INVESTIGATION OF ANT COLONY OPTIMIZATION ALGORITHM FOR EFFICIENT ENERGY UTILIZATION IN WIRELESS SENSOR NETWORK

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ABSTRACT

Maintaining the energy conservation is considered as an important approach to increase the lifetime of WSN. In fact, an energy reduction mechanism is considered as the main concept to enhance the lifespan of the network. In this paper, the performance analysis/evaluation of optimization technique, specifically, Ant Colony Optimization (ACO) and modified ACO (m-ACO) in the routing method are investigated. This network analysis is done by 100 iterations and differentiated with 50, 75 and 100 numbers of nodes. Finally, experimental results illustrate that the performance of m-ACO algorithm obtained the obvious performance, which is comparatively better than ACO algorithm, because it improves the routing efficiency by pheromone evaporation control and energy threshold value. It demonstrates that m-ACO algorithm gives better results than ACO in terms of throughput (1.41%), transmission delay (1.43%), packet delivery ratio (1.41%), energy consumption (2.05%), and the packet loss (9.70%). The convergence rate is analysed for ACO and m-ACO algorithms with respect to 100 number of iterations for WSNs.

KEYWORDS

Nature Inspired Computational (NIC) Algorithms, Energy Efficiency, Route Discovery, Convergence Rate and Wireless Sensor Network (WSN)

1. INTRODUCTION

This WSN is one of the emerging technologies which helped to gather highly meaningful information from various sources. In WSN, greater amount of sensor nodes are incorporated wirelessly and deployed in the problem area. Further, every sensor is an intermediator which supports successful data transmission by creating network connection between source and destination. The sensor node is an electronic device that contains four types of elements, namely, sensing unit, processing unit, communication unit and power unit. The sensing unit collects the required information and converts the analogue signal into digital signal. Moreover, the processing unit controls all other functionalities of the sensor node, using the microcontroller as well as microprocessor, and it maintains a tiny memory. The communication unit is responsible for transmitting and receiving the data packets in wireless sensor network. Energy unit distributes the power to all other components of sensor node which is considered an important part in WSN. Figure 1 illustrates the components of wireless sensor node. Energy utilization is an essential factor in WSN, because, every wireless sensor node contains tiny batteries for energy utilization.

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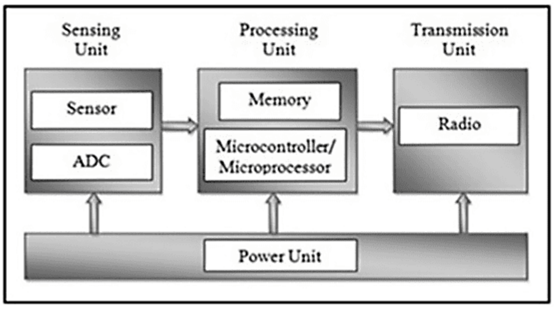

Figure 1. Components of Wireless Sensor

Many researchers solve these problems using different optimization techniques such as protocol optimization, route selection method, algorithms-based optimization, route discovery mechanism, node deployment methodology, etc. The route discovery mechanism mostly helps to minimize the nodes energy usage as well as improve the lifespan of WSN by selecting an efficient route [1][2]. Routing is a process to select the appropriate route to transmit the data from sender to receiver in WSN. Routing is divided into two types, namely, single-hop routing and Multi-hop routing. In single-hop communication, source and destination are directly communicated without using any intermediate nodes in single-hop communication. In multi-hop routing, the source node communicates that destination with the help of intermediate nodes. The sensor node is unable to communicate other nodes larger than radio range of a single node. The multi-hop routing is mostly used in WSN because it extends the network coverage and improves the connectivity.

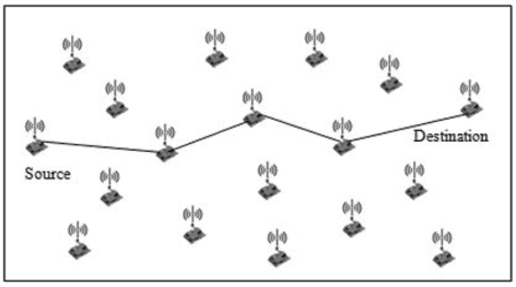

Figure 2. Multi-hop Routing in WSNs

Figure 2. illustrates the multi-hop routing in WSN scenario. This network contains a source and destination node to transmit the data packets. In this scenario, line indicates the path between source to destination with the intermediate nodes. In this path, all the sensor nodes, except source and destination, are considered as intermediate nodes which help successful data transmission. In this case, the network takes four hops to reach the destination in wireless sensor network.

This case investigates the comparative analysis of ACO and m-ACO algorithms to minimize the energy utilization and improve the WSN performance by route discovery mechanism. ACO algorithm is widely applied for scientific and complicated optimization problems like Traveling Salesman Problem (TSP), Quadrative assignment problem, Vehicle routing, Binary knapsack problem, Network routing and QoS (Quality of Service) [3]. Moreover, ACO algorithm is a major inspiration for developing several energy-efficient routing algorithms [4]. Further, ACO algorithm can identify the most optimal path to destination as well as reduce energy usage and increase network lifetime [5]. ACO algorithm is considered as a good solution to enhance the lifetime of WSN [6]. As per this analysis, m-ACO extends the performance more than traditional ACO such as stability and energy load balancing, and eventually, enhanced the network lifespan and minimized the energy utilization [7]. This conventional mechanism uses threshold value to each node in WSN for energy balancing and controls death nodes. Furthermore, the pheromone evaporation rate is increased to avoid the frequently used path when the node's energy is less than threshold. In this case, the results were differentiated by the metric of residual energy with different threshold values. This paper focuses on the comparison analysis of ACO and m-ACO algorithm in 100 iteration as well as differentiates with three increased number of nodes, namely, 50, 75 and 100. Therefore, the performance of both algorithms is investigated with various performance metrics, namely, energy consumption, packet delivery ratio, throughput, transmission delay, packet loss and the convergence rate. It inspires to conduct this work. The potential literature works of ACO and m-ACO in route discovery are cited. The major contribution of this work is analyses of various number of nodes, scenarios, and performance metrics.

The formation of the paper is organized as follows: Section II briefly discusses the literature study of this paper. Section III briefly discusses the comparative analysis of ACO algorithm, modified Ant Colony Optimization (m-ACO) and route selection process. Section IV presents the result and analysis of this comparative study. Finally, Section V concludes this paper and describes the future work.

2. LITERATURE REVIEW

There are more routing approaches based on NIC algorithms as well as optimization techniques to solve these energy-based routing challenges which illustrates in Table1. The authors have carried out a lot of optimization using the protocols and meta-heuristic algorithms which applied in many ways to WSN.

