implemented using matwork's Matrix Laboratory (MATLAB) software version 2016a. The MATLAB software is equipped with various functions needed to run the algorithm and view the results. Also, the algorithm will be run on a HP laptop powered with Intel's third generation processor with a speed of 2.14 GHz

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2.2 Methods

The methods employed in order to achieve the aims and objectives of this research work is summarized in figure 1 below

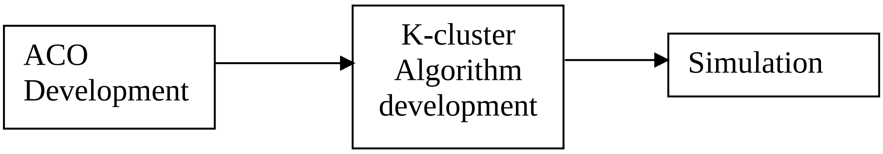

Figure 1 Block of Ant Colony Optimization with K-Means Algorithm

Ant Colony Optimization: There are two main phases present in ACO algorithm are transition probability and pheromone updating factor (Ghantasala, Atlas, Ponmaniraj, & Vidyullatha, 2025). Transition probability factor determines the next cluster node visited while the pheromone-updating factor determines the path to transmit (Ahmad, 2024). The probability of the transition function from one cluster head to another cluster head is defined as (Kulkarni and Venayagamoorthy, 2011) and (Raam and Rajkumar, 2015).

$$p_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha}.[\eta_{ij}]^{\beta}}{\sum_{k \epsilon allowed_k}[\tau_{ij}(t)]^{\alpha}.[\eta_{ij}]^{\beta}} \quad, j \in allowed_k \tag{1}$$

Where:

k represents the kth ant,

i and j represents the source and destination cluster head where ant k has to visit,

α represents the heuristic factor of pheromone,

β represents the expected heuristic factor of pheromone,

η_{ij} represents the degree of transit from i to j,

$allowed_k$ is the cluster head that the ant k does not visit and has to visit

For updating the pheromone value following formula is used (Jia et al., 2025)

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t) + \Delta\tau_{ij} \tag{2}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \tag{3}$$

Where:

$\Delta\tau_{ij}$ is the pheromone quantity that was laid on the edges of source i and destination j and

ρ is the evaporation factor

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Development of Parallel ACO is the method in which more than one ant takes part while doing the above phases as shown in figure 1. Every ant in ACO algorithm will find the transition probability and do pheromone-updating operation simultaneously. The major advantage of using ACO is reduction of computational time, resulting in faster detection of path (Redha, 2017). The following pseudo code implements the ACO algorithm.

```
Begin
    initialize
    while stopping criterion not satisfied do
        position each ant in a certain node
        Repeat
            For each ant do
                Choose next node by applying the state transition rule
                Apply step by step pheromone update
            End for
        Until every ant has built in solution
        Update best solution
        Apply offline pheromone update
```

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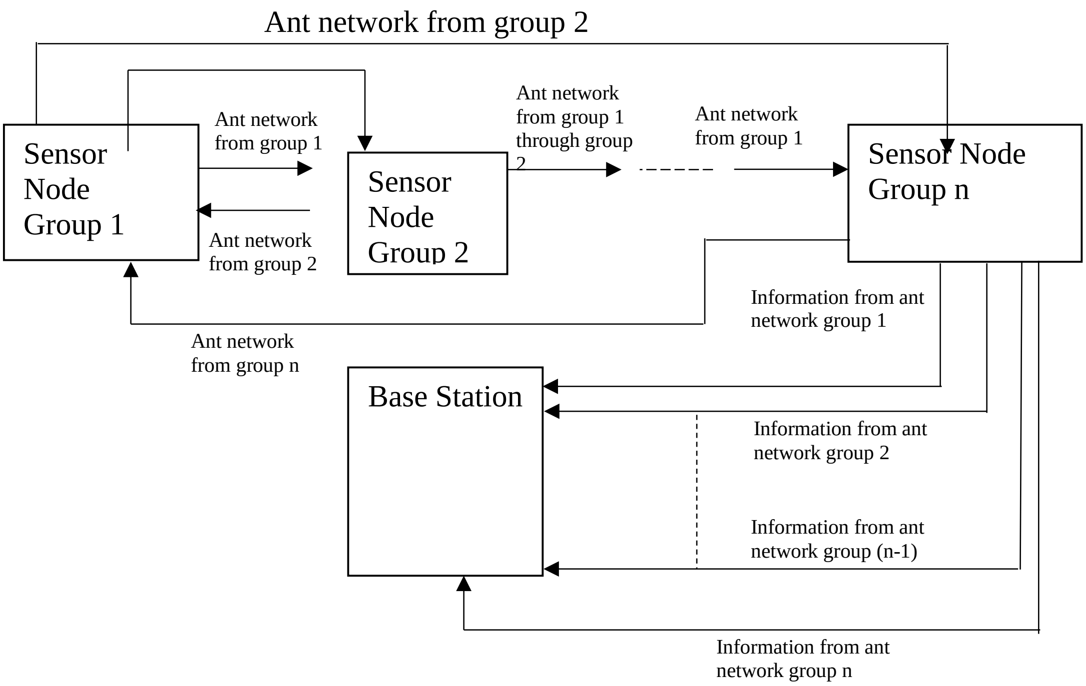

