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Power Aware Ant Colony Optimized Routing In Heterogeneous Wireless Sensor Network

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ABSTRACT
Wireless sensor networks (WSN) use small wireless sensor devices to communicate with one another, with minimum processing speed, power, and security restrictions. In recent years, wireless sensor networks have become a popular research subject area. In these types of networks, the routing algorithm is a critical component that must be studied in order to maximize network longevity. Because of the increased number of sensor nodes in the network, routing becomes significantly more challenging. Sensor nodes in Wireless Sensor Networks have memory, computation capacity, and battery capacity limitations. Therefore routing techniques based on Ant Colony Optimization have been designed to address the routing problem while dealing with routing power constraints. In this research we have developed and applied sensor node’s power source energy based Ant Colony Optimization algorithm to increase the overall lifetime of the WSN. The proposed algorithm developed and tested in MATLAB simulation environment. According to the results, the proposed power source energy based Ant Colony Algorithm increase the sensor network lifetime with compared to shortest path method.

Keywords-Ant Colony Optimization (ACO), Wireless Sensor Networks (WSN), WSN Reliability, Routing Algorithm, Energy Based Ant Colony Optimization (EACO)

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I. INTRODUCTION

A wireless sensor network (WSN) is a network of economical and simple processing device that are called sensor nodes. The typical architecture of a wireless sensor network is shown in Fig. 1. Wireless Sensor Networks have a lot of potential for a wide range of day-to-day applications in places where human labor isn't viable. It is made up of a huge number of sensor nodes that have been placed at random, which are battery-powered and restricted in terms of power sources, computational and communication capabilities are constrained, limited memory and processing speed. For an example, these sensors can be used as environmental sensor for sensing temperature. Sensor networks are made up of a large number of sensor nodes which possess self-organizing capabilities. The core of a sensor node is a small, low-cost, low-power microprocessor. The microprocessor monitors one or more sensors and connects to the outside world with a radio link. Many popular radio transceivers allow a mote to transmit to a distance of a few hundred meters. The typical power consumption is about 10 milliamps when the mote is running, and about 10 micro amps in sleep mode. Each sensor node is driven by one or two 1.5 V cells. The microprocessor, sensors, antenna and batteries are all packaged in small containers, typically a few millimeters thick [1].

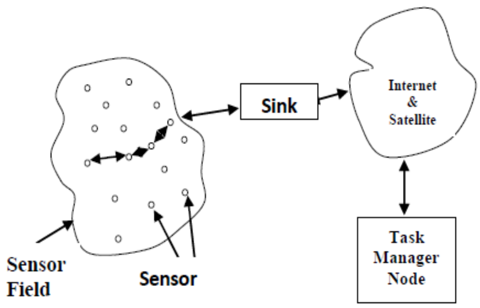

Figure 1.A network architecture of a typical wireless sensor network (WSN).

Sensors communicate with each other using wireless radio device.In wireless sensor networks most of applications require large number of sensor nodes. Sensor networks can include a variety of sensors, including seismic, thermal, electrical, optical, auditory, and other types. Sensor networks are being used in a wide range of applications in a variety of fields. Sensor network nodes may be deployed over a wide geographical region, say over a field of a few square kilometers. Typically there are one or more sink nodes or base stations which serve as collection points and connect the wireless nodes to a wired infrastructural network, for example, the Internet. In a single hop transmission, the farthest nodes may not be capable of reaching the sink node, be-cause sensor nodes have a radio range of only a few hundred meters.

Moreover, the nodes may be deployed over uneven terrain in a non-uniform manner (as would be the case for example when several sensor nodes are airdropped over a mountainous region).These factors combined with the re-source limitations of sensor nodes make the problem of routing highly nontrivial. The obvious solution to this problem is to resort to multi-hop routing, wherein sensor nodes communicate with the sink node via multiple hops through other intermediate nodes. Each sensor node serves as a router in addition to sensing its environment. Conventional link state routing algorithms consume a lot of expensive memory space for maintaining their tables and are hence unsuitable for the sensor network scenario.

The lifetime of a fully active sensor node is of the order of a few days. The most energy intensive operations for a node are those of radio transmission and reception. The energy consumed is determined to be related to the number of packets transmitted or received. To maximize the net-work lifetime, therefore, the amount of network traffic should be minimized. One way of accomplishing this is for certain network nodes to collect raw sensor readings from a number of sensor nodes and combine them into a single composite signal which is then forwarded towards the sink node. This process is called data aggregation. Data aggregation can greatly reduce the number of packets transmitted, which can result in large energy savings. There are different types of wireless sensor network with different approaches such as single sensing and multi sensing approach and there are also wireless sensor networks with different infrastructure such as Heterogeneous and Homogeneous WSNs [2]. Under the homogeneous WSN systems, all nodes have the same battery power and hardware specifications and this is a simple network with a single network topology [3]. In conclusion, we may state that the Homogeneous sensor networks are sensor networks in which the sensor nodes have equal hardware complexity and battery energy [4]. Under the heterogeneous networks, more than one and different types of nodes with different battery functionality are employed and Different topologies are utilized, making the network extremely complicated. So we can conclude in case of heterogeneous WSNs, there are two or more different sorts of network nodes, each with its own set of functions and battery energy is used to power them. The most of networks are implemented in a heterogeneous manner in real world applications [5].