Table 1. Simulation Parameters

S.No	Algorithms	Performance Metrics	Comparative Algorithms	Results
1.	Introduced Fuzzy based Ant Colony Optimization to find the shortest path.	Average running time, Fitness value and Convergence rate of algorithms	Genetic Algorithm (GA), PSO (Particle Swarm Optimization) and ABC (Artificial Bee Colony Optimization)	The proposed ACO algorithm has taken minimum time to converge the optimum solution comparatively than other algorithms [8].
2.	Investigated the performance analysis of Ant Colony Optimization technique incorporated with gradient based routing protocol and energy aware routing protocol to optimize the effective energy utilization path for WSN.	Remaining energy of the nodes	Energy aware routing with ACO and Gradient based routing with ACO Algorithm	Energy aware routing with ACO algorithm obtained a feasible path for routing and increased the lifetime of the network comparatively better than the other gradient protocol [9].
3.	Proposed an (ACO Optimized Self-Organized Tree-Based) AOSTEB energy balance algorithm to discover the optimum path for intra-cluster communication in WSN. This algorithm performs	Number of rounds, Dead node, Energy consumption, Remaining energy and Standard deviation	LEACH, PEGASIS, TBC, GSTEB, HEEMP, MOFCA and IACO	The proposed algorithm reduced the higher energy consumption and enhanced the lifetime and stability [2].

	three functionalities, namely, data transmission, multi-path creation and cluster formation.			
4.	Introduced an effective hybrid routing algorithm, namely, ACO with Hop Count Minimization (ACOHCM) based on ACO and minimum hop count scheme for WSN.	Energy consumption and lifespan of WSN	ACOHCM, Lifetime Aware WSN, ACO-GA, Classic ACO, and Energy Aware Ladder Diffusion (EALD)	The proposed ACOHCM algorithm minimized the energy consumption and enhanced the network lifetime comparatively than others [3].
5.	Introduced a novel routing protocol based on clustering technique using Firefly Algorithm and ACO algorithms. In this routing protocol, FA is used to find the optimal cluster head, and ACO algorithm is used to discover the optimal route to selected cluster head.	Residual energy, Network stability, Lifetime and Throughput	LEACH-C, FIGWO and PSO algorithms	The proposed algorithm gives the highest lifetime than LEACH-C, FIGWO and PSO algorithms [10].
6.	Initiated the Dijkstra algorithm to improve the ACO for distributing nodes in a directed graph and it is used to improve the initial efficiency and ensure stability of WSN.	Energy and Lifecycle of network	ACO algorithm	Proposed algorithm balancing the energy consumption and extending the lifetime of the network and improving ACO algorithm give better result than basic ACO algorithm [11].
7.	Conducted the comparative analysis based on ant colony algorithm and greedy algorithm for finding the available routes which increased the sensor node count and different number of ants.	Node’s energy with two different network layouts and energy of the node with various pheromone evaporation rate.	ACO and Greedy algorithm	ACO algorithm finds several routes compared to greedy algorithm [12].
8.	Introduced a new routing model based on security and routing efficiency. This proposed model is a multi-objective routing technique that uses ACO algorithm which integrates the trust-based security for WSN.	Distance covered, Node usage levels and Overhead selection time.	TRMA (Trust based Routing using Modified ACO) and PSO based model	The proposed model effectively discovers the shortest path with minimum time consumption [13].
9.	Proposed an ACACO (Adaptive Chaotic ACO) algorithm using intelligent sensor node for clustering method. This method used an adaptive strategy to increase the transition	Energy Consumption	GA and PSO algorithms with three different node density	ACACO algorithm gives best results compared to PSO and GA algorithms [14].

	probability and updated the local pheromone by releasing the advanced ants. This chaos factor modifies the current pheromone content.			
11.	Introduced an AEACO (Adaptive Elite Ant Colony Optimization) algorithm to reduce the energy usage in High-density WSN (HDWSN) routing. This algorithm used two operators to accelerate the convergence speed, namely, Adaptive and Elite.	Energy consumption	GA and PSO with various node density	The results show that AEACO reduced 30.7% energy when compared with Genetic Algorithm and 22.5% energy reduced when compared with PSO algorithm [15].
12.	Developed an Improvised Energy Efficient Multipath ACO based Routing Protocol (IEEMARP) to find the optimal path for dynamic sensor network.	Packet delivery ratio, Routing Overhead, Energy consumption, Pend to End Delay and Throughput	ACEMA, Ant Chain, EMCBR and IACR	The proposed algorithm gives the better performance in all metrics compared with other algorithms [16].
13.	Proposed a EMUC (Energy-efficient multi-hop routing with Unequal Clustering) approaches for creating clusters in various sizes based on node distance. This approach focuses on increase the lifetime of network.	Cluster generation and lifespan of network	Various clustering formation	The proposed algorithm gives the better lifetime and minimum energy consumption as well as balance the node's energy [17].

In this literature study, ACO algorithm was used to various routing problems to increase the network lifetime in WSN. Moreover, it was applied in different approaches, namely, fuzzy-based technique, routing mechanism, clustering methods, hybrid technique and optimization. In this investigation, the optimized and hybrid ACO algorithms give better performance when compared with ACO algorithm. However, sill some network problems are not completely solved in wireless sensor network. The results were taken in different performance metrics according to the problem. The next section briefly describes ACO and m-ACO algorithm and this comparison analysis.

3. Route Discovery Method using ACO and m-ACO Algorithms

3.1. Route Discovery using ACO Algorithm

The ACO algorithm is a heuristic approach and it applied to multiple computational problems for finding the optimum solutions by graphs. In this algorithm, the artificial ant is categorized into two types, namely, forward and backward ants. These ants support to find optimum route to reach the target in WSN. Concurrently, each node maintains a unique routing table for storing information on the neighbour nodes. They are, distance between node, neighbour node ID, nodes balance energy and the pheromone concentration of the path. Following that, this process will continue to occur till it reaches its destination.

In all the available routes, high level of pheromone concentration is considered the best route during the route discovery process. The ACO algorithm followed the probability selection method which is expressed from zero to one. Here, zero indicates non-occurrence and one indicates the probability of occurrence. In ACO algorithm, the probability selection is used for an ant selecting the neighbour nodes which represent the next hop node and the hop count. Moreover, the following equation (Equation (1)) is used to compute the probability selection of next hop selection [7].

$$P_{ij} = \frac{[T_{ij}]^{\propto} * [\delta_{ij}]^{\beta}}{\sum_{n \epsilon N_i} [T_{ij}]^{\propto} * [\delta_{ij}]^{\beta}} j \epsilon N_i \quad (1)$$

In this equation, P_{ij} is the probability of next hop from node i to j which is considered the hop count and i is represent the current node of route discovery and j is the next node. In this selection, the decision was made based on pheromone levels and heuristic data. T_{ij} denoted the pheromone concentration in the route of i and j. δ_{ij} described the heuristic energy of route node i and j. Moreover, $\propto$ and β indicate the various weight factors, and the pheromone concentration controlling weight indicated $\propto$. The weight of inspiration energy is indicated by β. The next hop node set is denoted by N_i. Those ants can select only next hop nodes of $i$is stored except the passed nodes.