Figure 2: System model

End

while

end

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K-Means Clustering Approach: Here n-objects are partitioned into k clusters in which each object belongs to one cluster. Several advantages of k-means algorithm make the system much more efficient and effective such as: If k-value is small, k-means clustering computes faster than hierarchical clustering method even though the objects need to be clustered are huge. M Compared to other hierarchical clustering method k-means produces better cluster (Wan et al., 2021).

Figure 3 shows the flow chat that depicts the procedure for K-Means clustering. K-Means clustering algorithm is mainly used here for grouping of sensor thereby implementing ACO.

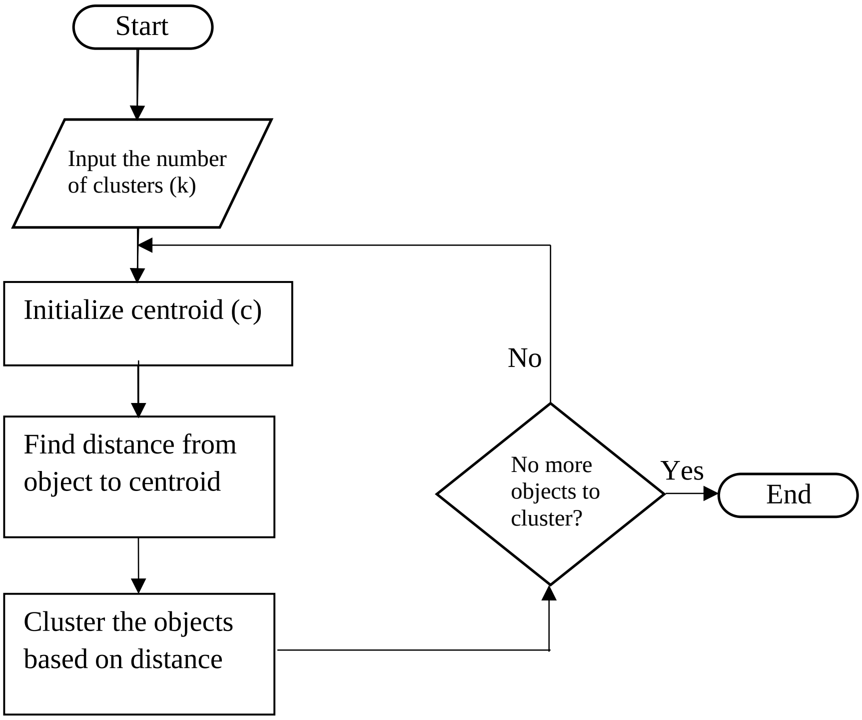

Figure 3: Flow chart of K-means Cluster

Clustering of sensor nodes and using transition probability with single ant between the cluster heads was shown in figure 4 below