Wireless sensor networks have different power consumption in different types of their functions. Sensing, processing, transmission, position finding systems and power units are just some of the activities that wireless sensors perform. However, WSNs have some limitations, such as a finite amount of energy, computational power, memory, band-width of links connecting sensor nodes, etc. The typical power consumption of the wireless sensor is about 10 milliamps when the mote is running, and about 10 micro amps in sleep mode. Each sensor node is driven by one or two 1.5 voltage cells. The microprocessor, sensors, antenna and batteries are all packaged in small containers, typically a few millimeters thick. The most energy intensive operations for a node are those of radio transmission and reception. Since sensor nodes have limited battery power, energy efficiency is a key issue in designing a topology for a sensor network, which affects the lifetime of it greatly [6]. There-fore this research conducted to implement the power aware routing in heterogeneous WSNs by using Ant Colony Optimization (ACO) technique based on power source energy levels of sensor nodes. Furthermore increase overall life time of the Heterogeneous WSNs and improve the power optimization and utilization in the WSNs.

II. RELATED WORKS

In this research, researchers successfully developed and applied an ant colony based uneven clustering APTEEN algorithm (ACUCAPTEEN) in to the cognitive wireless sensor networks [7]. The approach combines a cross-layer de-sign approach with routing and spectrum allocation, improvements and introduces an energy-efficient uneven clustering mechanism to APTEEN, and the inter-cluster path search is completed using the ant colony algorithm, which simplifies the workload for the base station. During the selection of candidate cluster heads, the leftover energy is not taken into account, and the competition radius is set in stone, therefore cluster heads are nodes with a large number of idle channels but low residual energy, and even if the cluster heads are far away from the base station, they still have more inter-cluster activities to complete and have less transmission power. To optimize all these issues in the candidate cluster heads, an improved ACUCAPTEEN method is proposed, the candidate cluster head probability is multiplied by the remaining energy, and the competitive diameter is adjusted.

In the current WSN systems [8], data gathering difficulty and network energy usage are two main issues. This has a significant impact on the WSN's reliability. In this research improved ant colony algorithm is proposed. The energy consumption of wireless sensor network nodes based on an upgraded ant colony algorithm is reduced and there is higher residual energy in sensor nodes.

Additionally, in the WSN transmission target function, the energy model and data transmission balance model are developed and validated. The experimental results reveal that the WSN node, after using an upgraded ant colony method to assist in determining the public node's location data, then uses that knowledge to make the protocol have efficient routing performance and efficient target node lo-cation discriminating ability. Thus, the modified ant colony method investigated in this paper has significant practical implications for wireless sensor network life cycles and energy usage. In addition, focusing on wireless sensor network features and routing efficiency, the message is transmitted to the target node safely and efficiently using a low-power routing approach depending on the location and direction, which boosts the data packet transfer rate effectively.

The mobile ad hoc network (MANET) is a multi-hop, non-centralized network made up of self-organizing mobile terminals [9]. Attempting to solve the problem of excessive energy consumption in MANETs caused by node motion, in this research an improved energy and mobility ant colony optimization (IEMACO) routing algorithm is proposed. Firstly, by providing an offset factor of the transition probability, the technique improves the convergence speed of the routing protocol and minimizes the number of path discovery packets. Then, depending on the rate of energy usage, the nodes' residual lifespan (RLTn) is taken into ac-count. The link (RLT1) remaining lifetime is predicted using the position and velocity data. To develop the pheromone generation method, the algorithm integrates RLTn and RLTl, which chooses the better quality option based on the transition probability to make sure that the information is continuously transmitted. As an outcome, the network's energy usage is controlled. According to the simulation results, when contrasted to the Ant Hoc Max-Min-Path (AntHocMMP) algorithm and Ad Hoc on-demand multipath distance vector (AOMDV) algorithm taking into account node energy usage and mobility [10], The AOMDV algorithm can minimize path discovery rate and has a reduced end-to-end delay as well as a reduced packet loss rate, mainly when nodes relocate, allowing the network lifetime to be extended.

HEED Algorithm periodically selects CHs according to their residual energy [1]. It is also a distributed clustering algorithm. HEED has eliminated the non-uniform cluster forming problem observed in LEACH [11] and SEP. Since, HEED algorithm considers node residual energy in CH election; it can perform in a heterogeneous network as well. However, HEED uses a complex weight-based cluster setup procedure, where CH is selected with many rounds of iterations [12]. This results of the communication overhead during cluster setup phase. HEED too rotates CHs after a constant predetermined number of data gathering rounds. Hence, same problems faced by LEACH on fixed time-based CH rotation are applicable to HEED.

In the proposed methodology [13], each node in a wire-less sensor network can save the distance and leftover energy of its neighbors. Furthermore, in perspective of node probability choosing and pheromone updating, by com-paring the distance between the nodes and the remaining energy, this method concentrates on the next hop node. As a result, there are low opportunities of low-energy nodes being chosen as the next hop. Therefore, the suggested approach increases energy load balancing, wireless sensor network reliability and wireless sensor network life span. The routing algorithm explained in [14], considers the energy efficient phenomenon in the wireless sensor networks. By eliminating the error correction and error control and sending same packets to tow different sink nodes. It will be transferred to a central location, where the information will be extracted using a variety of combining methods. Even in the lack of any error correction coding, the reliability of diversity must be acceptable.