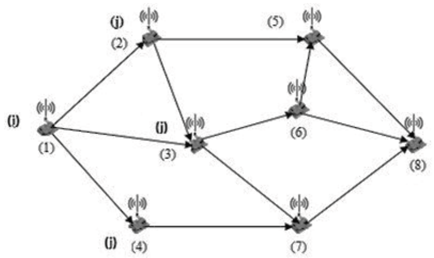

Figure 3. Example Scenario of WSNs

Example network scenario is created to explain the working process of ACO algorithm which is shown in Figure 3. This scenario totally contains eight nodes, and the nodes numbers is represented there. The node 1 (1) is the sender and node 8 (8) is the receiver node in the scenario. The purpose of this scenario is to select the optimum path in the meanwhile. Here, the i mentioned in equation 1 indicate the source node (Node (1)). Moreover, j indicates the neighbour nodes of i(Node (2), Node (3) and Node (4)) which is considered as next hop. In this case, node i chooses the following node j which is based on probability selection using equation 1. For example, if node3 is probably chosen as the next hop of node 1, it will change the position of i and j.

The next time node (3) is considered as the i node and neighbour nodes are considered as j such as node (6) and node (7). The same process is repeated till they find their destination which is indicated inFigures4 (a) and (b). In Figure 4 (b), the i node finds its destination as the node (8). Finally, data is transmitted from sender node (Node (1)) to target node (Node (8)).

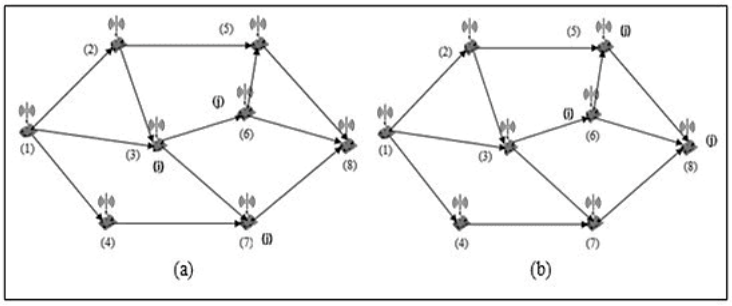

Figure 4. Next hop selection in WSNscenario

The following equations describe how to compute the probability selection of next hop node in WSN.

$$T_{ij} = \frac{1}{d_{ij}} \quad (2)$$

The pheromone concentration or pheromone initialization of the route from node i to j is calculated by Equation (2) The interspaces of the nodes between node i to node j is represented in d_{ij}. The heuristic energy of the node i and j is calculated by using Equation (3).

$$\delta_{ij} = \frac{y}{\sum_{n \epsilon N_i} E_n} \qquad (3)$$

where, y indicates the present energy of the node j and the overall energy of the node set is denoted by $\sum_{n \epsilon N_i} E_n$. Here, if node j has a higher remaining energy, it has more possibility to be chosen. Every artificial ant records the information about passed path in its memory. This information supports the ant in returning to the starting point along the same route and updating the pheromone level in the path. Pheromone evaporation is an important factor in ACO algorithm which is to avoid increasing pheromone concentrations on the path. If there is no evaporation, the paths chosen by the first ants would be overly appealing to the following ones. In this algorithm, the pheromone evaporation is used to avoid increasing the pheromone concentration rate. The pheromone evaporation rate is computed by Equation (4).

$$T_{ij} = (1 - \rho) * T_{ij} \qquad (4)$$

where, ρ represents the evaporation rate of pheromone concentration and this range is $0 \leq \rho \leq 1$. In this way, the backward ants produce some quantity of pheromone into the path from node i to j which is calculated by using Equation (5).

$$\Delta T_{ij} = \frac{w}{c_i^d} \qquad (5)$$

where, the weight factor is denoted in w and it controls the pheromone concentration of the path (i,j). In this case, the cost of the link from node i to node j is denoted by c_i^d. The Equation (6) is used to compute pheromone discharge level in the path i to j.

$$T_{ij} = T_{ij} + \Delta T_{ij} \qquad (6)$$

All the nodes participated in route selection process in wireless sensor network when using ACO algorithm. Figure 5. illustrates the route discovery process with ACO algorithm in WSNs. Thus, the node with the minimum residual energy is involved in communication, and hence these terminals can easily go to the death stage.

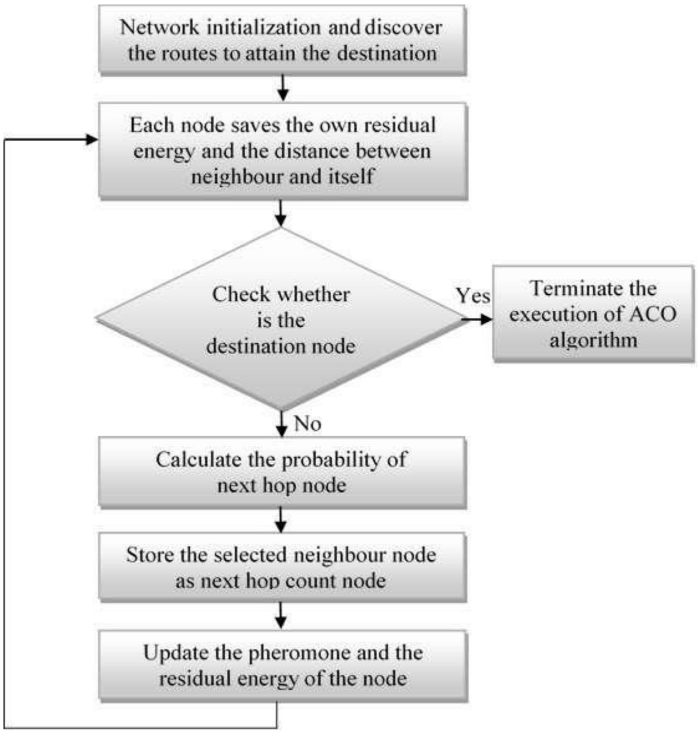

Figure 5. Flowchart of ACO algorithm

Also, it considers the best route with the high-level pheromone rate as the optimal route used frequently for data transmission. Therefore, it creates some network issues in wireless sensor network. There is link breakage, energy load unbalancing, and too much energy utilization in the nodes as well as decrease in the network lifespan. This paper introduces a new approach (m-ACO) solving these problems based on the threshold value, pheromone evaporation rate and the remaining energy of the nodes. Further, modified ACO (m-ACO) algorithm and their functionalities are explained below.

