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Energy Efficient Approach in Wireless Sensor Networks Using Game Theoretic Approach and Ant Colony Optimization

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Abstract In the cluster based wireless sensor network architecture, an effective way to optimize the energy consumption is to implement an energy efficient scheme amongst the participating nodes for major activities such as construction of the hierarchical structure on the regular interval and the data communication from a node to the base station. This paper proposes an energy efficient approach for a cluster based wireless sensor network architecture by employing the game theory and ant colony optimization technique. Initially, the proposed work forms various clusters within the network and thereafter, the coalitions are formed using the proposed algorithm based on the game theory. The proposed algorithm considers the extent of spatially correlated sensed data that are generated by neighbouring nodes in order to form a coalition within a cluster. The proposed coalition scheme reduces the number of transmissions across the network. It is compared with the competing clustering protocols. The simulation results confirm that the proposed algorithm achieves the increased network lifetime under the specified quality of service specification (QSS). The results of the proposed work are compared with that obtained through the existing low energy adaptive clustering hierarchy (LEACH) and the deterministic stable election protocols (D-SEP). The overall improvement gain achieved by the proposed work is 31% and 10% at specified QSS, when compared with the LEACH and the D-SEP protocols respectively. Thus, the simulation results obtained in the proposed work confirm their superiority over the LEACH and the D-SEP protocols.

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1 Introduction

A wireless sensor network (WSN) consist of multi connected nodes attached to small sensors in which nodes can communicate with each other through wireless technologies. The nodes are programmed to gather data through the sensors by sensing the data from the environment and further sending the gathered data to the base station. In this way the WSN generates a variety of useful information to the outside world. These small size sensor nodes have limitations such as limited storage capacity, low processing speed and limited battery backup. The major challenge associated with WSN is how to enhance the lifetime of the network. This can be effectively achieved by designing an efficient network communication protocol for optimal resource utilization. A WSN works in two different environments—homogeneous and heterogeneous. A homogeneous sensor network consists of sensor nodes having the same hardware architecture including energy capacity, radio range and processing speed while in heterogeneous sensor network, the sensor nodes may have different hardware architecture under the same conditions. The network lifetime plays a vital role in WSN and is dependent on the battery capacity and underlying applications. The lifetime of a sensor network is defined as the time till all the sensor nodes deployed in the sensing field run out of their energy. The nodes may be deployed randomly or at predefined locations based on node deployment strategy. The node deployment is application specific while the node density may vary depending on its application. The number of nodes deployed per unit area is termed as node density. The node density in WSN can be sparse or dense. In sparse WSN, the nodes deployed are few and scattered, whereas, in dense WSN, the nodes are deployed in close proximities. In densely deployed WSN, the data collected from sensor nodes may vary in similar fashion over a period of time. This is called spatial correlation, where as when the sensor nodes collect the data at different time interval, then the correlation among the data sensed is known as temporal correlation. The WSN having high density nodes, collects similar information and sends the data to the base station. Basically there are three energy conservation schemes namely, duty cycling, data driven and mobility based. The strategy used by the authors in this paper is application of game theory (GT) and ant colony optimization (ACO) which comes under data driven scheme of energy conservation. A detailed description and sub schemes of these schemes are given in [1]. In this paper, the concept of spatial correlation among the data sensed by various sensor nodes is exploited in order to maximize the lifetime of the network.

Section 2 of this paper presents the existing literature survey regarding energy efficient protocols in the WSN. Section 3 describes a radio model and an energy consumption model for WSN. Section 4 explains formulation of the problem. Section 5 provides a solution to the formulated problem. Section 6 discusses a detailed analysis of the performance evaluation of the proposed solution. Finally, Sect. 7 concludes the entire work.

2 Related Work

The LEACH [2] classifies the sensor nodes into two classes namely cluster head and normal node. In the LEACH, the cluster head is selected with probability p depending on the threshold $T(n)$ given as

$$T(n) = \begin{cases} \dfrac{p}{1 - p \times \left(round \times \ \bmod \dfrac{1}{p} \right)}, & \text{if } n \in G \\ 0, & otherwise \end{cases} \tag{1}$$

where p is the probability of the desired cluster head percentage, *round* is the number of the current iteration and G is set of nodes that have not yet been considered in the selection of cluster heads in last $\frac{1}{p}$ rounds. The remaining sensor nodes take the decision of joining the cluster head depending on their energy requirement for communication. Each cluster head collects the data from its own members, performs data aggregation and further communicates the aggregated data to the base station. Selvakennedy et al. [3] propose T-ANT protocol to prolong the life of the network. The protocol T-ANT, uses data gathering algorithm based on the heuristics of ACO. The authors did not use spatial correlation among the data sensed by those sensor nodes which reduces the total transmission cost to the base station. The algorithm used by them uses heuristics to regenerate information from the selected sensor nodes. Chiasserini et al. [4] proposed a clustering approach, aiming at prolonging the lifetime of the WSN. In their work also, the authors did not consider the spatial correlation among sensor nodes. Moreover, their approach required the knowledge of topology in advance which does not seem to be possible in some cases.

Yoon and Shahabi [5] proposed a lossy clustering algorithm in accordance with the error tolerance level. This algorithm was designed for real time data. The performance was evaluated qualitatively through probabilistic approach and quantitatively through simulation. The authors claimed that the complexity of the messaging algorithm was $O(\sqrt{\mathcal{N}} log \mathcal{N})$ and the transmission algorithm complexity was $O(\mathcal{N})$ where $\mathcal{N}$ denotes the number of nodes. The Elink algorithm proposed by Meka and Singh [6] created δ clusters based on message forwarding that, in turn, was based on δ rule. The k-hop overlapping clustering algorithm (KOCA) algorithm proposed by Youssef et al. [7] is a $\mathscr{k}$-hop clustering algorithm and creates clusters of same size. The performance of KOCA is evaluated by adjusting the radius of clusters members in the clusters and the probability of the cluster head. The evaluated time complexity is $O(\mathscr{k})$ and communication complexity is $O(\mathscr{n})$. The Max–Min d-cluster protocol in Ref. [8] generates clusters based on the hop distance. Amis et al., in the afore mentioned work, claim that the run time complexity of Max–Min $\mathscr{d}$-cluster protocol is $O(\mathscr{d})$ rounds. This algorithm generates fewer number of clusters and achieves better load balancing among the cluster head nodes. Foss et al. [9] have considered two level hierarchy used in telecommunication network in which lower levels are linked to the nodes which are on high level. Artemis et al. [10] presented coalition GT [11, 12] based clustering scheme. The authors, in their work, present a coalition scheme that minimizes the node communication by using the spatially correlated data collected by the nodes. However, it was assumed that the representative nodes that interacted with the base station were already fixed and known in advance. A fixed representative may soon get depleted of its energy leading to a partitioned network. The work proposed in this paper aims to exploit the data sensed by spatially correlated sensor nodes to form a coalition within the cluster using game theoretic approach.