III. PROPOSED METHODOLOGY

Through the literature survey, it is obvious that there are many algorithms, in order to increase the overall lifetime of the wireless sensor networks (i.e. the energy aware routing algorithms). Ant colony optimization method is a basic and well-defined optimization technique [15]-[16]. In this project to optimize the power of the wireless sensor as well as improve the overall lifetime of the WSNs. Here going to use the Ant Colony Optimization method. The Ant Colony Algorithm (ACA) is a revolutionary biological algorithm de-signed to solve combinatorial optimization challenges. It was first utilized to answer the Traveling Salesman Problem by Italian academic M. Dorigo in the 1990s [17]. The for-aging behavior of actual ant colonies inspired this optimization technique, which has positive feedback and parallel computation characteristics. Blind ants can discover the quickest way between food sources and their nests, according to biologists. ACA communicates through a chemical compound called pheromone, which is left behind by real ants, as an oblique way of remembering previously discovered facts. Based on the ant colony system, this study provides an energy sensitive routing method for heterogeneous networks. As a consequence on routing selection, the algorithm examines the available power of nodes and the energy usage of each route. It can avoid depleting the energy of nodes on the best path and extend the net-work's lifespan while maintaining communication link.

Conventional wireless network routing protocol development focuses on avoiding network congestion and improving service quality. However, due to node energy limitations, in wireless sensor networks, the routing protocol must be designed to be more energy efficient. Therefore, it must make certain that network energy consumption is kept to a minimum and it is necessary to balance global energy consumption in order to extend the network's lifecycle. According to the previous researches, the ant colony algorithm offers a fresh approach to the problem of wire-less networks. Because of this, we combined the characteristics of wireless sensor networks with ant colony algorithm and proposed new wireless sensor network routing algorithm based on sensor node energies. In order to discover the most energy efficient route from the source node to the destination node. The energy component is factored into the probability selection of the path and the increase of the communication level by the algorithm. As a result, the network's overall life cycle is extended.

3.1. The Typical Ant Colony Algorithm

The Ant System is the first suggested ACO algorithm in the research [6]–[8]. Its major feature is that the pheromone quantities are modified at every iteration by all the m ants who have created a solution during that iteration. The pheromone τ_{ij} which is connected with the edge connecting cities *i* and *j*, has been modified as follows,

$$\tau_{ij} \leftarrow (1-\rho).\tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \qquad (1)$$

Where ρ is the evaporation rate, m is the number of ants, and $\Delta\tau_{ij}^{k}$ is the quantity of pheromone laid on edge (i, j) by ant k:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_k} \; if\ ant\ k\ used\ edge\ (i,j) in\ its\ tour, \\ 0\ otherwise, \end{cases} \qquad (2)$$

Q is a constant, and L_k is the distance of the tour completed by ant k. Ants use a stochastic approach to choose the next city to visit in the creation of a solution. The probability of ant k is moving to point *j* to *i* is calculated by following,

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{\alpha}.\mu_{ij}^{\beta}}{\sum_{c_{ij}\epsilon Ns^{p}} \tau_{ij}^{\alpha}.\mu_{ij}^{\beta}} \; if\ c_{ij}\epsilon Ns^{p}, \\ 0 \quad otherwise, \end{cases} \qquad (3)$$

Where Ns^{p} is the set of feasible components; that is, edges (*i*,*j*) where l is a city not yet visited by the ant k. The parameters α and β control the relative importance of the pheromone versus the heuristic informationμ_{ij}, which is given by:

$$\mu_{ij} = \frac{1}{d_{ij}} \qquad (4)$$

The distance between points *i* and *j* is denoted byd_{ij}.

3.2. Proposed Ant Colony Algorithm for Sensor Network

To show how the proposed methodology presented in this research work, in the example sensor network with distances, the reliability path between node 1 and node 5 shown in Fig.2 will now be evaluated. Node 1 represents the source node and node 5 sink node. The assumed network initial node energies are given in Table 1. It is also that the pheromone vaporization factor ρ can be varied 0 to 1, for the calculation we assumed ρ is equals to 0.5 and the starting pheromone density is 1.

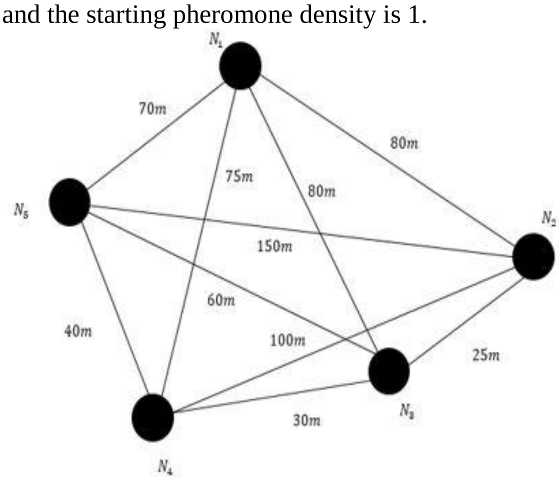

Figure 2. Sensor node map based on the distances.