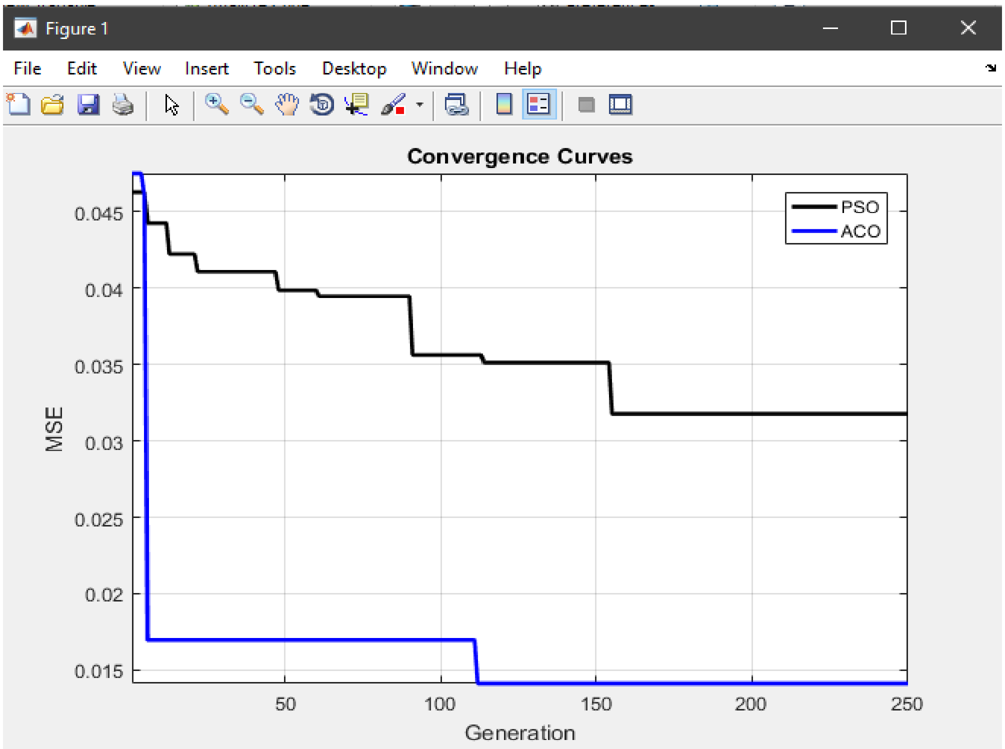

Figure 13 Performance evaluation of ACO with PSO optimization technique

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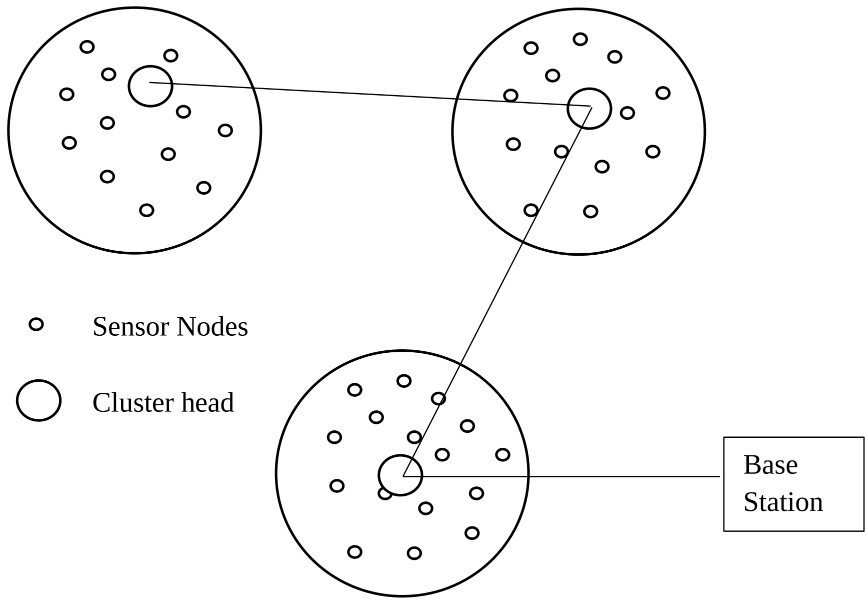

Figure 4: Clustering of Sensor nodes

To improve the overall network lifespan, it is necessary to change the cluster head because when maintaining a single cluster head energy loss by that single node will be more, resulting in lesser network lifetime. The change in cluster head is based on the energy of the nodes in a particular cluster (node which has higher energy, will become a cluster head for particular iteration). For the next iteration, cluster head is determined again based on the residual energy of nodes in a particular

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cluster. The sender cluster head will dissipate the energy based on the following formula (Lin et al., 2024).

$$E_T(l,d) = \begin{cases} l\left(E_\epsilon + \epsilon_f d^2\right), if\ d < \delta \\ l(E_\epsilon + \epsilon_m d^4), if\ d \geq \delta \end{cases} \tag{4}$$

Energy dissipated by receiver cluster head is given by the following formula:

$$E_R(l) = lE_\epsilon \tag{5}$$

Where:

$E_T(l,d)$ and $E_R(l)$ indicate the energy dissipated for transmitting l bit of data over the distance d and energy dissipated for receiving l bit of data respectively.