3.2. Route Discovery using M-ACO Algorithm

M-ACO algorithm followed the same routing methodology of ACO algorithm. Moreover, m-ACO algorithm pseudo-code is explained in Algorithm 1. The node energy will be decreased rapidly in the path when the pheromone level is high, because of the same nodes being used frequently. Thus, the energy optimized technique is used in this algorithm for minimizing too much of energy utilization and energy load balancing in wireless sensor network. Then, the threshold value is applied to each node of the network to avoid the death nodes and follow uniform energy consumption. Therefore, m-ACO algorithm also prolongs the lifespan of the network. In this algorithm, ant can be seen selecting the optimal path with high residual energy, and as if it has minimum pheromone rate in that path.Additionally, it includes the pheromone evaporation rate in a different way for reducing the high-level pheromone of the path. The packet structure of ant is illustrated in Figure 6 which contains the information of routing.

In this format, Type represents the ant type like forward ant and backward ant, and Src_Add illustrates source address. It contains the source node ID. Moreover, serial number of ants is illustrated in Seq.No and Visit_Node store the nodes ID that the number of nodes visited in each node. The Dest_Add indicates the destination address and the ant each time checks whether it is destination. Time represents the ant travelling time from source to destination.

Type	Src_Add	Seq.No	Visit_Node	Dest_Add	Time

Figure 6. Packet structure of ant

The following Figure 7 illustrates the table format of sensor node. It stores the neighbor node information in the route discovery process. Nodes ID is stored in ID and the neighbor nodes' names stored in Neighbor ID format. Distance is represented by the distance between one node to neighbor nodes. The node's residual energy is stored in Res_Energy column. Then the amount of pheromone contained in each path is stored in Pheromone_Rate7.

Type	Neighbor_ID	Distance	Res_Energy	Pheromone_Rate

Figure 7. The table format of neighbour node

Algorithm1: Pseudo-Code for m-ACO Algorithm

```
Initialize the parameters
    // X indicates the current node and Y indicates the neighbor nodes
    // M is denotes source node and T is denotes the threshold value
for A = X    // Select the current node
 if X <= T    //Get the neighbor node of X based on transmission range
    K = [];    //Store the neighbor nodes in K array
 End if
  for j = K
     while Y== N   // N is indicates the destination node
          C = [];    // Created the empty array for store the selected neighbor nodes
  if Y <= Threshold (Check the residual energy of neighbor node)
          // if yes, go to the probability selection otherwise increase the pheromone evaporation rate
  end if
  end for
     end while
       for Y = i
         Calculate the probability for selecting the next hop node
         The same process followed till reach their destination
       The backward ant goes to starting point and update the pheromone
        end for
end for
```

The energy optimization of m-ACO algorithm depends on various energy levels, namely, initial energy, remaining energy, and current energy of the nodes. The Equations (7) and (8)are used and compute the energy usage which is used to find various energy levels [4][5][7]. The transmission energy is calculated by using Equation (7), and received energy is calculated by Equation (8). The structure of these energy models of WSN is described in Figure 8. The parameters and values of energy consumption formula are presented in Table2.

$$E_{Tx} = \begin{cases} l * E_{elec} + l * \varepsilon_{fs} * d^2, d < d_0 \\ l * E_{elec} + l * \varepsilon_{amp} * d^4, d \geq d_0 \end{cases} \quad (7)$$

$$E_{Rx} = l * E_{elec} \quad (8)$$

where,

E_{Tx} : Energy consumption for data transmission.
E_{Rx} : Energy Consumption for data receiving.
l : Data bits.
E_{elec} : Circuit energy loss.
ε_{fs} : Free space model.
ε_{amp} : Multipath Fading model.
d : Distance between nodes.

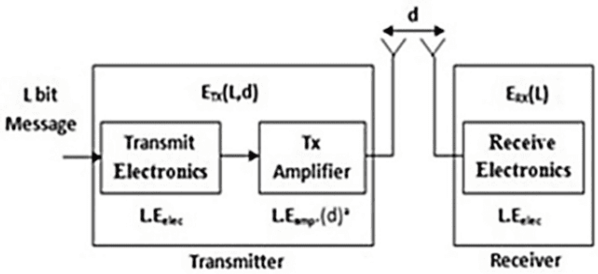

Figure 8. Energy analysis of radio energy model

Table2. List of Parameters used to Compute Energy Consumption in m-ACO

Parameter	Value
Initial Energy	10J
α and β	1.5
μ	0.8
E_{elec}	50 nJ/bit
ε_{amp}	0.0013 pJ/bit/m^4
ε_{fs}	10 pJ/bit/m^2

The following Equation (9) is used to compute the probability of next hop node selection, for node j is the probability that ants will choose node j as the next hop from node i. The target of this probability selection is maximum of P_{ij}.

$$P_{ij} = (1 - \mu) * \frac{[T_{ij}]^{\propto} * [\delta_{ij}]^{\beta}}{\sum_{n \epsilon N_i} [T_{ij}]^{\propto} * [\delta_{ij}]^{\beta}} + \mu * \frac{E_j}{E_{init}} j \epsilon N_i \quad (9)$$

where, P_{ij} represents the probability selection of next hop node from i to j. T_{ij} represents the pheromone concentration value in the path of i and j.δ_{ij} indicates the heuristic energy of the route. $\sum_{n \epsilon N_i} [T_{ij}]^{\propto}$ is the pheromone level of between current node and the neighbour node in the path and $\sum_{n \epsilon N_i} [\delta_{ij}]^{\beta}$denoted the reciprocal energy of the nodes. After that, μ is indicates the weight factor of energy of the node j. Therefore, α and βindicate the weight factors of pheromone and distance of the nodes in this equation. $E_{ij}$and E_{init}indicate the balance energy of node j and the earliest energy of node j, respectively.

$$T_{ij} = (1-\rho) * T_{ij} + \Delta T_{ij}(0 < \rho < 1) \quad (10)$$

$$\Delta T_{ij} = \frac{E_j}{E_{init}} * \frac{w}{d_{jb} * H} \quad (11)$$

The Equation(10) and Equation (11) are the pheromone updating formula. The ρ indicates the pheromone evaporation rate and ΔT_{ij} indicates the pheromone secreted rate in the route of node i to j respectively. The pheromone evaporation rate is updated as $0 < \rho < 1$ which is used to control the high level of pheromone concentration. In this, H denotes the total number of intermediate nodes through which node i has traversed. The distance between the candidate node j and the target node b is given by d_{jb}. E_j and E_{init} indicate the energy of node j and remaining energy ratio respectively.