According to the uniform randomization rule, some artificial ants are created and initially placed on n nodes [18]. In our observations, number of different paths cam determine by analytically. Let the number of nodes of a system is N. The number of different path can be calculate by using (5).

$$number\ of\ different\ paths = \sum_{n=1}^{N-1} n \qquad (5)$$

As an example, let we consider above sensor node map for five fixed nodes. The total number ofdifferent paths between node 1 and node 5 equals to number of ten paths.

$$number\ of\ different\ paths = \sum_{n=1}^{4} n = 10$$

Then the artificial ants are placed on the start node and by using initial parameters the ants' stars move to the source node to sink node through different paths. According to different energy levels of the sensor nodes, ants tend to move the source to sink by using an energy optimized path. The next step will be calculate pheromone level for each path. In this method, we use the average energy level in between two nodes to calculate pheromone level of an k^{th} edge for N_i and N_j nodes, where $k, i, j \in \mathbb{N}$. The average energy level calculated by (6).

$$Average\ energy\ level\ (e_{i,j}) = \frac{E_i + E_j}{2} \qquad (6)$$

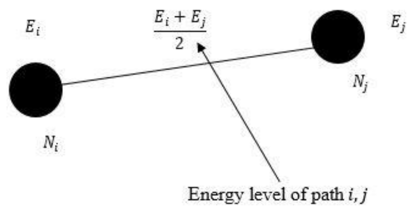

Figure 3. Energy level for each edge.

Table 1. Initial node energies of sensor nodes

Node	Energy
N_1	3
N_2	2
N_3	6
N_4	8
N_5	1

According to the assumed energy levels of the nodes as shown in the table. We can calculate the average energy levels of between nodes. The calculated energy levels between nodes shown in the node map shown in Fig. 4.

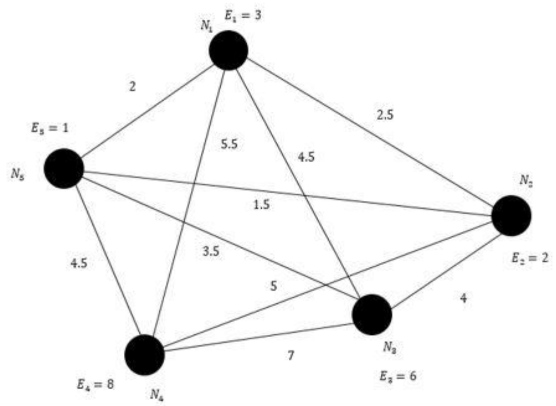

Figure 4. Calculated energy level map.

Furthermore the energy levels can represent using the square matrix (7), in this the diagonal values become assumed as zero because average energy level calculate only between two nodes.

$$\begin{bmatrix} 0 & 2.5 & 4.5 & 5.5 & 2 \\ 2.5 & 0 & 4 & 5 & 1.5 \\ 4.5 & 4 & 0 & 7 & 3.5 \\ 5.5 & 5 & 7 & 0 & 4.5 \\ 2 & 1.5 & 3.5 & 4.5 & 0 \end{bmatrix}_{5\times5} \qquad (7)$$

Then calculate the pheromone level $(\tau_{i,j})$ in between two nodes by using (8). The calculated Pheromone level values shown in Fig. 5

$$\tau_{i,j} = \frac{1}{e_{i,j}} \ , i, j \in \mathbb{N} \qquad (8)$$

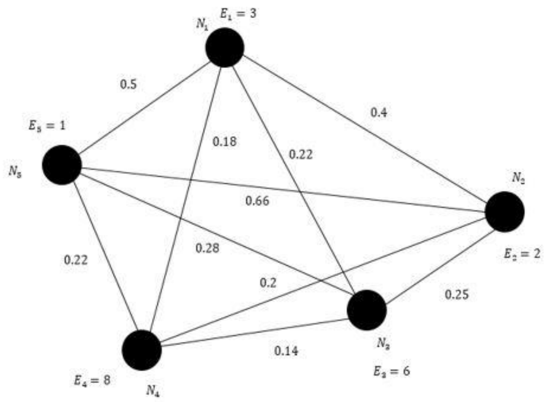

Figure 5. Calculated Pheromone level map.

Defining the pheromone level matrix (9), using the pheromone level graph,

$$\begin{bmatrix} 0 & 0.4 & 0.22 & 0.18 & 0.5 \\ 0.4 & 0 & 0.25 & 0.2 & 0.66 \\ 0.22 & 0.25 & 0 & 0.14 & 0.28 \\ 0.18 & 0.2 & 0.14 & 0 & 0.22 \\ 0.5 & 0.66 & 0.28 & 0.22 & 0 \end{bmatrix}_{5\times5} \qquad (9)$$

Define the total pheromone level density for each path. Useful existing formula (10) to calculate the pheromone level in between two nodes $\Delta\tau_{i,j}^{k}$,

$$\Delta\tau_{i,j}^{k} = \begin{cases} \frac{1}{L_k} & ; k^{th}\ ant\ travels\ on\ the\ edge\ i,j \\ 0 & ; \qquad otherwise \end{cases} \qquad (10)$$

Where the total pheromone level L_k of each path $k \in \mathbb{N}$, is defined by the formula (11).

$$L_k = \sum \Delta\tau_{i,j} \qquad (11)$$

The total pheromone level density could be calculated as follows. This density is described using two formula (12), with vaporization,

$$\tau_{i,j}^{k} = (1-\rho)\tau_{i,j} + \sum_{k=1}^{m} \Delta\tau_{i,j}^{k} \qquad (12)$$