δ Represent residual energy threshold that node must exceed to qualify as a cluster head.

d distance between a sensor node and a cluster head.

E_ϵ indicates the energy dissipated to operate the circuit per bit.

ϵ_f and ϵ_m are free space propagation model and

$$\delta = \sqrt{\frac{\varepsilon_f}{\varepsilon_m}} \tag{6}$$

Next is path detection. The network traffic loads and communication delay are reduced by using multi-hop communication between the cluster heads. This path detection is done only after doing k-means algorithm. The algorithm for path detection is illustrated in the pseudo code below:

```
begin.
    Maximum number of iteration = 300
    Number of counts = 0
    while Number of counts < Maximum number of iteration
        increment Number of counts by 1
        Assign value of ant K to be same as number of clusters
        Calculate transistion probabilib ty
        If Ki < number of clusters
            Continue
        End if
        Calculate cluster head
        Update pheromone value
    End while
```

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Optimal cluster head detected

End

Figure 5 represent the flow diagram of the path detection algorithm. The above steps are represented as a flow diagram. ACO algorithm has an advantage of maintaining entire colony memory instead of having only previous generation in memory with less affected to poor initial value.

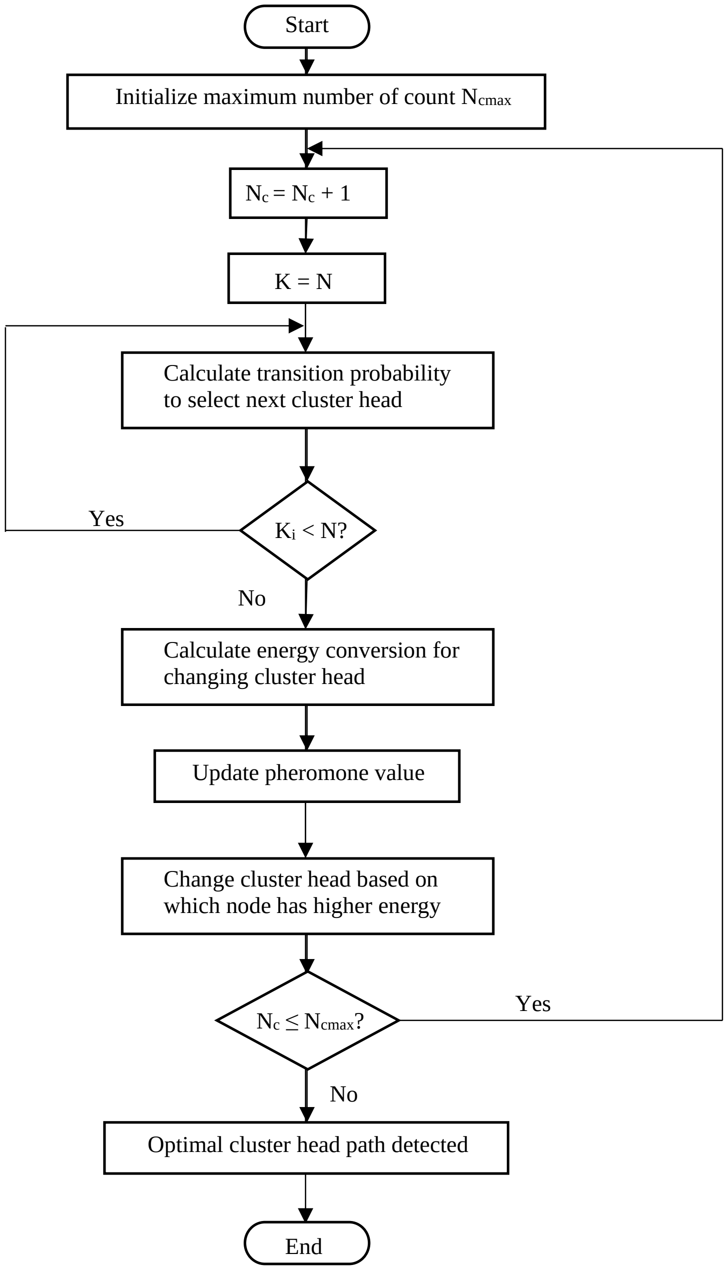

Figure 5: Flow chart of path detection using ACO

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The simulation of this algorithm is done using MATLAB 2016a. The assumptions are made according to survey [25] that nodes are deployed in the region of 100m x 100m network field with 200 nodes randomly distributed between (x = 0, y = 0) and (x = 100, y = 100), implemented using MATLAB functions (see appendix i). The algorithms of ACO and k-means employed in this research work proves to be faster in detecting the path and also it increases the lifetime of complete network due to change of cluster head for every iteration. This protocol takes the advantage of the parallel ACO algorithm to detect best path for routing. For reducing the energy from the sensor node equations, (4) and equation (5) formulas are used. Table 1 below summarizes the parameters used in running the simulation.

