



# A Meta-heuristic Based Clustering Mechanism for Wireless Sensor Networks

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**Abstract.** Wireless Sensor Networks are usually the application specific networks that consists of nodes which gathers some data from its surrounding environment continuously or intermittently based on user specifications. In practical use case scenarios, WSNs will consist of densely populated sensor nodes where each node will have a greater number of neighboring nodes. Establishing direct communication with more neighboring nodes results high energy consumption because large transmission power is required. To overcome the most critical issue of poor network lifetime, efficient use of energy resources is required. The goal of the proposed study is to create an efficient cluster head selection model based on Ant Colony Optimization technique that helps to save energy and extend network lifetime by selecting cluster heads wisely.

**Keywords:** Clustering · Wireless Sensor Networks · ACO

## 1 Introduction

As a well-developed technology, Wireless Sensor Networks is recognized as one of the integral parts of the fourth industrial revolution (Industry 4.0) and also it is the developing direction of next-generation computer networks. For the first time, the notion of “Industrial Internet” or “Industrial IoT” was defined, i.e., connecting devices and equipments, people, and data analysis over an open, worldwide network [12, 13]. Because of the significant growth and advancement of sensor technology, Wireless Sensor Networks (WSNs) have recently become widely used for both military and commercial applications and are mostly deployed to perform periodic monitoring activities in hostile environments. Sensors in such networks usually have limited resources, such as energy, storage capacity, and processing capabilities. Furthermore, resources, particularly the energy of sensors, may not be replaceable due to the hazardous working environment. As a result, the network’s lifetime is determined by its total energy usage. Therefore, high-performance routing protocol and decreasing energy consumption are the critical requirements for WSN applications. Some researchers proposed the concept of cluster network topology as the first clustering routing protocol in WSN to reduce energy consumption. The essential idea here is to select cluster nodes equiprobably in a random cycle, assigning total network resource energy to each sensor node averagely. This

decreases the energy consumption and prolongs the network survival lifetime. But the way of randomly selecting a cluster node makes each node qualified to become the cluster node, and it also makes it possible for the low-energy node to qualify as the cluster node. If a cluster node has lost all its energy from its energy source, the node becomes a blind, ending up in premature death. Clustering is one of the energy management strategies used in wireless sensor networks, in which the network is divided into a number of clusters, each with its own cluster head. Rather than each node transmitting its data to the base station directly, nodes in a cluster have the freedom of sending their data to the cluster head sensor node, which again, aggregates the data and sends it to the respective base station. Because fewer nodes or only appropriate nodes provide data to the base station and this mechanism introduces an approach for conserving energy in resource-constrained WSNs. Computationally, selecting  $m$  cluster heads among  $n$  nodes of network has a total of  $nC_m$  possibilities [11]. So, Cluster Head selection in WSNs is an NP hard problem. Hence, the proposed work uses Ant Colony Optimization based approach for clustering instead of brute force approaches. The rest of the paper is organized as follows. Section 2 presents the review of related works. Section 3 explains about the Ant Colony Optimization algorithm. Section 4 explains about the proposed work. The simulation results and analysis are discussed in Sect. 5 followed by conclusion in Sect. 6.

## 2 Related Work

Halil Yetgin et al. [1], in their paper, describe about recent developments in network lifetime maximization approaches that were in the technical literature. Halil Yetgin et al. [1] also gave a clear definition of Network Lifetime design objective along with practical design constraints of Wireless Sensor Networks for maximizing the Network Lifetime. Halil Yetgin et al. also has tabulated and suggested various network lifetime optimization techniques in the context of various methods like resource allocation techniques, opportunistic transmission techniques, sleep-wake scheduling techniques, routing techniques, mobile relay/sink techniques, coverage and connectivity improvement techniques, optimal deployment techniques. Halil Yetgin et al. [1] also suggest some design guidelines for maximizing the network lifetime of wireless sensor networks like QoS requirements, NL Design objective based on application, computational complexity. Similar to [1, 16] explains and surveys various implementations of the k-means clustering combined evolutionary based optimization approaches for clustering of WSNs. Work in [17] elaborates about the use of low power communication protocols to improve battery life. Paper [18] proposes a strategy that uses clustering and resource scheduling approach that brings energy efficiency. L. Xu et al. in [2] present an overview of several clustering algorithms in Wireless Sensor Networks, as well as obstacles in using such strategies in 5G IoT applications. L. Xu et al. examine existing protocols from the perspective of Quality of Service (QoS), with three goals in mind: energy efficiency, reliable communication, and latency awareness. Rather than providing a limited perspective on how to improve network lifetime, [2] suggests Quality of Service is a crucial factor when it comes to developing intelligent Wireless Sensor Networks. In paper [3], Heinzelman et al. proposed the famous Low Energy Adaptive Clustering Hierarchy Protocol (LEACH), which