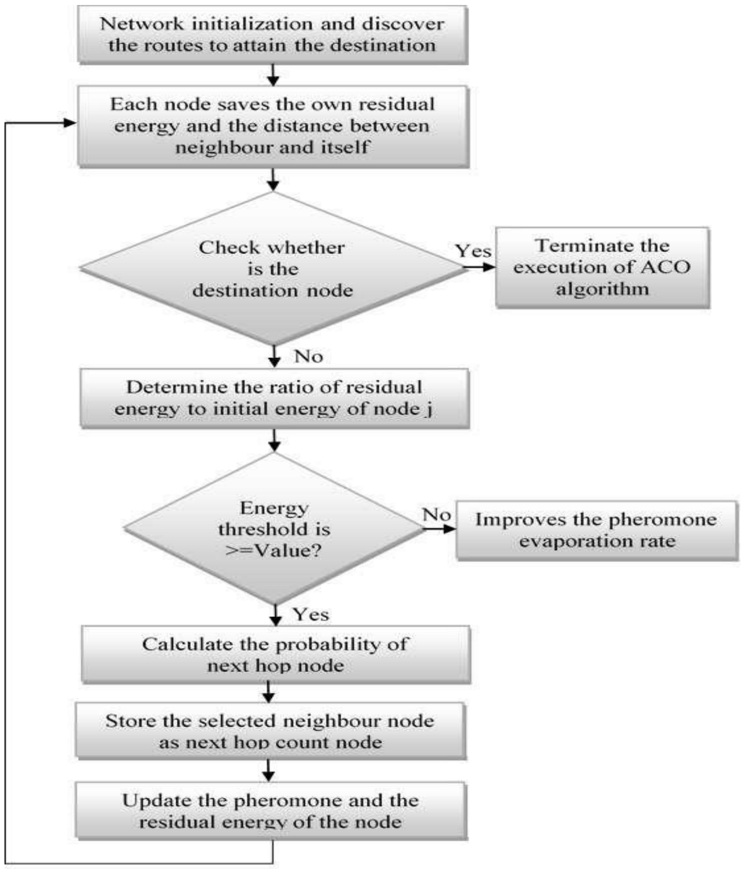

Figure 9. Flowchart of m-ACO algorithm

This algorithm controls the death node improves the network lifespan and minimizes the energy consumption. Figure 9 illustrates the flowchart of m-ACO algorithm working process. Nodes energy is substantially decreased in the current path of data transmission. Thus, there are chances of death node occurring in high level when the same path is used frequently. Moreover, the pheromone evaporation technique is introduced to solve this problem and avoid the current path of data communication. The pheromone evaporation rate is increased substantially when the energy of the node decreases to its threshold value. This method is used for avoiding the same path being used frequently and avoid death nodes of this network. In this case, m-ACO algorithm found the more available paths for probable selection when increase the node density.Moreover,the pheromone evaporation rate is increased and decreased based on the nodes energy of the route which also reduced the frequent path. However,it works effectively when usinglarge number of nodescomparatively than minimum node density.

4. RESULTS AND ANALYSIS

The experimental scenario is created to investigate the performance of ACO and m-ACO algorithms using WSN parameters. Moreover, the experimental scenario and the results are briefly discussed in the following section.

4.1. Simulation Parameters

In this experimental analysis, there is randomly deployed three different node density on the targeted region, and the size of the region is 1500*1500 meters. For this analysis, 50,75 and 100 number of nodes are selected, and every node in this network is deployed at various individual places on the targeted region. Moreover, these nodes are interconnected wirelessly with 500 transmission range to create the connection between them. This study not only focuses on 500 meters, it is inclusive of 200 to 300 meters range. This range is used for the evaluation of the performance efficiency of this transmission range. Further, the experimental scenario is created using wireless network parameters to data transmission. Table 3 illustrates the parameters that create WSN scenarios.

Table 3. Simulation Parameters

Parameter	Value
Nodes Density	50,75 and 100 Nodes
Optimization Algorithms	ACO and m-ACO
Iterations	100 Numbers
Node Type	Wireless Sensor Node
Transmission Range	500 Meters
Terrain Area	1500*1500 Meters
Traffic Type	Constant Bit Rate (CBR)
Node Placement Strategies	Random Node Placement
MAC Protocol	802.11
Packet Size	2000 bits
Simulation Time	30 Seconds

The following Figure 10 illustrates the experimental scenario with 50 number of nodes for this experimental analysis. In this scenario, the green color circles are represented in source and destination nodes. In this case, Node 1 is the source node, which is highlighted with green color, and node 2 is the destination which is represented with red color. Network transmission range represents the communication range of one node to another node and the range is 500 meters. A node communicates with the other node with more than 500 meters apart with the help of intermediate node. Therefore, intermediate nodes are indicated by blue color dots. Moreover, the X-axis and Y-axis represent the region of data communication.

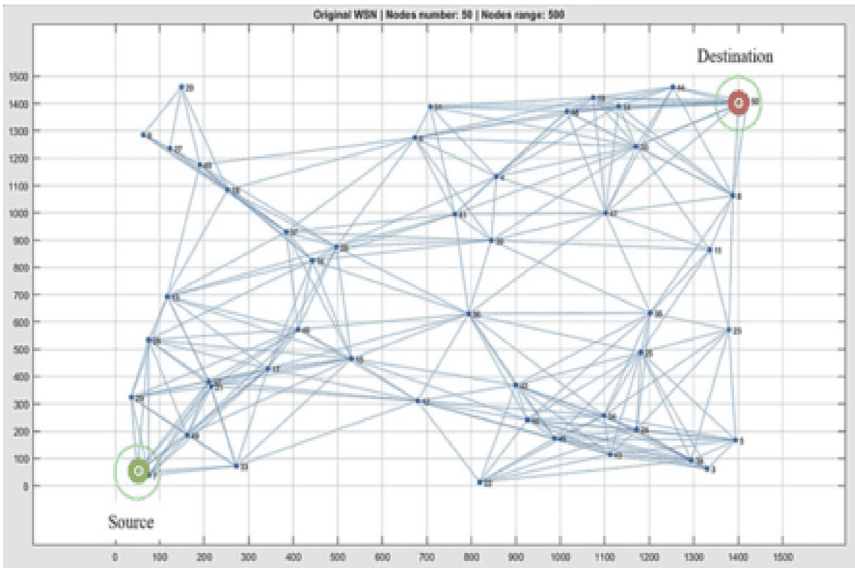

Figure 10. Experimental scenario of 50 nodes

The following experimental scenario (Figure 11) was differentiated with 75 number of nodes with random deployment. In this scenario, the intermediate node is placed randomly, but source and destination nodes followed the same region of 50 number of nodes.