Table 1: Parameters used for simulations [25]

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S/N	Parameter	Value
1.	Network area	100m x 100m
2.	Number of nodes	200
4.	Number of ants	20, 30, 40
5	Maximum iteration	300s
6	α, β	1,1
7	P	0.05

III. RESULTS AND DISCUSSIONS

The results obtained after running the k-means cluster algorithm and the improved Ant Colony Optimization Algorithm. The combination of these two algorithms is then compared.

3.1 Results

Figure 6 shows how the result when MATLAB was used to generate the WSN over a 100m x100m space using the codes were shown in appendix ii

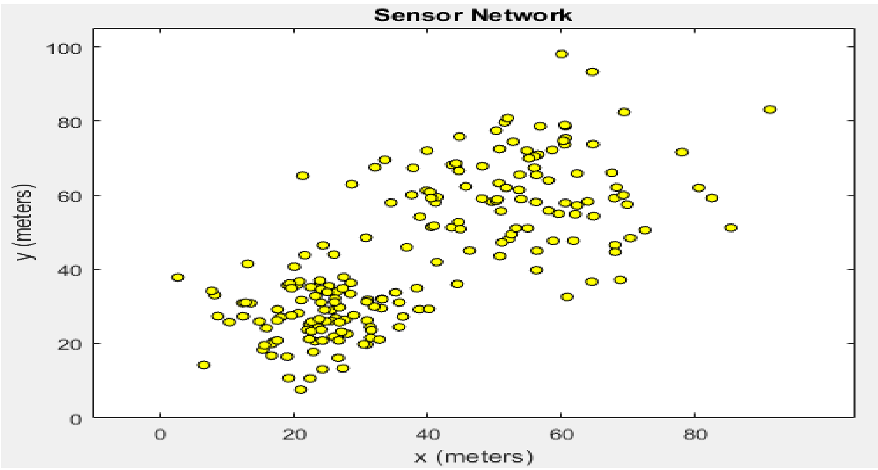

Figure 6: Simulation of wireless sensor network in MATLAB environment

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After generating the data that is use to implement the WSN, the k-means, for two-cluster partition algorithm, three-cluster partition algorithm, and four cluster partition algorithm was then executed on the generated data and the result are shown graphically in figure 7. .The code used to implement the k-means algorithm is in appendix ii.