was one of the oldest works proposed in researches for saving energy in applications of wireless sensor networks. In the research [3], Heinzelman et al. demonstrated that direct approaches, such as traditional direct transmission protocols, multi-hop routing, and static clustering, are not ideal for practical use-case scenarios of wireless sensor networks. The suggested LEACH protocol [3] is primarily a clustering-based technique that employs a randomized station of cluster heads to distribute the network's energy load equitably among other available sensor nodes. The simulation work by Heinzelman et al. from [3] claims to have reduced the energy consumption by as much as a factor of 8 compared to that of conventional protocols, which had the potential to almost double the lifetime of the network. In [4], A. Verma et al. had proposed a clustering scheme called FLEC. The algorithm proposed in [4] uses a fuzzy logic model with average energy of cluster head sensor nodes as one of the extra input membership functions for the model and battery power, Base Station mobility, Base station centrality as the other input membership functions. The proposed method in [4] was compared with DEEC, LEACH-Fuzzy, LEACH clustering methods and quite surprisingly FLEC had a better performance in terms of stability, throughput and network lifetime when compared with all of them. In [5], T. M. Behera et al. suggested a cluster head selection technique that took into account the network's challenging circumstances and increased energy dynamics. The Fuzzy model in [5] attempts to select the cluster head by taking into account the optimal number of clusters in the network, which is determined by the network's residual energy. Also, the simulation results from [5] proves that the solution is one of the effective ones in terms of robustness and efficacy as it had improved performance in throughput by 46% and reduced energy consumption by 66% in the considered simulation scenarios. In [6], H. Ali et al. had proposed a novel cluster head selection algorithm called ARSH-FATI. The main novel idea employed in proposed work from [6] is the use of a separate meta-heuristic called novel rank-based clustering (NRC) scheme with main aim of reducing the communication energy consumption of the sensor nodes. During the run-time of cluster head selection, the methodology from [6] employs a metaheuristic that dynamically alternates exploration and exploitation search nodes. When ARSH-FATI is combined with the NRC technique, [6] claims that the suggested proposed algorithm achieves an overall improvement of 60%, 40% over LEACH and PSO-C respectively. H. El Alami and A. Najid present a strategy called ECH in their study [7], which uses a waking mechanism for overlapping and neighboring nodes to achieve efficiency in terms of energy usage in Wireless Sensor Networks. The work from [7] also assumes that all sensor nodes and Base stations are motionless after a network distribution is made, and every node in the network, irrespective of the type, performs a set of periodic tasks (Sensing, computing, communication). The main idea of the algorithm proposed in [7] is that the energy consumption of Wireless networks is optimized by reducing data redundancy in the network. Using the sleeping-waking mode, the ECH approach from [7] optimizes energy consumption in WSNs while simultaneously lowering node failure probability. The key idea here is that only waking nodes are used to detect data from the environment of interest, and takes care of aggregating these data and communicating it to BS via the CHs. [7] compared the performance of the ECH method along with other approaches like LEACH, TEEN SEP, DEEC, and the results also were in favour of the method in terms of the overall energy consumed. In paper [8], Gupta P and Sharma