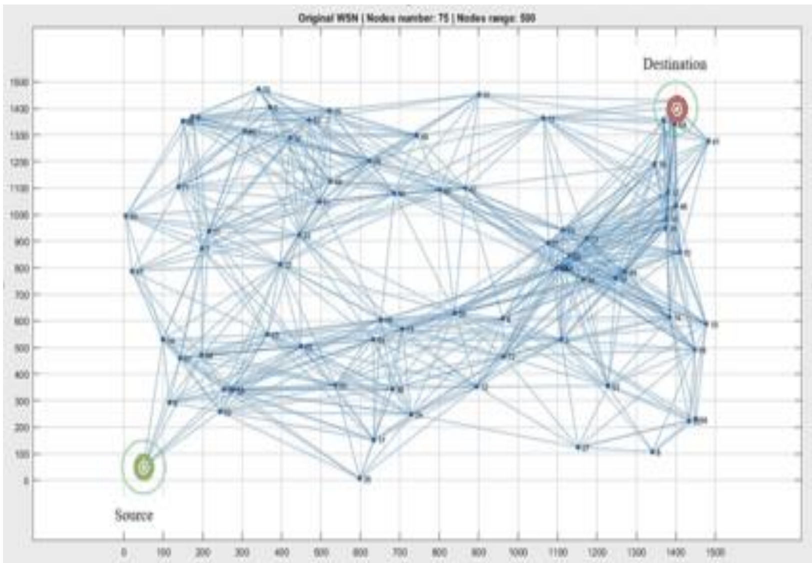

Figure 11. Experimental scenario of 75 nodes

The following figure represents the experimental scenario of 100 number of nodes (Figure 12). This scenario also followed the random node placement strategies for the intermediate nodes, but source and destination nodes followed the same region of all above experimental scenario.

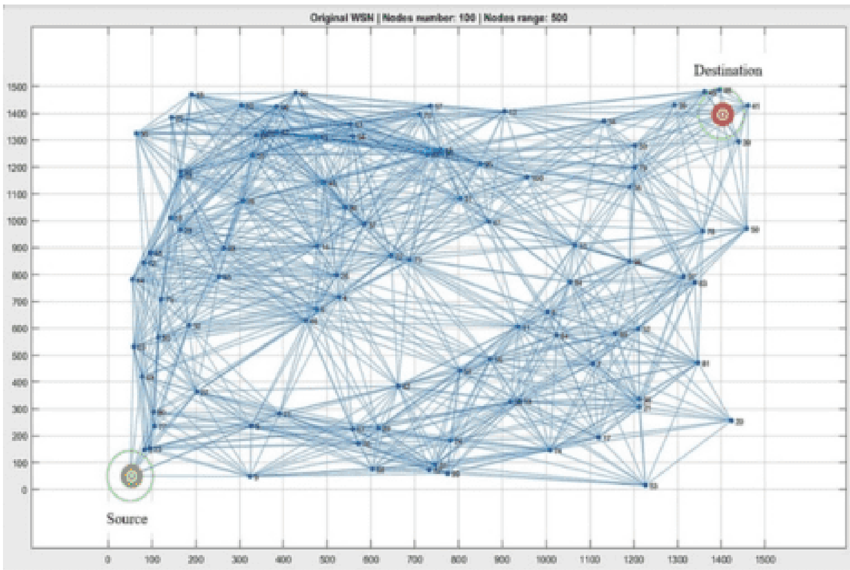

Figure 12. Experimental scenario of 100 nodes

The following Figure 13 represents the routing selection of ACO and m-ACO algorithms in the created WSN scenario. This figure shows the optimal route between source and destination which is represented with green and red color. Further, the violet color circles illustrate the intermediate nodes from source to destination. This scenario mainly focused on the optimal path of data transmission indicated with black color lines. In this case, both algorithms find a greater number of optimal routes to destination.

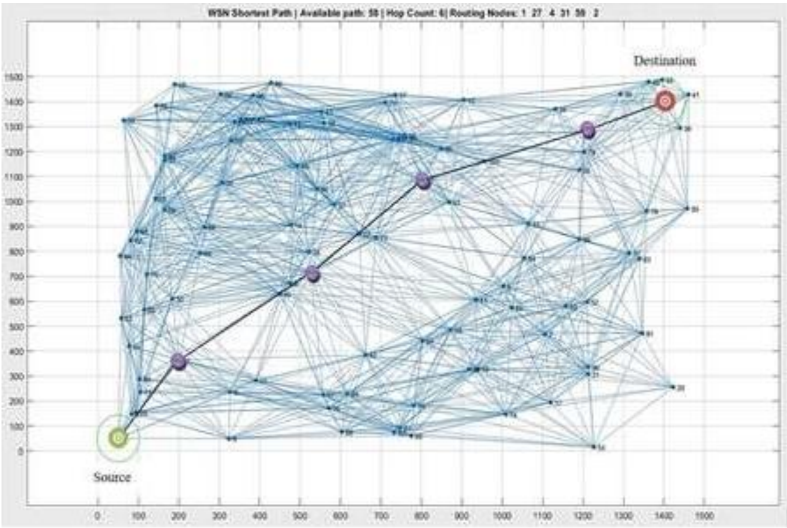

Figure 13. Route selection scenario in WSN

4.2. Discussion

The comparative analysis of ACO and m-ACO algorithms is carried out by 100 numbers of iterations with various node density. In this validation, three different node density, namely, 50, 75, and 100 nodes are used. This study uses 100 number of iterations to evaluate the performance of algorithms in each iteration. Moreover, the average performance is also analysed in both algorithms based on the performance of each 10 iteration. The following sections describe the performance of both algorithms with different node density. In this evaluation, the network performance is analysed by various metrics such as throughput, packet loss, transmission delay, packet delivery ratio, energy consumption and convergence rate. The following figure 14 described the performance of ACO and m-ACO algorithm.

4.2.1. Throughput

The number of data packets are successfully transmitted from source to destination in the given amount of time. The average throughput performance of ACO and m-ACO algorithms are illustrated in Figure 14 (a). The throughput performance is decreased in some iterations and improved at the end of the iteration when using ACO algorithm with 50 number of nodes. In ACO using 75 number of nodes, it is effectively prolonged till the 90^{th} iteration is reached when compared with initial performance. Nevertheless, throughput decrease comparatively than ACO with 50 nodes end of the simulation but reached the best result in the overall performance. The analysis of ACO with 100 numbers of nodes is observed to gradually improve until 70th iteration is reached after which there is decrease until the last iteration. In the analysis of ACO algorithm, the best throughput value is obtained when placing 100 nodes than others and reaches the nearest best value of 70^{th} iteration. In m-ACO algorithm, it was observed that it initially increased, and then decreased and increased a few times until reaching the 90th iteration when placed 50 nodes. However, the best throughput is obtained when reaching the 100^{th} iteration comparatively than other algorithm with three increased number of nodes. Moreover, m-ACO algorithm has the most similar performance till 50^{th} iteration when deployed 75 number of nodes. After 50^{th} iteration, there is effective enhancement in most of the iterations, and the nearest best performance is obtained when 100 iteration is reached. In m-ACO with using 100 nodes, before 50^{th} iteration the results effectively improved. There is the highest performance of this experimental analysis in 30^{th} iteration. Moreover, after 50^{th} iteration, it is slower than the previous performance and again effectively improved at the end of the iteration.