c b a

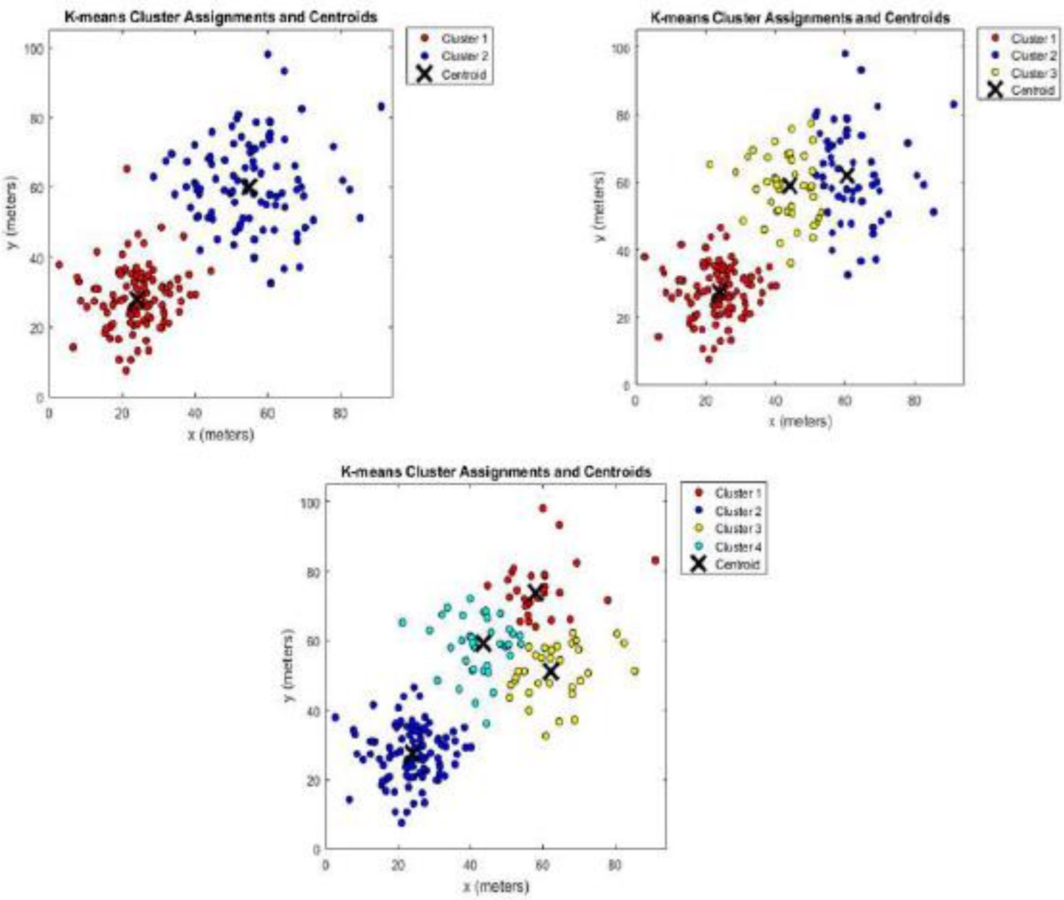

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Figure 7: Result shown graphically for K-means algorithms for different clusters: (a):k-means, two-cluster partition algorithm; (b)k-means, three-cluster partition algorithm; (c)k-means, four-cluster partition algorithm

In figure 7 respectively, the cluster head indicated in the legend as centroid and marked in the graph as the point “X”.

After implementing the k-means algorithm for the desired cluster partition, each of these desired k-means cluster partitions used to run the improved Ant Colony Optimization Algorithm using the codes of appendix iii.

Graphical result of the Ant Colony Optimization Algorithm using k-means, two-cluster partition algorithm, three-cluster partition algorithm, and three-cluster partition respectively ate shown in figure 8.