The GT [13, 14] has been widely used in many applications such as economics, biology, war, networking, politics, wireless communications etc. wherein, the decisions are based on some strategy and co-operations. Formally, a game [15] $\mathcal{G}$, is represented as $\mathcal{G} = <n, \mathcal{S}_i, \{u_i\}>$, where, n number of players participating in a game are denoted as $\mathcal{H} = \{1, 2, 3, \ldots, n\}$. An individual player $i, i \in \mathcal{H}$ chooses its own strategy $s_i \in \{\mathcal{S}_i\}$, where $\mathcal{S}_i$ is the set of all possible strategies in a game. Therefore, ith player can choose a single strategy from its own set $\mathcal{S}_i = \{s_i^1, \ldots, s_i^m\}$, where $\{s_i^1, \ldots, s_i^m\}$ are all possible strategies for ith player. In this way, every player has his own strategy. Hence, for n number of players, the strategy profile is given as $s = \{s_1, \ldots, s_n\}$. A utility function $u_i = \{u_1, \ldots, u_n\}$ is associated with each player that decides the most preferred strategy of ith player when the strategies followed by other players are known. Coalition is used in the proposed work in order to minimize the number of transmissions to achieve an energy efficient WSN. Coalition games in [15, 16, 17] is represented by $(\mathcal{H}, \vartheta)$, where $\mathcal{H} = \{1, 2, \ldots, n\}$ denotes in the same way as the number of nodes in a WSN and ϑ is the coalition value. Any non empty subsets $\mathcal{Z} \in \{\mathcal{H}\}$ is called coalition. Coalition size is determined by the number of players participating in its formation. A coalition with size $|\mathrm{C}| = 1$ is called a singleton coalition while a coalition with size $|\mathrm{C}| = n$, is called a grand coalition. Total number of possible coalitions using n players $\{1, 2, \ldots, n\}$ is $(2^n - 1)$.

In this paper, the extent of coalition is optimized by using one of the nature inspired algorithms ACO [18, 19]. An ACO technique is motivated by the concept of foraging behaviour of ants. Ants can find their optimal path between *Food source* and *Nest* by using foraging behaviour as shown in Fig. 1. The ACO [20–22] technique is widely used in graph theory to find an optimized path between the source and the destination. Initially, ants explore the graph in a random fashion. If food is found then ants carry a quantum of food to its nest. During returning to its nest, ants deposit the pheromone on its path. The pheromone trail is used as a metric by other ants to find the optimal path (edges). The edges are chosen probabilistically [23] according to the evaporation value of the pheromone and the attractiveness of path. Probability $P(e)$ that a given edge e considered for optimal path construction is given as

$$P(e) = \frac{\tau(e).\eta}{\sum_{Available\,Edges} \tau(e).\eta} \tag{2}$$

where τ is evaporation rate of the pheromone deposited and η is inversely dependent on the distance between the two vertices. Each ant maintains a list of infeasible solutions for the

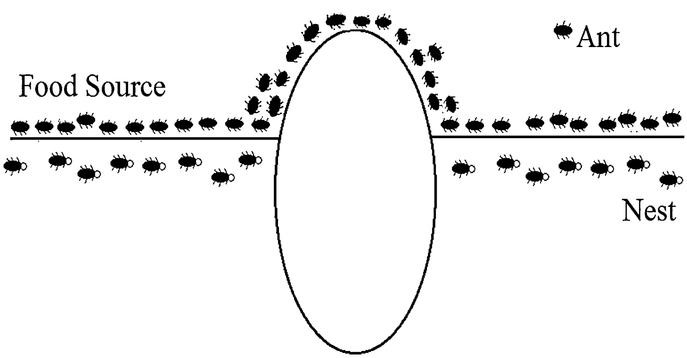


Fig. 1 Ant colony optimization

iterations and updates the attractiveness of the path. Mathematically, the pheromone update [23] is given by

$$\tau(e) = \begin{cases} \rho.\tau(e), & \text{if edge is not traversed} \\ (1-\rho).\tau(e), & \text{if edge is traversed} \end{cases} \quad (3)$$

where $\tau(e)$ is the updated value of the calculated evaporation rate and ρ is the pheromone evaporation constant which is chosen according to optimization criteria.

3 Radio and Energy Consumption Model

In this work, a similar radio model as reported in literature [2, 24, 25] is used. The transmitter is used to transmit the signal while the receiver receives the transmitted signal with the help of the receiver electronics as shown in Fig. 2. Here, d denotes the distance between the transmitter and the receiver. The threshold distance d_0 between the transmitter and the receiver is given by

$$d_0 = \sqrt{\frac{E_{fs}}{E_{mp}}} \quad (4)$$

If the distance d is less than the distance d_0, the energy dissipated is estimated using free space (*fs*) loss model. For the distance d greater then d_0, the multipath (*mp*) loss model is used. The free space and multipath loss models are given as

$$E_{Amp} = \begin{cases} E_{fs}.d^2, & \text{if } \mathrm{d} < \mathrm{d_0} \\ E_{mp}.d^4, & \text{if } \mathrm{d} \geq \mathrm{d_0} \end{cases} \quad (5)$$

Here, it is assumed that the radio model has the transmitter mechanism that can transmit two different types of signals depending on the distance from the receiver. The first kind of signal is the one when the distance between the transmitter and the receiver is less than the distance d_0. The radio model used in this case is the free space loss model. In case of the second kind of signal, the distance between the transmitter and the receiver is more than the distance d_0. The radio model used in this case is the multipath loss model. E_{fs} is known as the free space signal loss, measured in J/bit/m^2 and E_{mp} is the multipath signal loss, measured in J/bit/m^2 and E_{Amp} is the energy of the nodes involved in the transmission. The energy used in transmitting L bits at the distance d is given by

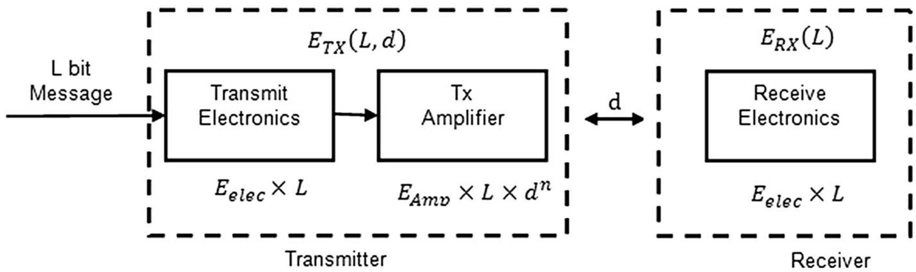


Fig. 2 Radio model

$$E_{TX}(L,d) = E_{TX-elec}(L) + E_{TX-Amp}(L,d) \tag{6}$$

Here, E_{TX}, L, d, $E_{TX-elec}$ and $E_{TX-Amp}(L,d)$ are the transmission energy, number of bits, distance in transmission, energy used by the hardware circuit for the transmission of L bits and the energy used in the transmission of L bits at a distance d respectively.