A.K. had proposed a clustering-based optimized Hybrid Energy-Efficient Distributed Protocol (HEED), which is claimed to be a modified variant of normal HEED protocol. Paper [8] proposes six different variants of Optimized HEED protocols (OHEED). The key contribution of [8] is the use of intra-cluster and inter-cluster communication in the conventional HEED protocol to provide better load balancing across sensor nodes, hence avoiding overburdening of respective cluster heads. The Bacterial Foraging Optimization technique is also used in the approach proposed in [8] for selecting optimal cluster heads, with residual energy as the major parameter. The simulation of both 1 tier and 2 tier protocols from [8] showed that there is a good increase in terms of network lifetime, especially the ICFLOH1TC and ICFLOH2TC showed a 350% and 275% increase in network lifetime, respectively in the considered simulation scenario. In paper [9], a novel improved energy-efficient clustering mechanism for wireless sensor networks is proposed by A. A. H. Hassan et al. In [9], the fuzzy C-means method is paired with a method to reduce and regulate energy consumption of nodes in the network. Secondly, Cluster heads are formed by a new algorithm called the CH Selection-rotation algorithm, which has been integrated with a back-off timer mechanism. Mohamed Elshrkawey et al. suggested a new cluster head selection technique as an addition to the standard LEACH protocol for lowering energy consumption in wireless sensor networks in their study [10]. The work from [10] addresses the energy-hole problem by employing a 2D elliptical Gaussian distribution function to define the position of sensor nodes and base stations. The suggested work in [10] is based on a cluster head election method, which is a variant or modified form of the LEACH algorithm where the threshold function is modified by a factor that represents the sensor nodes' current energy level. The aim is to close the energy gap between all sensors in each cluster, and the algorithm is effective at doing so since a modified TDMA schedule has been applied in this proposed algorithm, which differs from the original one used in the LEACH protocol. In paper [11], an evolutionary computing algorithm is employed for clustering in Wireless Sensor Networks, fairly similar to the work proposed in [8]. In [11], a new energy-efficient clustering technique is proposed, which is based on variable population-based swarm intelligence meta-heuristics inspired by the chemical reaction process. For the Chemical reaction optimization process, the potential energy function of the molecules are chosen based on parameters like intra-cluster distance, sink distance, energy ratio. The results from the proposed work in [11] were compared with various existing algorithms like LDC (Least Distance Clustering), PSO-C (Particle Swarm Optimization), DECA (Differential Evolution based Clustering Algorithm) etc. and it was very promising in terms of features like network lifetime, Packet Delivery Success, Convergence rate.

### 3 Ant Colony Optimization

Ant Colony Optimization is a meta-heuristic technique in which a set of artificial ants collaborates to solve complex discrete optimization problems with clean solutions. Ant Colony Optimization allocates resources to a group of relatively simple artificial ants based on indirect interaction indirectly via stigmergy. Best solutions are an emergent property of cooperative interaction between agents. The ants release a chemical called pheromones in the path through which they move. As more number of ants move in a

direction, the pheromone concentration in that path becomes more. So, the idea here is that the higher the concentration of pheromones, the higher is the possibility for any new ant to take up that respective path to reach the food from the anthills. The path that gets chosen by the ants will be the least distance from anthills to food. The mechanism is very similar to a distributed optimization mechanism. Every single ant has a major contribution to the obtaining the solution. The ants use an incremental methodology to obtain a viable optimal solution. The given problem is solved in Ant Colony Optimization by simulating a number of artificial ants moving across a graph that encapsulates the problem itself. Each graph vertex has a node, and presence of a graph edge that indicates the existence of connectivity between two nodes. A pheromone value is always present for each edge. The quantity of pheromone can be read and modified as the iteration proceeds further. An ant chooses the next vertex to visit at each phase of the solution construction process based on a stochastic mechanism influenced by the pheromone: when in vertex  $i$ , the following vertex is selected among the previously unselected ones. In particular, if a site  $j$  has not been visited before, it can be selected with a probability value depending to the pheromone linked with edge  $(i, j)$ . After each iteration, based on the quality of the solutions constructed by the ants, the pheromone values are modified to develop solutions that are similar to the finest ones that have already been built.

In terms of optimization problem, to apply ACO, a model is required as follows:

A model  $P = (S, \Omega, f)$  of a combinatorial optimization problem consists of:

- A search space  $S$  - defined over a finite collection of discrete variables  $X_i, i = 1, 2 \dots n$
- $\Omega$  - a set of constraints that exist between variables
- An objective function  $f : S \rightarrow R_0^+$  to be minimized

The generic variable  $X_i$  takes values in  $D_i = \{v_i^1, \dots, v_i^{|D_i|}\}$ . By moving over a fully connected construction graph  $G_C(V, E)$ , where  $V$  is a set of vertices and  $E$  is a set of edges, an artificial ant creates a solution using the ACO technique. Also, ants deposit a certain quantity of pheromone on the components i.e. either on vertices or on the edges that they traverse. The volume of  $\Delta\tau$  of pheromone deposited on a path depends on the solution that is found and its quality. The ants that follow utilise the pheromone information to find the most promising areas of the search space.