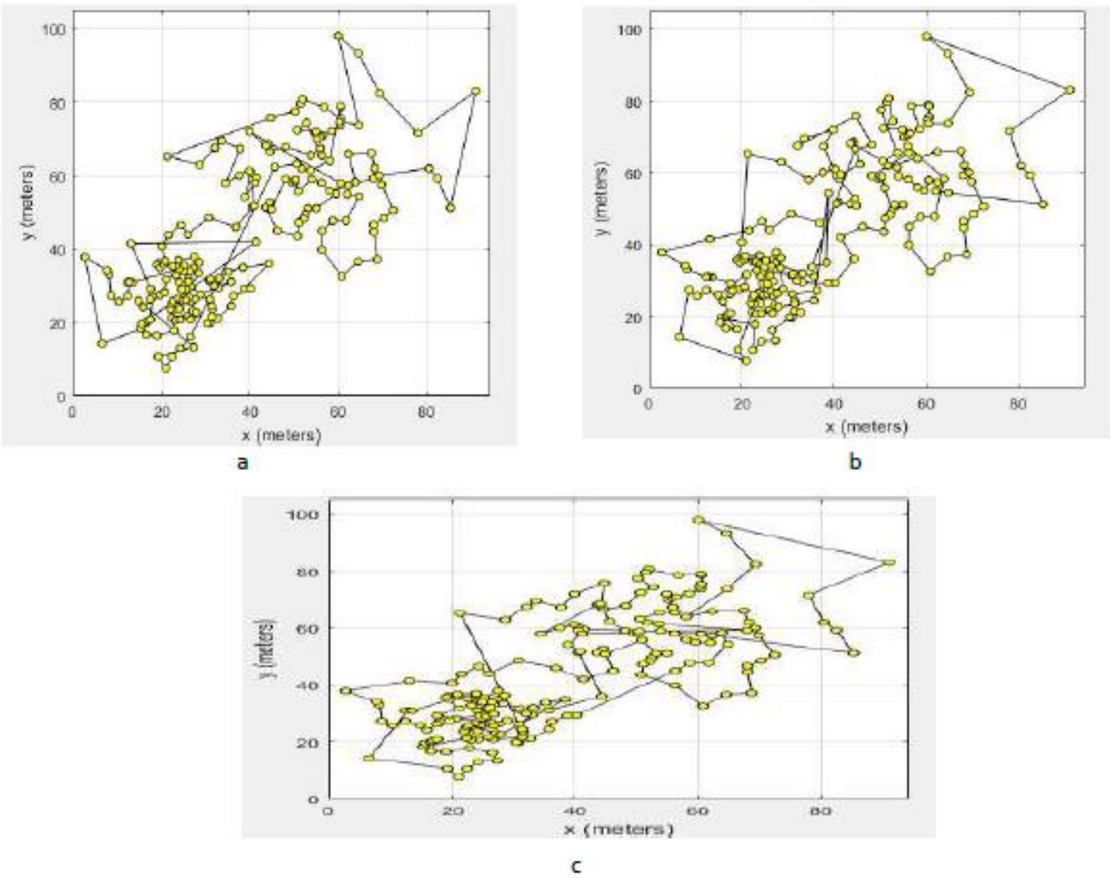

Figure 8: Implementing Ant Colony Optimization Algorithm with k-means; (a) Two-cluster partition; (b) Three-cluster partition; (c) Four clusters partition

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In figure 9 is the graphical result of the shortest path obtained when the improved Ant Colony Optimization Algorithm is executed for different values of the k-means cluster.

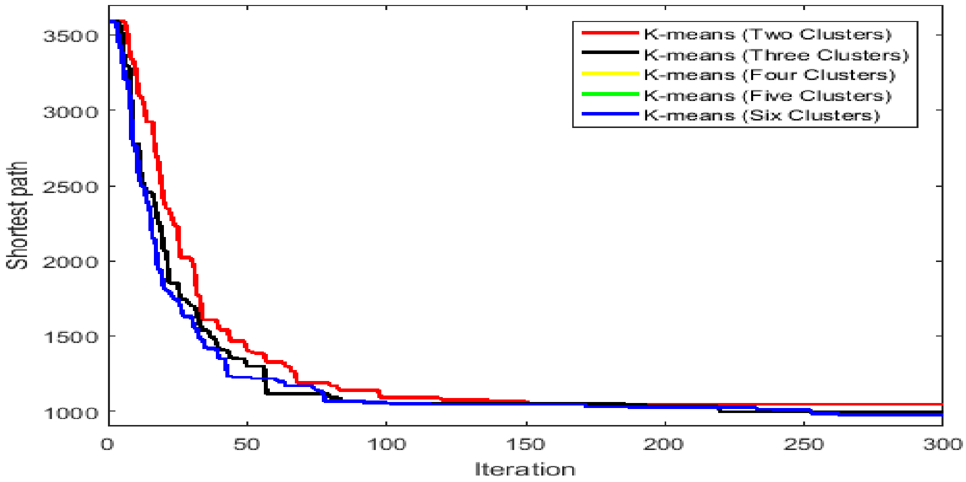

Figure 9 ACO Shortest path with different K-means cluster value

3.2 Discussions

The result presented in figure 7 shows clustering results from the k-means, two-partition algorithm. The k-means algorithm successfully partitions the data into two. The centroid of these clusters are marked with the symbol “X” as shown in figure 7 The result presented in figure 7 also shows clustering result from the k-means, three-partition algorithm. The k-means algorithm successfully partitions the data into three. The centroid of these clusters are marked with the symbol “X” as shown in figure 7 similarly result presented in figure 7 shows clustering result from the k-means, four-partition algorithm. The k-means algorithm successfully partitions the data into four clusters. The centroids of these clusters are marked with the symbol “X” as shown in figure 7c.

The result presented in figure 8 shows the ACO algorithm. The yellow circles indicate the sensor node in this case they are 200 in number. The black line linking the yellow circles are final pheromone trails that represents the best (shortest) path of communication for the sensor network in other to prolong the life of the sensor. As the algorithm is being executed, the system shows and updates all the possible path of communication or transmission of data through the sensor nodes until the best path is established using formulae described in chapter three. Figure 8a shows result of the ACO algorithm when k-means, two-cluster partition is applied to the WSN. Result presented in figure 8b shows the ACO algorithm after 300 iterations. The yellow circles, just like in figure 8b, indicate the sensor nodes, in this case they are 200 in number. The black line linking the yellow circles are final pheromone trails that represents the best (shortest) path of communication for the sensor network in other to prolong the life of the sensor. As the algorithm is being executed, the system update all the possible path of communication or transmission of data through the sensor nodes until the best path is established using formulae described in chapter three. Figure 8b shows result of the ACO algorithm when k-means, three-cluster partition was applied to the WSN. Lastly, figure 8c, the yellow circles, just like in figure 8b indicate the sensor nodes, in this case they are 200 in number. The black line linking the yellow circles are final pheromone trails that represent the best (shortest) path of communication for the sensor network in other to prolong the life of the sensor. As the algorithm is being executed, the system shows and updates all the possible path of communication or transmission of data through the sensor nodes until the best path is established using formulae described in chapter three. Figure 8c indicated the result of the ACO algorithm when k-means, four-cluster partition is applied to the WSN.