For the demonstration select common paths to cover the all nodes as a close contour. Every ant holds a path list and a tab list to keep track of the sensor nodes they've reached on the network. Each ant will construct a tour by repeatedly using a stochastic greedy algorithm known as the state transition rule. Each ant modifies the quantity of pheromone on the edges that it recently travelled by applying the locally update rule while travelling between nodes in the network. When all ants have returned to their initial nodes, the global update rule is used to change the amount of pheromone on the edges. The following Fig. 6 shows that two ants are covered two closed paths, by closed loop path 1 and the closed loop path 2. At real time, need to use more ants to cover the closed paths to determine that which path contain more pheromone. Start from node 1, follow the arrow

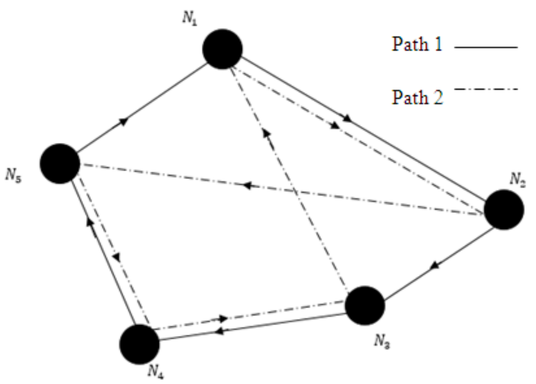

Figure 6. Two closed paths for two ants.

Let draw the pheromone graphs with vaporizations. This will more accurate due to higher number of paths completed by the ants. In this case we assign two ants for demonstrate calculation. Next calculate the total pheromone level for the two closed paths, using (11),

Path 1,

$$L_1 = 0.4 + 0.25 + 0.14 + 0.22 + 0.5 = 1.51$$

$$\Delta_{i,j}^{1} = \frac{1}{L_1} = \frac{1}{1.51} = 0.66$$

Path 2,

$$L_2 = 0.4 + 0.66 + 0.22 + 0.14 + 0.22 = 1.64$$

$$\Delta_{i,j}^{2} = \frac{1}{L_2} = \frac{1}{1.64} = 0.609$$

Let we consider the pheromone density graph with vaporization factor and calculate pheromone level by using the formula (13), Here vaporization factor can be varied 0 to 1. Let we assume ρ=0.5 and the starting pheromone density is 1. The node map with pheromone densities shows in Figure 7.In the next step, consider the pheromone density matrix (14) is defined by using the pheromone density graph representing each path in the node map. As an example, let consider a sample pheromone density matrix defined for Pheromone density graph (with vaporization) is shown in the Fig. 7.

$$\tau_{i,j}^{k} = (1-\rho)\tau_{i,j} + \sum_{k=1}^{m} \Delta\tau_{i,j}^{k} \qquad (13)$$

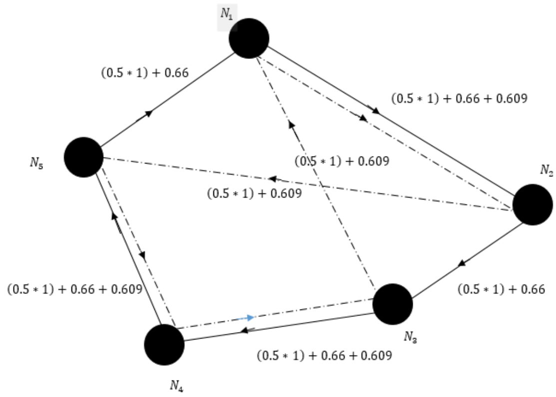

Figure 7. Pheromone density map with vaporization.

Here some elements of the pheromone density matrix with vaporization is not defined due to the less number of ants were send through the different closed paths.

$$\begin{bmatrix} 0.000 & 1.7690 & 1.090 & **** & 1.160 \\ 1.7690 & 0.000 & 1.160 & **** & 1.090 \\ 1.090 & 1.160 & 0.000 & 1.769 & **** \\ **** & **** & 1.7690 & 0.000 & 1.765 \\ 1.160 & 1.090 & **** & 1.7650 & 0.000 \end{bmatrix}_{5\times5} \qquad (14)$$

Using the pheromone density matrix, we can calculate the probabilities due to the energy level of the nodes. The Ant Colony Probability formula use for determining in which path is optimal. The Ant Colony Probability formula defined in (15),

$$P_{i,j} = \frac{(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}}{\sum(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}} \qquad (15)$$

Where, α andβ are experimental values, we assume α=1, β=1. Therefore the equation (15) becomes,

$$P_{i,j} = \frac{(\tau_{i,j})^{1}(\eta_{i,j})^{1}}{\sum(\tau_{i,j})^{1}(\eta_{i,j})^{1}} \qquad (16)$$

Where,

$$\eta_{i,j} = \frac{2}{E_i + E_j} \qquad (17)$$

Let consider a sample Ant Colony Probability value based on the node energies for node 1 and node 2.

$$P_{1,2} = \frac{\tau_{1,2} * \eta_{1,2}}{(\tau_{1,2} * \eta_{1,2}) + (\tau_{1,3} * \eta_{1,3}) + \cdots \quad \ldots (\tau_{1,4} * \eta_{1,4}) + (\tau_{1,5} * \eta_{1,5})} \tag{18}$$