**Construct Ant Solution:** A group of  $m$  artificial ants aims to find solutions using elements from a finite set of solution components  $C = \{C_{ij}, i = 1, 2, \dots, n, j = 1, 2, \dots, |D_i|\}$ . Starting with an empty partial solution  $S^P = \emptyset$ , a solution is built. At each solution step, the partial solution  $S^P$  is enhanced by the addition of a viable solution item from the set  $N(S^P) \subseteq C$ , which is defined as a set of components that can be included to a partial solution that has already been acquired  $S^P$  without disregarding any of the given requirements in  $\Omega$ . The choosing of a component from  $N(S^P)$  is controlled by a technique that is directly influenced by the volume of pheromones linked with each element of the set  $N(S^P)$ . The rule for selection of solution component varies between Ant Colony Optimization algorithms, although it is all based on real-world ant behaviour.

**Apply Local Search:** It is prevalent practice to improve the quality of solutions acquired by the all of the ants via a local search after they have been formed and before updating the pheromone. This step is optional, but it is prevalent in most use cases of ACO.

**Update Pheromones:** The pheromone update process increases pheromone values linked all promising solutions while lowering those associated with irrelevant ones. It is achieved (i) by using the pheromone evaporation process to minimize all pheromone values, and (ii) by raising the levels of pheromones linked with a chosen set of good solutions.

The basic version on ACO i.e. Ant System algorithm is being implemented initially for the current problem statement chosen. Its main feature is that the pheromone matrix values are modified at each iteration by all the  $m$  ants which created a solution during that iteration. The pheromone quantity  $\tau_{ij}$ , linked with the edge between nodes  $i$  and  $j$ , is modified according to the following equation:

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

where,

$\rho$  - evaporation rate  $m$  - Number of ants, and  $\Delta \tau_{ij}^k$  - the quantity of pheromone deposited on the edge  $(i, j)$  by ant  $k$ , given by:

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

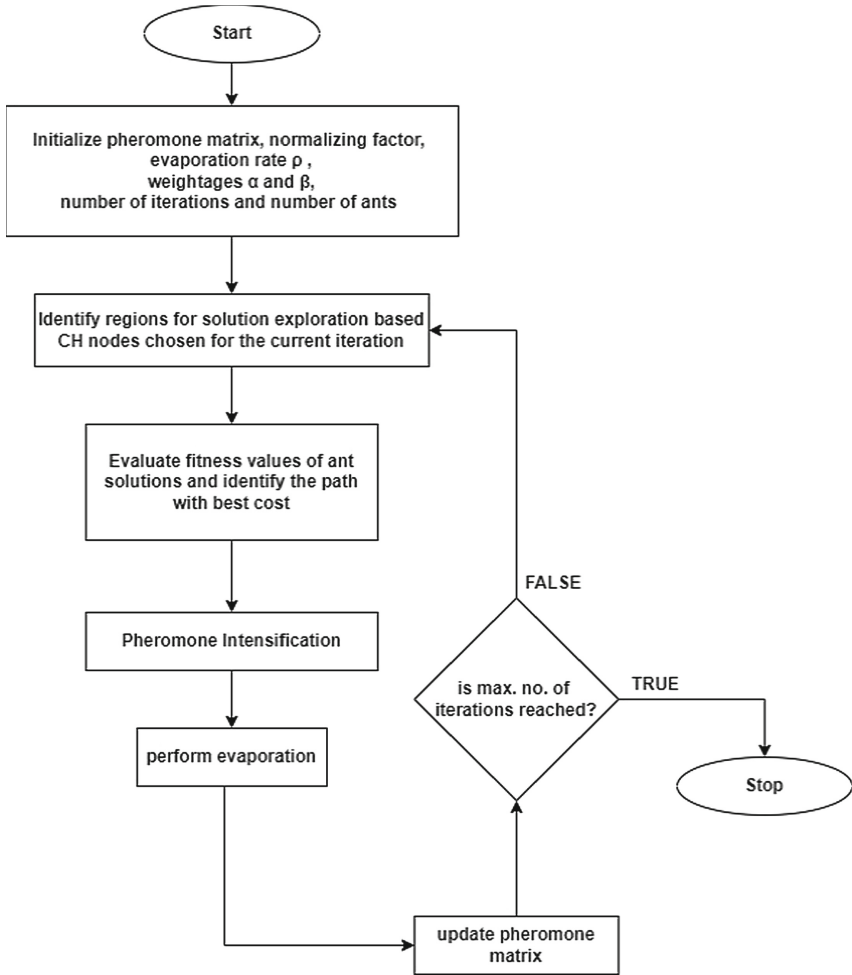
In the construction of a solution, ants select the node to be visited next via a probabilistic or stochastic mechanism. If an ant  $k$  is in node  $i$  and has so far has come up with the solution  $S^P$ , the probability of proceeding to node  $j$  is:

$$p_{ij}^k = \begin{cases} \frac{\tau_{ij}^\alpha \cdot \eta_{ij}^\beta}{\sum_{c_{i,l} \in N(S^P)} \tau_{il}^\alpha \cdot \eta_{il}^\beta}, & \text{if } C_{ij} \in N(S^P) \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where  $N(S^P)$  - the a group of components that are feasible; that is, edges  $(i, l)$  where  $l$  is a city that is unvisited by the ant  $k$ ,  $\alpha$  and  $\beta$  – weightage factor of the pheromone and the heuristic information  $\eta_{ij}$  is given by  $\eta_{ij} = 1/d_{ij}$ ; where  $d_{ij}$  - distance value between nodes  $i$  and  $j$ .

## 4 Proposed Work

For the Ant Colony Optimization to be used for chosen clustering problem, on a weighted graph, the network lifetime maximisation problem is viewed as a challenge of finding the best optimum path. As the ants walk over the graph, they will incrementally build up solutions. The solution construction in Ant Colony Optimization is highly influenced by a pheromone model [14] i.e. set of parameters associated with graph components whose values are modified dynamically at runtime by the controlled ants. WSNs are made up of a number of distributed set of sensor nodes that are spread out over a small geographical area and have limited power. It is considered that renewing the sensor node's battery is a challenging operation. The primary objective is to achieve efficiency in terms of total energy consumption in WSNs. The node which has the highest probability value and the maximum energy is selected to become the dominant cluster. The Energy function includes Alive and dead nodes as one of the parameters, so the overall performance of the network is aggraded. In this scheme, the Energy value of each and every sensor node present in the network is calculated. The Energy value will get changed dynamically. Each node's Energy value is calculated based on its neighbour nodes. The ratio of the value collected from a neighbour sensor is assigned as the Energy value of the node. For the particular period, the setup server should update the Energy value based on its neighbour's vote. The below given Fig. 1. depicts the overall working of the algorithm. The sensors are considered to be placed randomly in the area of interest by an uncontrolled method and to create and form an ad-hoc network. Then the network is split into a set of interconnected substructures i.e. clusters. Each cluster present, has a particular node which is acting as Cluster Head (CH) that is chosen based on a specific metric or a combination of multiple metrics (id, degree of node, weight). Within its network substructure, the Cluster Head serves as a coordinator. CH has the information including a contained list of nodes present in the cluster and the direct path to every node. The main role of the CH is to communicate with all the nodes of its cluster in the communication network. A Cluster Head, on the other hand, should be able to have a communication going on with nodes in other clusters, either directly or via the respective CH or gateways. Three steps are involved in communication. The CH firstly, receives the data sent by its sub-ordinate nodes. It then compresses the data before sending it to the BS or another CH, allowing the relevant CH to decrease energy consumption and relatively maximize the network lifetime. None of the algorithms make use of a set of key metrics combined together like: power, lower id, maximum degree, mobility, and node connectivity etc. CH is chosen in the proposed work, based on the total number of neighbours, residual energy, and distance of a node from the cluster's centre. The Cluster Head selection model is applied only to nodes near the cluster's centre. Hence, in WSNs, a method for selecting a CH is presented based on the following iteration parameters: residual energy ( $E_{res}$ ), connection capability of ( $C_n$ ), and node degree ( $D$ ). During the setup phase, the Base Station sends a message to all of the sensor nodes in the network. The sensor nodes will respond with their respective position, node ID, and distance between them in a reply message. All sensor nodes will keep their receivers turned when the CH selection phase is happening.