Therefore, using the Eqs. (5) and (6), the total energy used in the transmission of L bits at the distance d can be calculated by

$$E_{TX}(L,d) = \begin{cases} L.E_{elec} + L.E_{fs}.d^2, & \text{if } \mathrm{d} < \mathrm{d}_0 \\ L.E_{elec} + L.E_{mp}.d^4, & \text{if } \mathrm{d} \geq \mathrm{d}_0 \end{cases} \tag{7}$$

Here, L, E_{elec} are the number of bits to be transmitted and the energy loss in the hardware circuit needed for the transmission of L bits used by the radio model as given in Eq. (5) for the transmission of L bits respectively.

The energy dissipated by the receiver to receive the data is given by

$$E_{RX}(L) = E_{RX-elec}(L) = L.E_{elec}. \tag{8}$$

Here, $E_{RX-elec}$, is the energy used in the hardware circuit to receive L bits and is measured in J/Bit in reception electronics.

The energy consumption model used here is according to LEACH [2, 24, 25]. In LEACH the clusters consisting of nodes are made. The cluster heads are chosen according to the LEACH protocol. The cluster heads in LEACH protocol collect data from its member nodes, aggregate the data and transmit the same to the base station.

Considering the sensing area of square size $M \times M$ as uniformly distributed with n number of nodes and β number of clusters. Then the average number of nodes in a cluster will be $\frac{n}{\beta}$. For each cluster, one node is represented as the cluster head while the others as cluster members or the non cluster head. Hence, the average number of non cluster heads per unit cluster $= (non - CH) = (\frac{n}{\beta} - 1)$. The energy consumption model for the non cluster head node while transmitting information of size 'L' bits to its cluster head is given by

$$E_{non-CH} = L.E_{elec} + L.E_{fs} d_{CH}^2 \tag{9}$$

Here, E_{elec}, E_{fs}, d_{CH}^2 are the energy loss in hardware circuit, the free space signal loss in transmission of L bits and the distance between members nodes and their respective cluster heads respectively. The distance d_{CH}^2 is given by

$$d_{CH}^2 = \frac{M^2}{2\pi\beta} \tag{10}$$

As n nodes are randomly deployed over $M \times M$ sensor field area with β number of clusters, one cluster occupies approximately M^2/β area of the sensor field. The distance d_{CH}^2 is the distance between a node and its cluster head. Substituting Eq. (10) in Eq. (9),

$$E_{non-CH} = L.E_{elec} + L.E_{fs} \frac{M^2}{2\pi\beta} \tag{11}$$

Total energy consumption by a cluster head is the sum of energies dissipated by the individual cluster members to send L bits data to its cluster head. The energy dissipated by the cluster head for the transmission of aggregated data is given by

$$E_{CH} = \left(\frac{n}{\beta} - 1\right).L.E_{elec} + \frac{n}{\beta}.L.E_{DA} + E_{TX}(L, d) \tag{12}$$

Here, E_{CH}, E_{elec}, E_{TX}, E_{DA} are the energy dissipated by the cluster heads in receiving L bits from their $(\frac{n}{\beta} - 1)$ cluster members, the energy used in the hardware circuit, the transmission energy used in transmitting L bits of data at the distance d and the data aggregation energy used for aggregating data from $\frac{n}{\beta}$ nodes (including its own data), each node transmitting L bits to their respective cluster heads respectively. As a standard practice E_{DA} is used according to the LEACH. As a cluster head transmits its data to the base station, multipath signal loss transmission is used. Substituting Eq. (7) in Equation (12),

$$E_{CH} = \left(\frac{n}{\beta} - 1\right).L.E_{elec} + \frac{n}{\beta}.L.E_{DA} + L.E_{elec} + L.E_{mp}d^4_{toBS} \tag{13}$$

Here, $(\frac{n}{\beta} - 1)$, L, $\frac{n}{\beta}$, E_{DA}, E_{elec}, d^4_{toBS} are the total members in a cluster, the number of bits transmitted, total data of size L to be aggregated, data aggregated energy which is a standard practice used according to LEACH, the energy used by hardware circuit and the distance between the cluster head and the base station respectively. Therefore, the total energy consumed in a cluster is given by

$$E_{Cluster} = E_{CH} + \left(\frac{n}{\beta} - 1\right)E_{non-CH} \tag{14}$$

Here, E_{CH}, E_{non-CH}, $E_{Cluster}$ are the total energy consumed by the cluster head, the energy transmission from $(\frac{n}{\beta} - 1)$ member nodes of a cluster and the total energy used in the transmission and the reception by a cluster respectively. Therefore, total energy consumed in the network for one round is given by

$$E_{Round} = \sum_{j=1}^{\beta}(E_{Cluster(j)}) \tag{15}$$

Here, E_{Round}, $E_{Cluster(j)}$ are the total energy consumed in one round and the energy consumed by jth cluster respectively where β is the total number of clusters. E_{total} is a special case of E_{Round}. When some number of nodes are nearer and some number of nodes are farther from the base station, E_{total} is given by

$$E_{total} = E_1 + L.E_{fs}\sum_{i=1}^{p}(d_i^2) + L.E_{mp}\sum_{j=1}^{q}d_j^4 \tag{16}$$

Here, E_{total} is the total energy of the network in one round of transmission, i and j are nodes, near and far nodes from base station respectively, p and q are total nodes, near and far from base station in a cluster respectively.

$$E_1 = L.\frac{n}{\beta}\left[(2n - \beta).E_{elec} + n.E_{DA} + (n - \beta).E_{fs}.\frac{M^2}{2\pi\beta}\right] \tag{17}$$

Residual energy of a node i in each round is given by

$$E_{Res} = E_i - \{E_{TX} + E_{RX}\} \tag{18}$$

Here, E_{Res}, E_{TX}, E_i, E_{RX} are the residual energy of the node, the energy consumed in transmission by the i node, the current energy of the node and the energy consumed in receiving the data by the ith node respectively.