By using all the calculated Ant Colony Probability values, we can deduce the Ant Colony Probability matrix (19),

$$\begin{bmatrix} P(1,1) & P(1,2) & P(1,3) & P(1,4) & P(1,5) \\ P(2,1) & P(2,2) & P(2,3) & P(2,4) & P(2,5) \\ P(3,1) & P(3,2) & P(3,3) & P(3,4) & P(3,5) \\ P(4,1) & P(4,2) & P(4,3) & P(4,4) & P(4,5) \\ P(5,1) & P(5,2) & P(5,3) & P(5,4) & P(5,5) \end{bmatrix}_{5\times5} \tag{19}$$

Above matrix is defined for the sample node map is shown in the figure 2. A general Ant Colony Probability matrix (ACP) is shown in the following,

$$ACP = [P_{i,j}] \tag{20}$$

Where,
$P_{i,j}$ = Ant Colony Probability value in the ACP at i^{th} and the j^{th} element of Ant Colony Probability matrix.

IV. SIMULATION ENVIRONMENT

In order to assess the route optimization algorithm performance, we have developed the ACO optimization simulation environment on MATLAB® to find the optimal path between Source node and Snick node. The graphical user interface (GUI) of the developed simulation algorithm shows in Figure 8. In the simulation environment the sensor nodes indicated in blue colour dots and the sink node indicate larger green dot. The predicted data transmission path sensor node to sink node according to the proposed algorithm, shown by blue line in the interface. To a considerable extent, the total energy usage in a WSN determines whether a routing algorithm is effective or not. In this section, we contrast the power capabilities of the proposed algorithm to the shortest route used to transfer the data packet.

The simulation scenario is configured as, the observation area for WSN was set to 200m × 200m region and the sensor nodes are arbitrary place in the simulation area as shown in Fig. 8. All the sensor nodes are stationary and each node's transmission radius is 10 meters, while a sink node is positioned at edge of the simulation area. Every 10 seconds, a random source node transmits data to the sink node, and the data frame will be 256 bits long. The starting energy of each node is set to 10J. Sending data takes 0.2J and receiving data takes 0.1J of each node every time they transfer data. We used the above settings to simplify the simulation model.The real time simulation can view by scanning the QR code provided on Fig. 8.

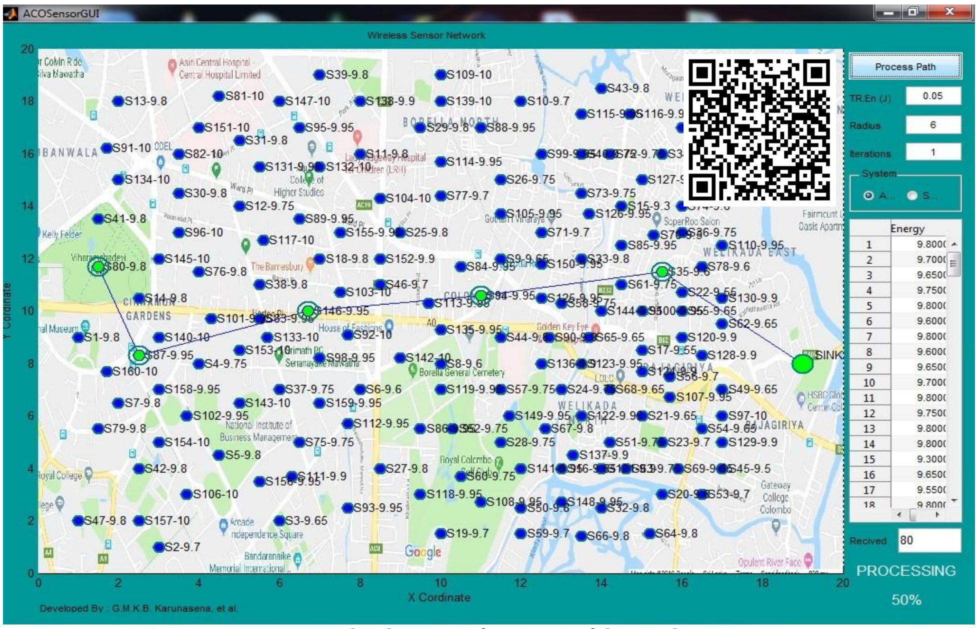

Figure 8.MATLAB graphical user interface (GUI) of the simulation environment

V. RESULTS & DISCUSSION

In order to get the simulation results from proposed algorithm, we have placed the 100 artificial Ants in the source node & it will randomly move along the sensor nodes, the destination of this ants should be node which ant starts randomly. We can clearly see the variation of the number of ants vs. energy optimized path. So, the number of the artificial ant is the one of the critical parameters in this algorithm. Below simulation shows the variation between numbers of ants vs. total number of data packet received by the sink node. Also, in other term we need to careful about the processing time. If number of ants increases the processing time will be increase. By considering both we have taken number of artificial Ants as 100. We have plotted this variation for a fixed time period & the variation of data received as shown in Fig. 9.In order to verify the efficiency of the propose algorithm, we have compared the proposed algorithm with the STP (Shortest transmission path) [19]. Normally in WSN, to reduce the complexity & cost, most of the vendors used the Static routing based on the transmission distance capability. The placement of the sensor nodes also based on the routing capability.