**Fig. 1.** Flowchart for ACO based algorithm for WSN CH selection

The peer-to-peer sensor network is considered to be a graph, and the location of each uniquely numbered sensor node is represented using Cartesian coordinates. In the chosen case, one node is within the range of the other node if the Euclidean distance value between the two nodes is within a specific limit. The Ant Colony Optimization algorithm identifies the set of optimal cluster heads using an iterative process that obtains a local solution. The cluster head selection process is performed based on two aspects, i.e. pheromone value of each node's edge and its visibility. The topology structure of the network affects visibility. Also, pheromone value associated with each node and it reduces or increases during each iteration of the ACO algorithm. The idea is, for each iteration, one node is selected as cluster head, and further, the next cluster head and so on, which is selected and influenced based on visibility and pheromone of the neighbouring nodes. The iteration process in the ACO algorithm does not terminate until



all nodes present in the network are covered. One node is said to be in coverage if it is chosen as cluster head or if it is present under a chosen cluster head. The algorithm actually works by determining the probability of a node as a function of both visibility and pheromone value. The pheromone value of each node that is chosen as a cluster head is updated. As a result, the likelihood of a node being chosen as cluster head is totally influenced and determined by the pheromone value and visibility, which vary as the algorithm progresses through the iterations. The energy remaining in a node at the current particular instance of time is called as remaining energy or residual energy (Eres). In order for a node to qualify as a CH, it must have a greater residual energy than its neighbours. In Data collection phase, once the CH is selected, the change is made known to all the cluster members. Now, the cluster members send the information to the respective CHs. The CH performs data aggregation after receiving data packets from cluster members.

For simulation purposes, the proposed work makes use of First Order Radio Model from [3]. In the simple radio model that is assumed, the radio dissipated  $E_{elec} = 50$  nJ/bit to run the transmitter or receiver operations on the network nodes. At each rotation or round  $r$ , the Cluster Head is chosen based on a priori probability  $p_{opt}$  based threshold  $T_{th}$ , which may be represented as:

$$T_{th}(r) = \frac{P_{opt}}{1 - p_{opt} * mod(r, \frac{1}{p_{opt}})} \quad (4)$$

Other than that, in the assumed energy model for the proposed work, the energy consumed by the individual sensor nodes is determined based on the radio energy that is affected by the distance between transmitter and receiver. For the assumed model, the energy consumed for communication process is given by,

$$E_{Tx/Rx}(r) = \begin{cases} l * E_{elec} + l * \epsilon_{fs} * d^2, & d < d_0 \\ l * E_{elec} + l * \epsilon_{mp} * d^4, & d \geq d_0 \end{cases} \quad (5)$$

where,

$E_{Tx/Rx}(r)$  - Energy consumption of a transceiver in a round  $r$ ,  $E_{elec}$  - The transmitter/receiver energy per dissipation,  $d$  - The distance between the sender and receiver nodes  $\epsilon_{fs}$  and  $\epsilon_{mp}$  - the amplifier energy dissipation in free space and multipath respectively, and the threshold distance  $d_0 = \sqrt{\epsilon_{fs}/\epsilon_{mp}}$  which is the boundary between free space and multi-path.

The presented work assumes that there are  $n$  number of sensor nodes and one main base station (BS) in the model of network. The considered scenario for WSN operation has the following properties/assumptions:

1. The sensor nodes are scattered randomly over a field (2-D Cartesian plane) such that no any exact overlap of nodes occur for one particular point.
2. Replenishing the battery energy source is impossible.
3. In terms of processing and communication capabilities, all of the sensors in the network are identical.
4. The Base Station is considered to be present at a fixed position inside of the WSN's area of operation and also no any constraints are given for the position of Base Station inside this particular sensing field.

5. Each Cluster Head assigned in the network, aggregates the data received. It then transmits the received aggregated data to the BS. The nodes may use a varying power level for transmission power according to the distance of transmission for the data to be sent.
6. Every nodes in the network are equiprobable in terms of getting qualified as Cluster Head and having the capability to operate as Cluster Head Node.
7. The communication links between any of the sensor nodes in the network are assumed to be wireless and coverage among nodes exist only if their fall under the specified range of distance within each other.