4 Formulation of the Problem

In a densely deployed WSN, the sensor nodes are situated in close proximities and can sense the physical phenomenon or an event. Due to the close proximity and the high density of sensor nodes, the data sensed by the sensor nodes are observed to be highly spatially-correlated. The degree of correlation between spatially-correlated data increases as the distance between the two sensor nodes decreases. The spatially correlated data in the network can prove to be useful in designing an energy efficient WSN. In the spatially-correlated data environment, it is not necessary for all the sensor nodes to transmit their data to the sink. In order to achieve minimum number of transmissions required for all the spatially-correlated data sensed by sensor node, the minimum number of sensed data should be transmitted to the sink if these data represent the entire network. If the same network is reorganized into a number of clusters, the number of transmissions in a cluster would be directly proportional to the node density of the cluster under consideration. Each cluster head collects data periodically from its members, performs data aggregation and finally communicates it to the sink. The presence of the spatially-correlated sensed data within each cluster would help to minimize the total number of transmissions required for the efficient communication. In view of this, there is a need to devise an approach to minimize the energy dissipation in transmitting the network data in such a densely deployed network. The objective of the proposed approach is, therefore, to minimize the transmissions in order to communicate the sensed data of the clusters to the cluster head. Reducing the number of transmissions is a major challenge within the cluster.

The proposed work in this paper, aims to minimize the transmission complexity of a WSN generating spatially-correlated data in the network. A cooperative scheme, from the GT is proposed in this paper that forms the coalitions within the clusters of the sensor network. Factors such as spatial correlation and data accuracy are considered in the formation of a coalition and the accuracy factor is specified as QSS metric. In order to optimize the size of each coalition, an ACO based technique is proposed in the present work. At every cluster level, the total number of transmissions are reduced and the number of transmissions depend on the number of coalitions formed. The proposed strategy in this work can, therefore, minimize the number of transmissions across the network thereby enhancing the network lifetime and the quality of service [26] in the network.

5 Proposed Algorithm

In this paper, a cluster based WSN is considered with n number of nodes deployed randomly in $(M \times M)$ square. A solution is proposed that aims at providing energy efficient means for the WSN under consideration using GT and ACO in order to reduce the energy dissipation. It is assumed that the participating nodes are selfish and are not willing to dissipate energy in excessively during transmissions. In order to achieve selfishness, the nodes cooperate with each other leading to a trade-off between the energy efficiency and the data accuracy which is a constraint. The accuracy is compromised as per predefined quality of service specification (QSS) to form a coalition. The cooperative GT is used for the coalition construction to generate the partial solution. Partial solution is then optimized with ACO technique by considering deposited pheromone [27] on the nodes, participating in partial solution as the objective function. An optimized partial solution refers to an optimized coalition. Coalition can be considered as a subcluster within a cluster. A representative sensor node is chosen from each subcluster to transmit its data to the cluster head on behalf of its subcluster, while rest of the nodes refrain from sending their data to the cluster head. This results in a decrease in the number of transmissions within the sensor network. The analysis of the complexity of the proposed solution in terms of the number of transmissions in the network will be clear from the following example.

Considering a scenario that consists of an area of size $M \times M$ uniformally distributed with n number of nodes having β number of clusters, each cluster consisting of $(\frac{n}{\beta} - 1)$ member nodes and a cluster head node. Therefore, the total number of transmissions in the clustered network would be $\beta + \beta \times (\frac{n}{\beta} - 1)$. If coalition technique is applied on the above mentioned scenario, the number of transmissions would be $(\beta + \ell.\beta)$ where, ℓ is total number of coalitions. In the best case, $\ell = 1$, hence the number of transmission in the network would be 2β. In the average case, $\ell < \beta$, hence the number of transmissions would be $(\beta + \ell.\beta)$. In the worst case, the number of transmission would be same as that in the clustered approach. Therefore, the number of transmissions in the network would be $(\beta + \ell.\beta)$, where $\ell = (\frac{n}{\beta} - 1)$.

It is found that, the number of transmissions with the coalition in the worst case, is same as that in the clustered network. In this case, the coalition is purely overhead. The existence of all non cluster head nodes as singleton coalition is rare in a dense sensor network. In the average and the best cases, coalition reduces the number of transmissions significantly.

The Algorithm 1, that is proposed in this paper works in different phases namely initialization, cluster head election, coalition formation, optimization, association and data aggregation phases.

Algorithm 1 Proposed Algorithm

Input **:** Set of nodes, $N = \{1, \ldots, n\}$ over $M \times M$ area
Output **:** Energy efficient clustering using coalition and ACO

```
I. Initalization Phase;
        // Network Parameters
II. Cluster Head Election Phase;
        // Cluster heads are elected as per existing protocol
III. Coalition Formation Phase;
        // Generates coalitions which is represented as partial solution.
IV. Optimization Phase;
        // Partial solution optimised by using ACO technique.
V. Association Phase ;
        // Representative of optimised coalition and every non coalition members are
        //associated with cluster heads.
VI. Data Aggregation Phase;
        // Cluster head aggregate data of optimised coalition and sends to sink
```

5.1 Initialization Phase

In this phase, a dense sensor network that is deployed with both the homogeneous nodes in LEACH and the heterogeneous nodes in D-SEP [28], is considered during implementation.

The nodes are assumed to be static. The network parameters considered to initialize the network field are initial energy (E_o) of nodes, pheromone density (τ_ϕ), pheromone evaporation rate (ρ), accuracy constraint (q), negotiation constant (λ) , number of sensor nodes (n), percentage p of cluster heads, $M \times M$ square area of sensing field and radio range (R).

5.2 Cluster Head Election Phase

In this phase, the proposed algorithm uses a cluster setup according to the LEACH and the D-SEP protocols to identify the cluster heads. The cluster heads are selected and memorized for usage only during association phase of the proposed algorithm. During simulation in the homogeneous environment, the cluster head election is based on the LEACH while in the heterogeneous environment, it is based on the D-SEP protocol. Here, the LEACH and the D-SEP protocols have been considered only for the purpose of making comparison. The cluster head for the LEACH protocol is elected with the help of Eq. (1).