The graph of figure 9 is the result when the ACO algorithm is executed for each of the cluster partition selected. Can be seen from the graph that the ACO algorithm that incorporates k-means with four, five and six clusters gives the same and best result as it provides the shortest path for the WSN compared to the other cluster partition.

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Table 2 shows the comparison of this research work with (Kulkarni & Venayagamoorthy, 2011). From the table it can be seen that the ACO algorithm performs better as it provides shorter paths in all the k-means cluster partition used (see appendix iv for complete data).

Table 2: Comparison results of shortest path based on k-means cluster partition

S/N	K-means Cluster Partition	Shortest path for WSN (ACO)	Shortest Path for WSN (Kulkarni & Venayagamoorthy, 2011)
1	Two partitions	1046.538 m	1051.146 m
2	Three partitions	997.8539 m	1003.125 m
3	Four partitions	976.1209 m	997.3812 m
4	Five partitions	976.1200 m	997.3800 m
5	Six partitions	976.1090 m	997.3500 m

It is, also, worth stating that as the k-means cluster partition increases, the ACO algorithm becomes much slower and yet gives the same results for higher values of k-means cluster partition. It was observed from figure 13 that the graphs overlaps from the fourth, fifth and sixth partition. It is for this reason that this research work stopped at four-cluster partition.

Performance Evaluation: *N* sensor nodes were distributed randomly in 100m × 100m area. Simulation results of ACO work are presented against the Particle Swarm Optimization (PSO) algorithms. Figure 10 shows the result when the algorithm used in this research work is compare to the PSO algorithm

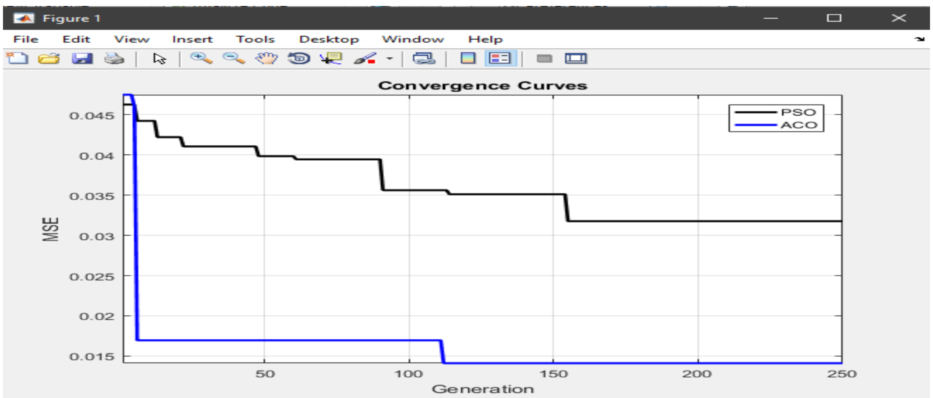

Figure 10 Performance evaluation of ACO with PSO optimization technique

IV. CONCLUSION

This study indicates that sensor network is clustered effectively using K-means algorithm and uses the parallel ACO algorithm for finding the path to route the data. Using the algorithm the time taken to find the optimal paths is less as compare to other existing methods. This algorithm is mainly depends on cluster heads and the lifetime of complete network which is incremented by changing the cluster head based on energy consumption. The study further proposed energy Efficient K-means Clustering with Ant Colony Optimization (ACO) Routing protocol performed 98.54% better compared with Particle Swarm Optimization. Lastly, it was effected that the higher the k-means cluster partition employed during clustering, the better the results obtained from ACO.

V. RECOMMENDATIONS

Future work can be carried out to improve on this work, such as: to find the optimal path by considering the internal nodes and applying ACO algorithm, using different nodes because nodes may have different data priorities.. In addition, data aggregation techniques may be applied for UWSN (underwater wireless sensor network) future.

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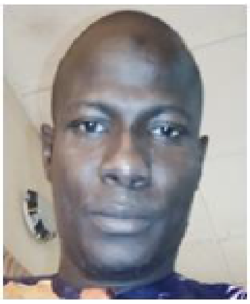

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