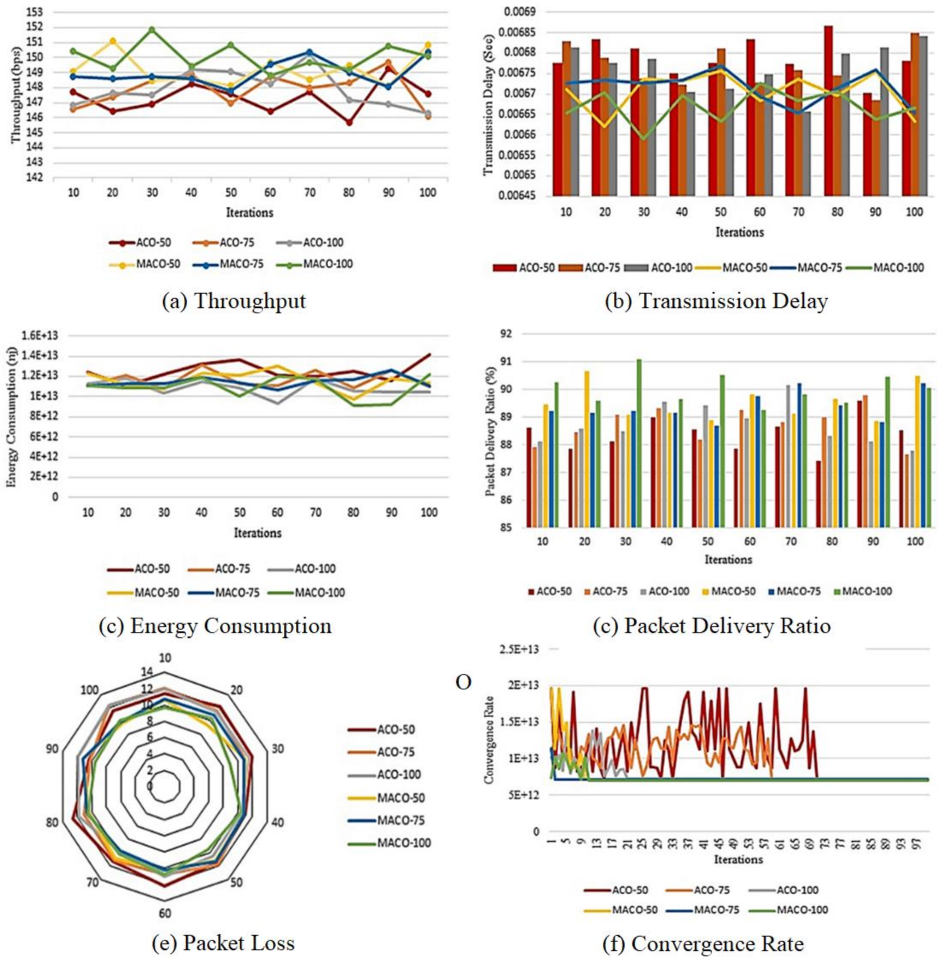

Figure 14. The performance analysis of ACO and m-ACO algorithms with various metrics

4.2.2. Transmission Delay

Transmission delay refers to the amount of time taken for a packet to travel from the source node to the destination node. The following figure (Figure 14 (b)) demonstrates the performance analysis of ACO and m-ACO algorithms with three different increased number of nodes. This delay time is measured by seconds, and the minimum time is considered as the best value. The performance of transmission delay deeply increased, but after a few runs, it decreased before 50th iteration when using ACO algorithm with 50 nodes. However, it gradually increased from 50th iteration but finally reached the best performance of this algorithm when 90th iteration was reached. ACO algorithm with 75 nodes shows highest delay in the early stage, and gradually decreased when reached 40th iteration, Therefore, poor performance is seen in 50th iteration, but after that, iteration gives better performance and reached the highest best value. Moreover, ACO with 100 nodes deeply decreased but after 50th iteration it gradually increased until 100 iteration. However, this algorithm achieved the nearest optimum results in 70th iteration. In the analysis of ACO algorithm with three different increased number of nodes, the average minimum delay obtained from 100 nodes comparatively than 50 and 75 nodes. At the same time, m-ACO algorithm obtained the maximum best solution in 20th iteration when using 50 number of nodes. After that, it gradually increased until it reached 90th iteration but became deeply slower in a few iterations. But, finally, better solution was gained compared to others in 100th iteration. When using m-ACO with 75 number of nodes, the similar performance was seen in first few iterations, and then it increased in 50th iteration. After that, it decreased deeply, but after 70th iteration delay time is seen, highly increased and obtained the minimum delay when reached 100 iterations. Finally, delay was exhibiting poor performance in a few iterations when using m-ACO algorithm with 100 number of nodes. However, it obviously reached better performance in most of the iterations, and particularly, this algorithm obtained lowest delay of this experimental analysis in 30th iteration.

4.2.3. Energy Consumption

Energy consumption represented the quantity of energy consumed to data transmission process until the data transmission is completed. This is measured by nanojoules, and the minimum value of this is considered the best value which described in Figure 14 (c).In the initial stage, minimum energy is consumed, but gradually it increased after 20th iteration when using ACO algorithm with 50 nodes. After that, it consumed minimum energy until it reached a few iterations. Suddenly it increased when it reached the end of the iteration. This analysis shows stable performance in higher number of iterations but increased few iterations in between when using ACO algorithm using 75 number of nodes. Using ACO algorithm with deployed 100 number of nodes shows minimum energy consumption in the beginning. After a few iterations, minimum consumption is seen comparatively. However, energy consumption effectively decreased in 60th iteration. After that, stable performance is seen, but it consumes minimum energy compared to previous node density. In m-ACO algorithm with 50 number of nodes, it gradually decreased in the beginning, but after a few iterations it gradually increased until it reached the 60th iteration. After that, it highly decreased, nevertheless consuming more energy than previous iteration when reached end of the iteration. In this case, similar energy consumption is seen from beginning to 80th iteration. It slowly increased when using m-ACO algorithm with 75 number of nodes. However, it obtained the similar performance of initial stage but it shows more stable consumption in each iteration. Finally, it obtained stable performance but consumed minimum energy when reaching 50th iteration in m-ACO with 100 number of nodes. After 50th iteration, the maximum energy consumption is seen, but it effectively decreased in 80th and 90th iterations. Moreover, the maximum energy of data transmission is seen at the end of the iteration. In this analysis, m-ACO algorithm obtained the minimum energy for data transmission comparatively than ACO algorithm and other node density.