## 5 Results and Discussion

The network is simulated and tested for performance comparison in MATLAB R2021b with 100 network nodes. The chosen 100 nodes are distributed and scattered over an area of  $100 \times 100$  sq. units to evaluate the performance of the suggested protocol. The network's nodes are assumed to be homogeneous in nature, with similar processing and communication capabilities. All nodes in the network are initially assigned a base energy value of 0.5 J. The below given Table 1 shows the parameters that are chosen for the simulation of Efficient Cluster Head selection algorithm using Ant Colony Optimization for Wireless Sensor Networks.

**Table 1.** Simulation characteristics for Wireless Sensor Networks

Parameter name	Value
Network Field size	$100 \times 100$ sq. units
Number of Sensors ( $n$ )	100
Base Station position value	(50, 0)
Initial energy assigned to each node	0.5 J
Cluster Radius ( $R$ )	10 m
Energy consumption for transceiver operation ( $E_{elec}$ )	50 nJ/bit
Energy dissipation by amplifier in free path propagation	10 pJ/bit/m <sup>2</sup>
Energy dissipation by amplifier in multi-path propagation	0.0013 pJ/bit/m <sup>4</sup>
Message size ( $l$ )	4000 bits
Threshold distance ( $d_0$ )	87.7 m

The existing models that are considered for the performance comparison of the proposed model are LEACH protocol and TEEN Protocol. The same network analysis is used to assess the performance of all current and new mechanisms. To assess the different simulation cases, the source and destination are given as inputs one by one. During the simulations, routes are chosen based on the following next hop option. The below given Fig. 2 shows an example iteration in the simulation. The red coloured nodes indicate the

node selected as Cluster Head for the current iteration of the simulation. The star shaped node indicated the Base Station node at the co-ordinate (50, 0). Since, the initial energy of the nodes was 0.5 J, the simulation was tested for 3500 rounds and appropriate for the testing of current scenario because almost all the algorithms may run out of alive nodes. If a different value of Initial energy is chosen, then number of rounds can be increased or decreased based on the value chosen.

The following metrics are chosen for the comparison of the performance of the algorithm with standard algorithms:

**Alive and dead nodes count:** total number of alive and dead nodes respectively at each  $i^{th}$  round of simulation.

**Throughput:** Total number of packets of data sent from respective Cluster head to the base station.

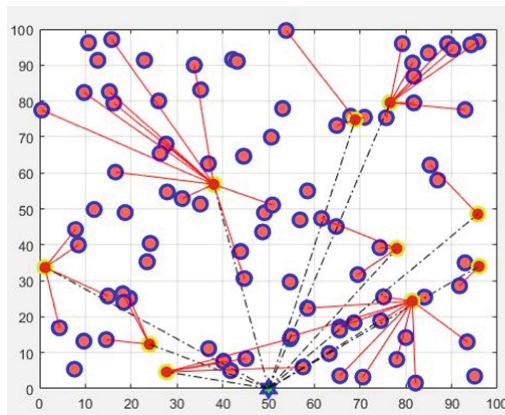


Fig. 2. One iteration of network simulation (Color figure online)