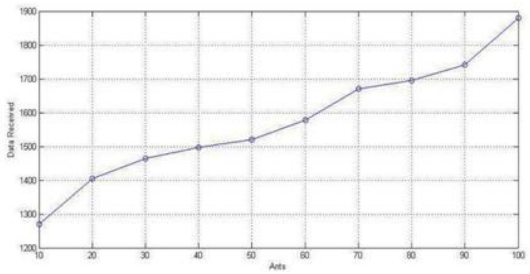

Figure 9. Variation of data received with number of ants

To differentiate the variation between these two algorithms, we have plotted the energy variation in the sensor nodes with number of the transmission iteration. Below plots shows the variation of the energy in the nodes at the end of each iteration. The blue dots show node energy variation in ACO method and the green dots shows node energy variation in STP method. The Fig. 10 to Fig. 22 shows energy variations of sensor nodes in several data transmission simulations. In STP method, node energy levels rapidly decrease in some nodes compared to the proposed ACO method. The simulation automatically terminated after the 13th iteration because sink node did not receive any data due to the large amount of dead nodes in transmitting paths.

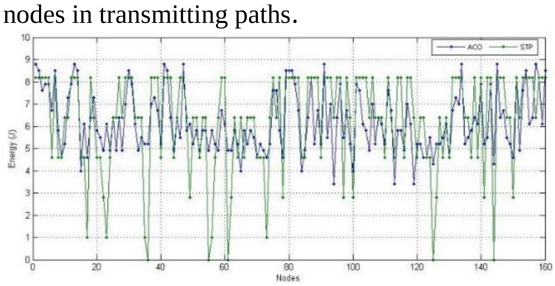

Figure 10. Remain energy of the nodes after 1st iteration.

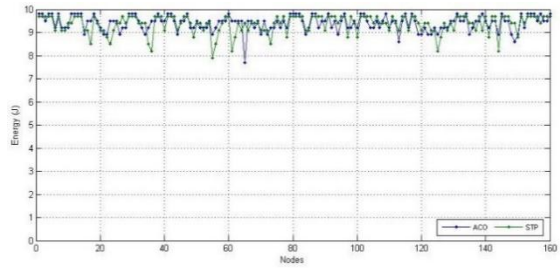

Figure 11. Remain energy of the nodes after 2nd iteration.

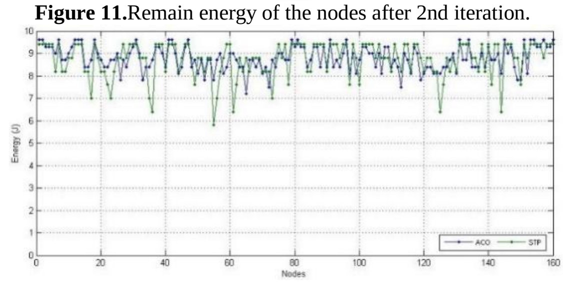

Figure 12. Remain energy of the nodes after 3rd iteration.

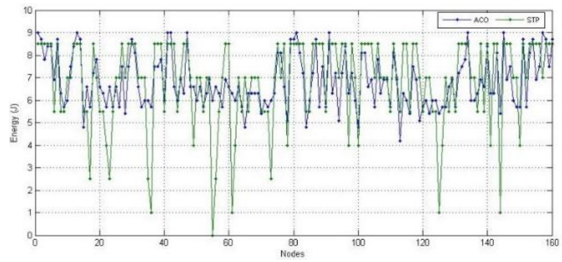

Figure 13. Remain energy of the nodes after 4th iteration.

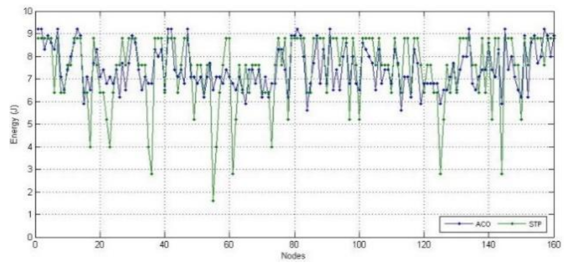

Figure 14. Remain energy of the nodes after 5th iteration.

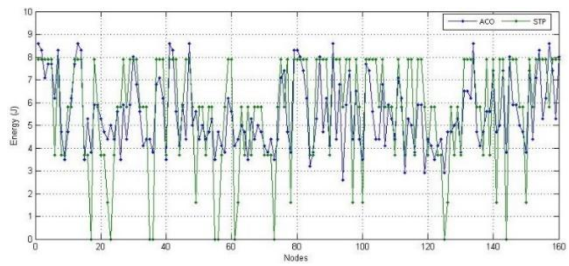

Figure 15. Remain energy of the nodes after 6th iteration.

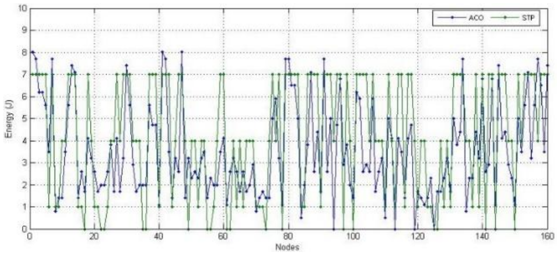

Figure 16. Remain energy of the nodes after 7th iteration.