The authors [28] propose D-SEP protocol that uses two level as well as three level hierarchical network. In this protocol, the selection of cluster head for the two level hierarchy is given by

$$T(n) = \frac{p_i}{1 - (p_i) \times r.mod\frac{1}{p_i}} \times \left[E_{residual} + \left(r_s \; div \; \frac{1}{p_i} \times (1 - E_{Res}) \right) \right] \tag{19}$$

Here, r, r_s, $E_{residual}$ are the current number of round, the number of rounds for which node has not been elected as cluster head, and the residual energy of the network respectively. The probability for cluster head election p_i is given by

$$p_i = \begin{cases} \dfrac{p_{opt}}{1 + \alpha.a} \times \dfrac{E_{residual}}{E_{average}}, & \text{if } \mathrm{n_i} \in \mathrm{G}' \text{ is the normal node} \\ \dfrac{p_{opt}(1 + \alpha)}{1 + \alpha.a} \times \dfrac{E_{residual}}{E_{average}}, & \text{if } \mathrm{n_i} \in \mathrm{G}'' \text{ is the advanced node} \end{cases} \tag{20}$$

Where a, α, $E_{average}$ are the number of advanced node, the energy increase in the advanced node and the average energy of the network respectively. p_{opt} is the optimal number of the cluster head and is given by

$$p_{opt} = \frac{1}{0.765} \times \sqrt{\frac{2}{\pi n}} \times \sqrt{\frac{E_{fs}}{E_{mp}}} \tag{21}$$

The average energy of n nodes is estimated as

$$E_{average} = \frac{1}{n} \times E_{Total} \times \left(1 - \frac{r}{R_{Total}} \right) \tag{22}$$

where, r is the current round and R_{Total} is the total number of rounds which is given by

$$R_{Total} = \frac{E_{Total}}{E_{Round}} \tag{23}$$

Here, E_{Round} is the energy spent in the round.

5.3 Coalition Formation Phase

In this phase, the non cluster head nodes participate in the coalition formation. It is assumed that the WSN consists of a total of n number of nodes, of which the number of non cluster head nodes and the cluster heads are $\beta \times (\frac{n}{\beta} - 1)$ and $\mathcal{X} = (n - \beta) \times (\frac{n}{\beta} - 1)$ respectively. The proposed coalition formation algorithm is presented as Algorithm 2. The coalition formation algorithm starts with the creation of singleton coalitions and then declares its partial solution, in which each non cluster head node is singleton coalition as shown in Fig. 3. All the singleton coalitions are declared as initiators of the coalition formation. For every node $x \in \mathcal{X}$, singleton coalition is represented by $s(b, rep)$, where b is the coalition with w nodes such that $w \in W$ where $W = \{1, 2...n\}$ and rep is the representative node of the coalition b. Only the representative node is allowed to transmit its data to the cluster head on behalf of its coalition. Next, the neighbours for each partial solution are discovered and stored for further computation. All the discovered neighbours are further explored to extend the coalition size. For every $s \in \{S\}$, where S is the set of all coalitions and all the nodes are identified as edge nodes, say E where $e \in \{E\}$. To extend coalition using ACO technique, an edge e is selected probabilistically using Eq. (2). For every $e \in \{E\}$, an ant packet to discover its one hop neighbours is sent out. A negotiation operation is performed between a single node (with $e \in \{E\}$) belonging to a coalition $S(k, rep_j)$ and one of its neighbours, (with $b \in \mathcal{X}$) belonging to coalition $S(b, rep_j)$. In the negotiation framework, a value of the utility function $U(e_k, b_i)$ is computed. The utility function is given by

$$U(e_k, b_i) = (|\bar{\sigma} - \sigma|) - \bar{o}.f(d(b_i, e_k), q) \tag{24}$$

where σ is the standard deviation of the residual energies of the coalition to which edge node belongs, and $\bar{\sigma}$ is the standard deviation calculated after the neighbour node b is added to the coalition. The difference of $\bar{\sigma}$ and σ should be greater than the offset $\bar{o}$. The offset $\bar{o}$ is considered to be directly proportional to the average residual energy and is given by

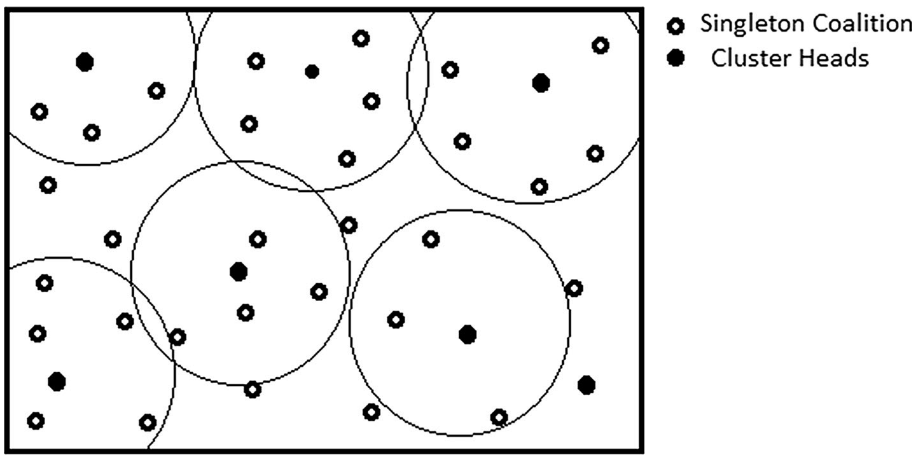


Fig. 3 Singleton coalition

$$\bar{o} = \lambda * average(E_{Res}) \tag{25}$$

where λ is a negotiation constant. The proposed utility function manages to accommodate two factors. The former always favours adding nodes with more diverse level of residual energies and the second part governs the coalition size. $d(b_i, e_k)$ reports the data measured between node b_i and the node which started the coalition formation, let it be denoted by b_c. If X_i, X_c are the measurements of b_i and b_c, dissimilarity metric [10] $d(b_i, e_k)$ is given by

$$d(b_i, e_k) = \left| \frac{X_i - X_c}{X_c} \right| \tag{26}$$

Accuracy function q specifies the constraint defined by QSS. The data sensed by the dissimilarity function should satisfy the Eq. (26). The accuracy function governs the size of coalition and is called q rule [10]. The accuracy function is given by

$$f(d(b_i, e_k, q) = \begin{cases} 1 - d(b_i, e_k), & \mathrm{d(b_i, e_k) <= 1 - q} \\ -1, & d(b_i, e_k) > 1 - q \end{cases} \tag{27}$$