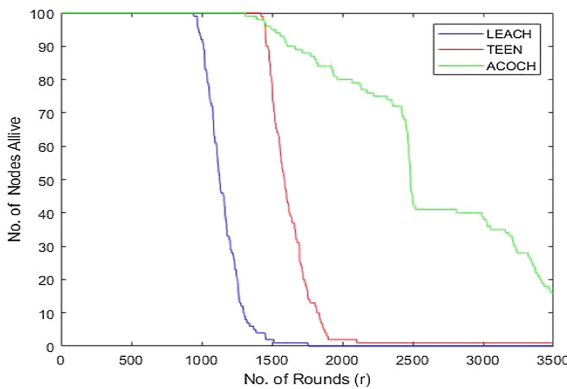
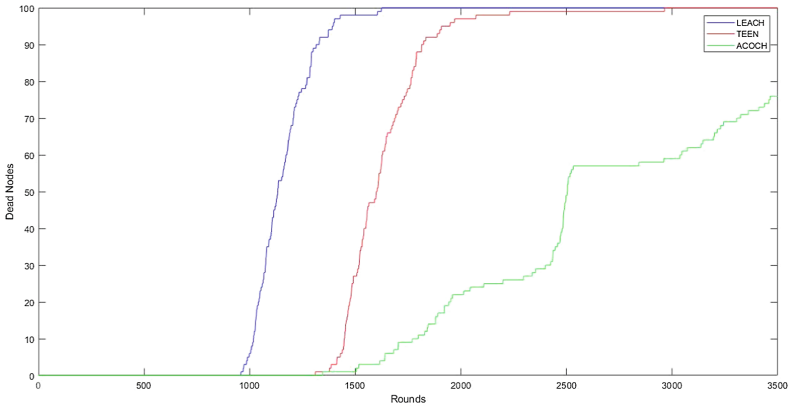
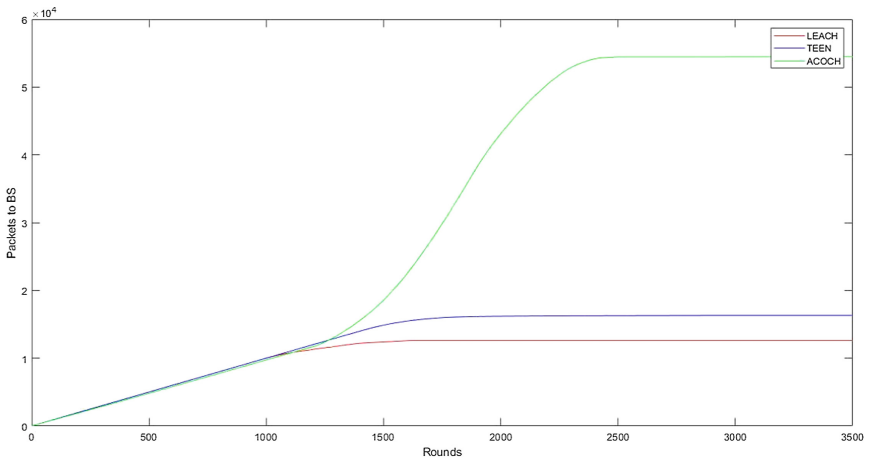


Fig. 3. Graph for alive node count



**Fig. 4.** Graph for dead node count

The above given Figs. 3 and 4 depicts the number of alive nodes and dead nodes respectively, which are present at each instance of the test iteration. Clearly, the above graphs indicate that the proposed CH selection scheme using Ant Colony Optimization is better as number of alive nodes are higher and hence the network lifetime is relatively higher in the proposed scheme. The key thing to be noted here is that, after 2000 iterations the standard LEACH and TEEN algorithms have more number of dead nodes (almost 90) and the proposed scheme outperforms these both algorithms as number of dead nodes are very less. One another key thing to be noted here is that, in standard algorithms considered, if one or more nodes begin to die, the decrease of alive nodes happens vary rapidly and exponentially.



**Fig. 5.** Graph for throughput comparison

The above given Fig. 5 depicts the throughput for the proposed scheme in comparison with the standard algorithms (LEACH and TEEN). Clearly, the proposed Ant

Colony Optimization algorithm outperforms both LEACH and TEEN because available resources in the network are used in an optimized manner. Upto 1000 iterations all the three algorithms considered had worked equally well, but, the point to be noted here is that after 1500 iterations the standard algorithms fail because of rapid decrease of alive nodes in the network. Hence, even beyond 1500 iterations the proposed scheme is doing better and hence has a higher throughput.

## 6 Conclusion

A wireless sensor network (WSN) is an embedded system comprised of randomly distributed sensor nodes and there is an absolute need for the use of an energy-efficient mechanism to prolong the network lifetime. The simulation and results reveal that the suggested technique has a significant improvement in terms of network lifetime. Thus, the use of proposed method can deliver a more extended stability period with more effective clustering as its better ability in exploring and exploiting the solution space. The suggested method, which utilizes the ant colony optimization algorithm, to determine the least number of cluster heads in a WSN. The method used is analogous to determining the topology graph's least dominating set, in which each CH is a component of the overall set. For future enhancements, bringing in features of secure routing or hybridization of the algorithm along with clustering can be taken forward for further feature enhancement of the proposed algorithm.

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