4.2.4. Packet Delivery Ratio

Packet delivery ratio describes the difference between the amount of data packets successfully obtained at the receiver and the amount of data packets generated by sender node. This performance analysis of ACO and m-ACO algorithm are illustrated in Figure 14 (d) which differentiated with various node density like 50, 75 and 100. In this analysis, packet delivery ratio shows that it slightly decreased in the first few iterations but improved when using ACO algorithm with 50 nodes. After 50thiteration, it gradually increased and nevertheless slowed down when it reached 100 iteration. However, the highest best performance of this algorithm is obtained from 90th iteration. When using ACO algorithm with deployed 75 nodes, it progressively increased but the performance decreased when it reached 50th iteration. After this iteration slightly increased in a few iterations and then decreased when it reached the end of the iteration. However, ACO with 75 nodes enhanced that performance comparatively than 50 node density. The performance of packet delivery ratio effectively prolonged and nevertheless obtained less performance when it reached 70th iteration in ACO with 100 nodes. Moreover, it gradually decreased from 70th iteration to end of the iteration but enhanced the average percentage when compared with other node density. In m-ACO using 50 number of nodes, it highly increased in the starting, but after 20th iteration, the ratio progressively decreased. However, the performance decreased continuously compared with previous iteration, but reached better results of this algorithm in the ending iteration. When using m-ACO algorithm deploying 75 number of nodes, the packet delivery ratio obtained the most similar results until 50^{th} iteration. After that, the highest best performance of this node density was reached in 70^{th} iteration. It slowed down again in a few iterations. Finally, the nearest best performance was obtained in 100 iteration but it was comparatively better than 50 nodes. In m-ACO with placing 100 nodes, packet delivery percentage improved in most of the iterations comparatively than ACO and all the other node density. This performance went down in a few iterations but obtained overall best performance of this experimental analysis.

4.2.5. Packet Loss

This parameter indicates the total number of data packets lost till end of the data transmission in network. The packet loss is created for some network problem. The following figure (Figure 14 (e)) represents the performance analysis of ACO and m-ACO algorithm with three increased number of nodes. In this analysis, the minimum loss percentage was obtained from initial stage, but gradually increased after a few iterations when using ACO algorithm with 50 numbers of nodes. However, the highest loss rate in most of the iterations nevertheless reduced in the end of the iteration when compared with other node density in ACO with 75 nodes. Although increasing in the beginning, it gives lowerloss rate in the next few iterations and suddenly increased in the ending. In ACO algorithm with 100 nodes, the performance of packet loss gradually decreased the beginning to until it reached the 70^{th} iteration. After the 70^{th} iteration, maximum percentage of loss was seen until the end of the iteration. The analysis of ACO algorithm obtained the minimum loss percentage when placed 100 number of nodes comparatively than 50 and 75 nodes. Initially, it gives best performance comparatively than ACO when using m-ACO algorithm with 50 number of nodes. It gives maximum loss rate in a few iterations but provides the same amount of highest best value obtained in some iterations. When using m-ACO with 75 number of nodes, the loss percentage is more stable in the first few iterations, but after 50^{th} iteration, the minimum values were obtained until 80^{th} iteration comparatively than previous iterations. Finally, the nearest best performance of less percentage of this node density was obtained when the 100 iteration was reached. The maximum best performance is achieved in most of the iteration when using m-ACO algorithm with 100 number of nodes. Moreover, the highest best performance of this experimental analysis is obtained from m-ACO with 100 nodes in 30^{th} iteration. However, it gives the minimum of loss percentage compared with ACO algorithm and other node density.

4.2.6. Convergence Rate

The convergence rate of an algorithm describes the number of iterations it takes to converge to the optimal solution. The following figure (Figure 14 (f)) describes the convergence rate of ACO and m-ACO algorithms with respect to 100 iteration. In this experimental analysis, ACO algorithm converged in after 70^{th} iteration when deploying 50 numbers of node. But the same algorithm converged in the 60^{th} iteration when placed 75 number of nodes. After that, this algorithm converged into the 20^{th} iteration itself when placing 100 nodes. In ACO algorithm, it quickly converged when using 100 nodes comparatively than 50, and 75 nodes and take more iteration to converge the solution when using 50 nodes. The performance of m-ACO algorithm, converged in 11^{th} iteration when deployed 50 number of nodes comparatively than ACO algorithm. In m-ACO algorithm, the convergence rate for 75 and 100 number of nodes was converged on before it reached the 5^{th} iteration and the 11^{th} iterations respectively. In m-ACO comparison, 75 number of nodes quickly converged the optimum solution comparatively than 50 and 100 nodes. After that, takes more time to converge the solution when deployed the 100 nodes than 50 nodes. However, m-ACO algorithm with 100 nodes find the better solution even though taking much time to converge the solution comparatively than 50 and 75 number of nodes.

The analysis of ACO and m-ACO algorithms effectively improved the performance of WSN when increasing the node density, because, it leads to increase route counts for data transmission. Therefore, m-ACO algorithm minimized the energy utilization, and also effectively prolongs the lifetime of the network than traditional ACO algorithm. This is because, m-ACO algorithm provides an energy limitation by threshold value to each node which maintains the alive node and increases the nodes lifetime nodes in this network. Moreover, it includes the pheromone evaporation technique which support to avoid current path when the energy of a node on that path falls below the threshold. In this case, m-ACO algorithm selects the next optimum path. This algorithm is analysed more performance metrics with various perspective when compared literature study. Moreover, this study is accomplished with large simulation parameters when compared with literature survey. Finally, m-ACO algorithm obtained the best performance in all the metrics comparatively than ACO when there is increase in the node density.

5. Conclusion and Future Work

The route discovery experimental analysis is conducted by ACO and m-ACO algorithm to minimize the over energy consumption and increase the lifetime of the network in WSN. Moreover, the optimum route selection improves the network performance and balances the energy in each node. In this analysis, m-ACO algorithm is modified using energy threshold value and increasing pheromone evaporation rate. The threshold value is applied in each node to maintain uniform energy level in each node and lively network. Further, pheromone evaporation rate controls the routing management as well as avoids the same path being used frequently. In the comparative analysis, m-ACO algorithm shows better performance in all performance metrics when compared with ACO algorithm. Moreover, enhanced network performance is seen in both algorithms when increasing the node density compared to minimum nodes. Finally, it is concluded that m-ACO algorithm with 100 number of nodes maximizes the network lifetime, enhances the performance, and keeps the lively network better than ACO algorithm and other node density. It can be further extended to incorporate other ACO variants as well as different optimization algorithm and other performance metrics to conduct better investigation of this study.

Conflicts of Interest

The authors declare no conflict of interest.

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