Algorithm 2 Coalition Formation

Input **:** K = {1,2,3.,m} set of non cluster head nodes
Output **:** Set of Partial Solutions

```
        // PS[ ]: Set of partial solutions , where each solution may consists of m nodes.
        // ND[ ]: Set of neighbours discovery, where each member may consists of m nodes.
        // Diss, Utility: Temporary variables.
        // RadioRange(X,Y): Returns true if node X is in radio range of Y.
        // Starter [ ]: Refers to an initial node of a partial solution or initiator of coalition.
       // SingletonCoalition(x ): Creates x as singleton coalition.

for node i=1 to m do
   PS[ i ] = SingletonCoalition( i );
   Starter [ i ] = PS[ i ]
end for
for node i=1 to m do
   Discover neighbours ND[ i ] of PS [ i ] ;
   while  (ND[ i ] members are unvisited ) do
      Select a neighbour node x from ND[ i ] with ACO probability P;
      if If (node x is already visited)  then
         Continue to next iteration of while loop;
      end if
      Calculate E_TX, E_RX and E_CH through Equations. (6),(8), (12) respectively;
      Calculate E_Res through Equation (18).
      Calculate ō using Equation (25).
      Calculate Diss = d(x, edge(created by selecting x )) using Equation (26).
      Calculate f (Diss, q) through Equation (27)
      Calculate Utility = U(edge(created by selecting x ), x ) using Equation (24).
      if (Utility AND RadioRange(x, Starter[ i ])  then
         Deposit Pheromone to x using Equation (28).
         PS[ i ]= {x} ∪ {PS[i]}
         ND[ i ]={ neighbour of x} ∪ {ND[ i ]}
      end if
      Mark node x as visited
   end while
end for
```

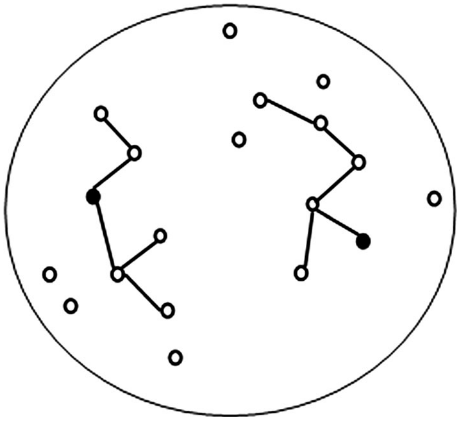


Fig. 4 Starter and non starter nodes participating in coalition formation process. *Filled circles* starter node initiating coalition process, *open circles* non-starter node agumenting coalition process

For the negotiation to be successful, the value of $U(e_k, b_i)$ should be positive i.e. $U(e_k, b_i) > 0$. If there is successful negotiation and the edge node lies within the radio range of the coalition starter then such a feasible solution component is added to the current partial solution. For each added solution, the ants mark it with pheromone. The pheromone density can be computed by

$$\tau_\phi(b_i, e_k) = 1 - \frac{\rho}{e^\imath} * \tau_\phi \tag{28}$$

where $\tau_\phi(b_i, e_k)$ is the pheromone value associated with the edge joining the edge node e to the neighbour node b, ρ is the evaporation rate, $\imath$ is the transmission delay of the ant packet, and τ_ϕ is the initial pheromone value. Once all the partial solutions are explored with all the possible neighbours, the partial solution serves as input to the optimization phase. The pheromone deposited on the edge nodes is used in the optimization phase.

The time complexity of this algorithm is estimated to be $O(n^2)$ in the worst case where n is the total number of nodes.

5.4 Optimization Phase

All the non cluster heads participate in this phase. The obtained partial solutions and the pheromone deposited during the coalition phase are used in this phase. For example, one of the partial solution is shown in Fig. 4. In this phase, the size of each partial solution is optimized to generate optimal coalitions. An optimization criterion is based on the deposited pheromone given by ACO technique applied during the coalition phase. The overall quantities of the pheromone deposited by the partial solutions are computed. The average quantity of the pheromone deposited in each partial solution is calculated. In a partial solution, if the quantity of the pheromone deposited on a node is greater than its average value for the partial solution, then such node is selected and added to the optimized coalition as mentioned in the Algorithm 3. Once a node is selected as the member of an optimized coalition, it cannot be a part of any another optimized coalition. The set of optimal coalitions is the result of the optimization phase.

The time complexity of this algorithm is also estimated to be $O(n^2)$ in the worst case where n is the total number of nodes.

Algorithm 3 Optimization

Input : $K = \{1, 2, 3., m\}$non cluster head nodes , Partial Solution Set, Pheromone Matrix
Output : Set of optimised coalitions

```
    //PS[ ]: Set of partial solutions , where each solution may consists of m nodes.
    //Starter( ): Refers to an initial node of a partial solution or initiator of coalition.
    //SingletonCoalition(x ): Creates x as singleton coalition.
    //CL[ ]: Set of optimised coalitions, where each coalition may consists of m nodes
     //PH[ ]: Pheromone deposited to node
    //PHav : Average of pheromone deposited to members of partial solution

for node i = 1 to m  do
  CL[ i ] = NIL
  Mark node as unvisited;
end for
for each Partial Solution PS[ i=1 to m ]  do
  Calculate pheromone average (PHav) of all nodes in PS[ i ]
  for each node x ∈PS[ i] do
    if ((x = Starter(PS[ i ]) AND ( x = unvisited))  then
      {CL[ i ]} = {CL[ i ]} ∪ x
      Mark node x as visited;
      Continue next iteration of for loop
    end if
    if ( (PH[x] ≥ PHav ) AND (x= unvisited))  then
      {CL[ i ]} = {CL[ i ]} ∪ x
      Mark node x as visited;
    end if
  end for
end for
```

5.5 Association Phase

In the association phase, a representative node is selected from each optimal coalition. The selection of the representative node is made on the basis of the maximum residual energy of the coalition. Each representative node is associated with its nearest cluster head.

5.6 Data Aggregation Phase

The cluster head generates Time Division Multiplexing Access (TDMA) schedule for each representative. Each representative sends the sensed data as per its allocated schedule to its cluster head. The cluster heads aggregate their self-sensed data with the data received from its representatives. The cluster head then sends the aggregated data to the base station.

6 Results

The WSN considered in this work consists of 100 nodes that are randomly and independently deployed in 100×100 unit square area. The Sensor nodes are assumed to be static. The simulation parameters for the evaluation of the proposed algorithm are presented in Table 1.

The proposed algorithm assumes that the nodes are deployed with Gaussian distribution with respect to the internodal distance g and is given by

Table 1 Simulation parameter and its meaning

Parameter symbol	Meaning	Value
Area (M)	Deployment area	100 sq. units
Nodes (n)	Sensor nodes to be deployed	100
τ_{ϕ}	Initial pheromone	1
ρ	Evaporation constant	0.01
E_o	Initial energy	0.01
q	Data accuracy	Ranging from 0.7 to 1(70–100%)
λ	Negotiation constant	0.025

$$D(g) = e^{-\frac{g^2}{2\sigma^2}} \tag{29}$$

where σ stands for standard deviation.