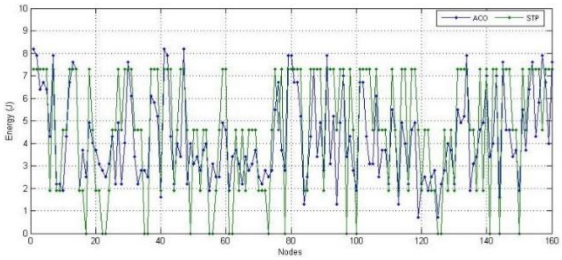

Figure 17. Remain energy of the nodes after 8th iteration.

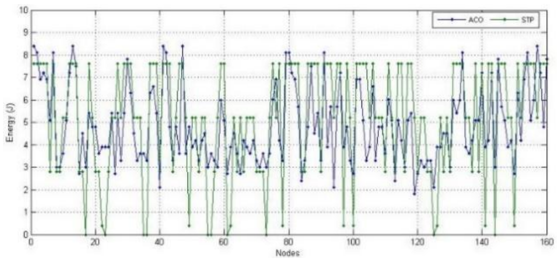

Figure 18. Remain energy of the nodes after 9th iteration.

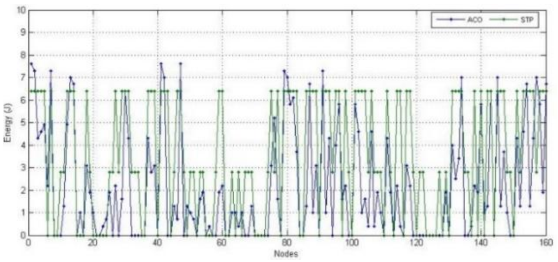

Figure 19. Remain energy of the nodes after 10th iteration.

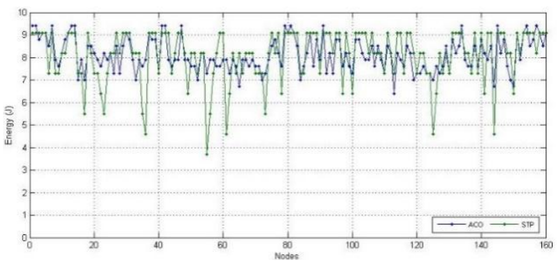

Figure 20. Remain energy of the nodes after 11th iteration.

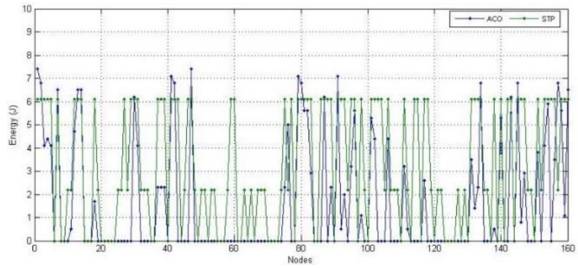

Figure 21. Remain energy of the nodes after 12th iteration.

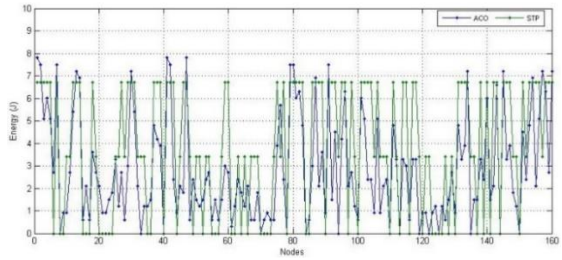

Figure 22. Remain energy of the nodes after 13th iteration.

To explore more about this algorithm, we have got the number of data packet which is received by the sink node with the iteration. From the below comparison it is very clear that by the increasing the number of the iteration, the data packet receiving to the snick node is decreasing due to dead sensor nodes as shown in Fig. 23. The following diagram shows the final outcomes of the two methods which are ACO and STP.

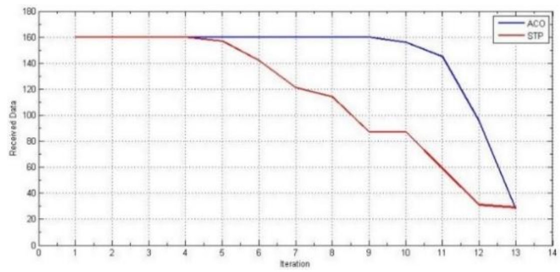

Figure 23. Variation of data received with number of iterations.

VI. CONCLUSION

Choosing the best path in a continuously changing WSN environment is a difficult task in communication industry. The suggested work's main purpose is to extend the system reliability in a dense environment, because in a heterogeneous networks network, the lifetime of the network is limited. It's very likely that sensor nodes in close proximity send duplicated data to the sink node, wasting energy. As a result, the network's entire lifespan is lowered. In the suggested method, an energy based developed Ant Colony optimization algorithm was used to find the best path between a sensor and a sink node in a densely deployed network. The outcomes of the experiments suggest that our proposed technique can provide improved network lifespan results, energy efficiency in the sensor network and long period of stability. By altering the number of nodes in a crowded environment, the suggested algorithm was tested for numerous wireless sensor network situations, and the results clearly capture the extended network lifetime and increased energy efficiency. We have identified many further tasks at the end of this research, we have identified some of future works which we could not perform in this level of the research, Changes the vaporization factor with this algorithm. In this research we have used a fixed value for the vaporization factor, Changes the two variables contain in the ACO probability formula, Identify the number of maximum and minimum ants need to cover the all paths in the map. Here we have used a fixed value for the numbers of artificial ants for path optimization.

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