6.1 Analysis of the Proposed Algorithm

Energy efficient approach in WSN using game theoretic approach and ant colony optimization (EEAGTACO), compared with LEACH and D-SEP protocol, has been implemented using MATLAB. Parameters such as lifetime of the sensor network, the number of message transmissions and the percentage gain have been considered for the purpose of comparison.

6.1.1 Comparison of Lifetime of WSN

The present analysis is based on the following definition of network lifetime [29] which is suitable for the applications considered in this work:

Lifetime of a sensor network is defined as the maximal duration of time in which the deployed sensors have the ability to monitor the area of interest.

In Fig. 5a, b, the number of dead nodes for each round are plotted. During simulation, the values of the parameter q considered for LEACH and D-SEP are 0.8 and 0.9 respectively. It is observed that EEAGTACO increases the lifetime of the network when compared with the traditional LEACH and D-SEP protocols respectively. Extending lifetime is achieved at the cost of quality of data by proposed algorithm. The EEAGTACO exploits the data sensed by spatially-correlated neighbouring sensor nodes to form the coalition. A representative sensor node is chosen from each coalition to transmit the sensed data to their respective cluster heads. This reduces the number of transmissions to the cluster head thereby saving the energy in the WSN. In the traditional LEACH and D-SEP protocols, all the member nodes of a cluster transmit their data to their respective cluster heads. The cluster heads aggregate the data received from their member sensor nodes and send the aggregated data to the base station. This results in an increase in the number of transmissions in the wireless sensor field. As a representative sensor node transmits only a single data on behalf of its coalition to its cluster head unlike in the case of traditional LEACH and D-SEP protocols, the lifetime of the network in the proposed EEAGTACO is more as compared to that in the traditional LEACH and D-SEP protocols.

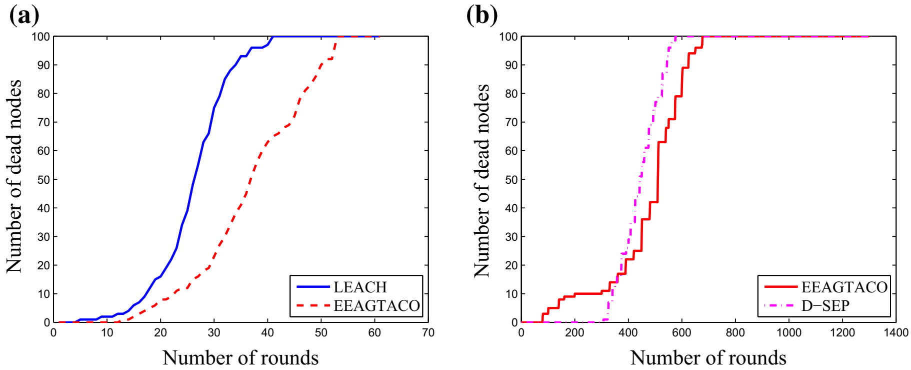


Fig. 5 Comparison of network lifetime **a** with LEACH at $q = 0.8$, **b** with D-SEP at $q = 0.9$

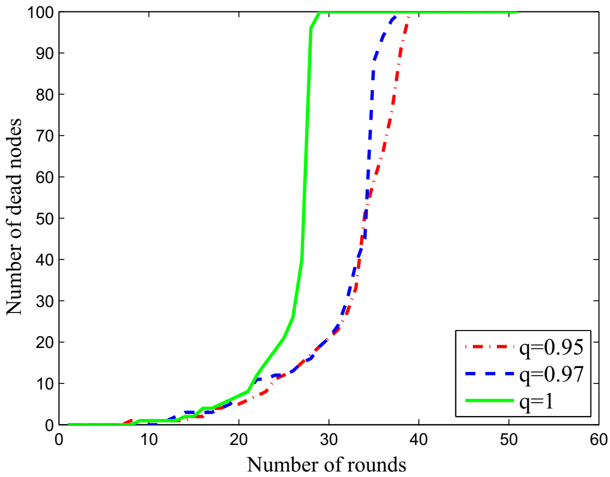


Fig. 6 Variation of network lifetime with data accuracy

The performance of the proposed coalitional scheme is examined with respect to the data accuracy. In Fig. 6, the number of dead nodes for each round are plotted corresponding to three different values of q. It is observed that there is a decrease in the network lifetime when $q = 1$, as compared to the cases when $q = 0.97$ and $q = 0.95$. The lifetime of the sensor network with $q = 0.95$ is more as compared to $q = 0.97$. Therefore, the energy saving potential of the network reduces as the value of QSS increases. This implies that the QSS is inversely proportional to the lifetime of the network. As expected, the simulation results plotted confirm that the scheme performance depends on the accuracy specified for the acceptable operation of the WSN. Relatively lower values of q allow the formation of large coalitions thereby increasing the average WSN lifetime.

The curves shown in Fig. 7 depict the variation of the number of representative sensor nodes with varying q for different values of radio range. It is observed that the number of representative sensor nodes increase with the increase in the values of q. All the representative sensor nodes communicate their sensed data to their respective cluster head resulting in an increase in the number of transmissions in the network for $q = 1$. Therefore, there is a decrease in the lifetime of the network with the increase in the number of transmissions. From the Fig. 7a–c for the radio range $R = 9$, $R = 12$ and $R = 15$

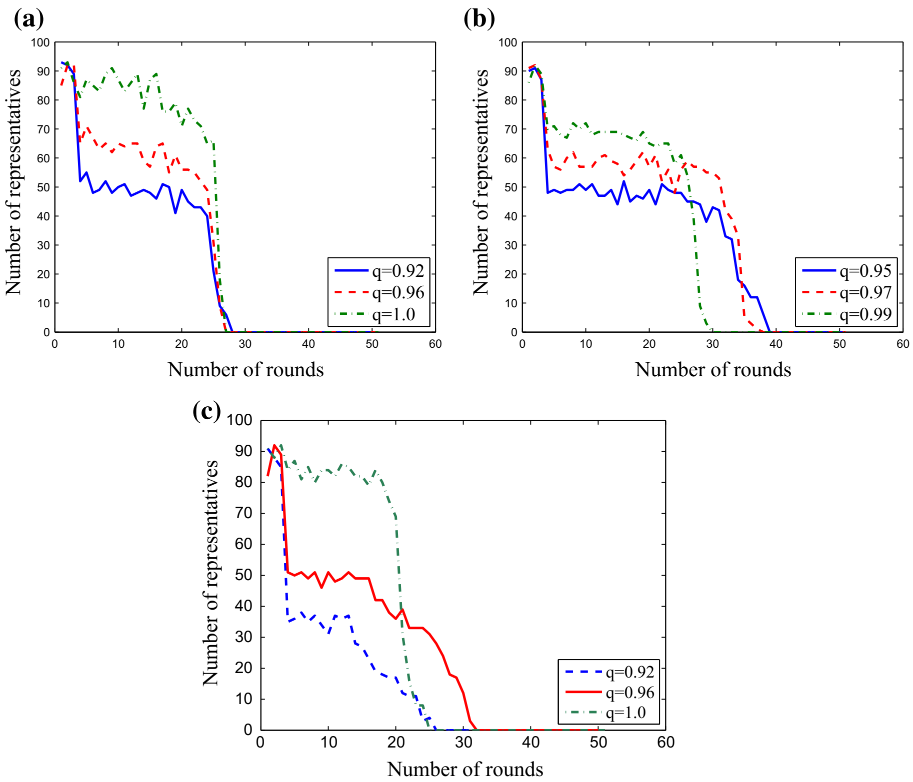


Fig. 7 Variation of number of Representative with data accuracy at different radio coverage. **a** Radio range R = 9. **b** Radio range R = 12. **c** Radio range R = 15

respectively, it is validated that increasing the radio range leads to more number of neighbours resulting in larger coalitions and hence, decrease in the number of representative sensor nodes, except for $R = 15$ in which $q = 1$ restricts the number of feasible coalition structures. It may be noticed that $q = 0.95$ with $R = 12$, gives the most optimal decay of representative sensor nodes resulting in the increased network lifetime.

It can be observed from the Fig. 8 that an increase in λ provides an increased offset hence allowing larger coalitions to be formed resulting in lower number of representatives. The negotiation constant (λ) directly controls the offset $\bar{o}$ which promotes a more diverse range of residual energies in a coalition. Widely distributed energies would ensure a more balanced and uniform consumption of energies throughout the network and would prevent any blind spot and maintaining the data accuracy as well. A higher value of λ prevents the nodes with similar energies, either low or high, to participate in the same coalition and therefore, should result in a more gentle decay in the number of representatives.

6.1.2 Number of Message Transmissions

The network lifetime obtained through the proposed algorithm is compared with that obtained through LEACH. Figure 9 shows the variation of the total number of packets sent with respect to the number of rounds representing the network lifetime for LEACH and for proposed algorithm. The LEACH takes into account the cluster formation whereas the

Fig. 8 Variation of number of representatives with negotiation constant

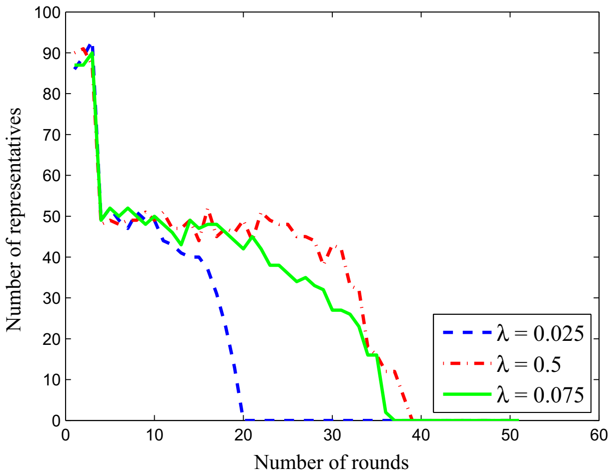
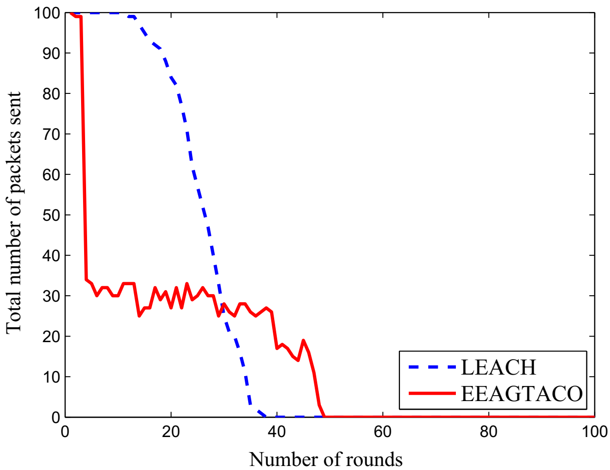


Fig. 9 Dead nodes per round



proposed EEAGTACO exploits the spatial redundancies and takes into account the residual energies for coalition formation. This comparison confirms that in case of LEACH there is an increase in the number of packets transmitted due to randomized clustering as compared to the proposed EEAGTACO. In the EEAGTACO, the representative nodes transmit packets on behalf of its coalition members, resulting in decrease in the number of messages sent per round.

Relationship between the network lifetime and the data accuracy under varying network sizes is shown in Fig. 10a. The graph so obtained represents the dependency between the performance of the proposed algorithm and the extent to which the data sensed by the sensor nodes are correlated. In this simulation, large size WSNs offer lower spatial correlation leading to optimal number of coalitions and its size. This results in increased network life time due to optimal number of transmissions.

Further, the analysis of the packets sent versus data accuracy with respect to data accuracy under consideration of data correlation (σ) is carried out and is illustrated

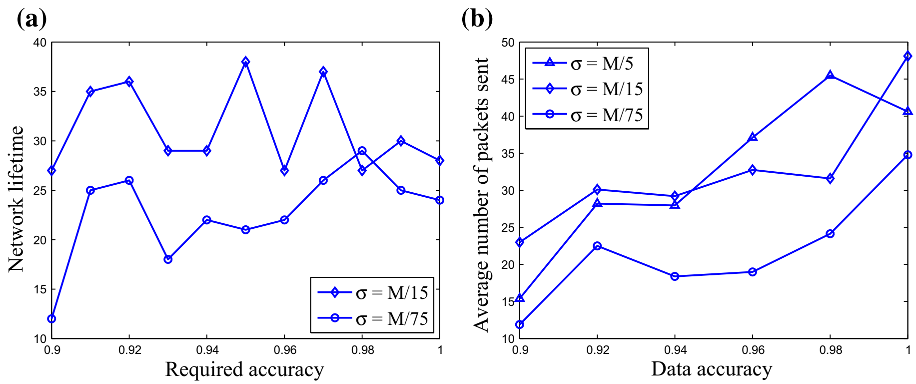


Fig. 10 Correlation of data with respect to data accuracy for different values of σ. **a** Variation of network lifetime, **b** variation of average number of message transmissions

graphically by Fig. 10. From the graph, it can be observed that at $\sigma = M/75$, the data correlation is at its maximum. This leads to larger coalition size and reduced number of transmissions as compared to $\sigma = M/15$ and $\sigma = M/5$. It infers that $\sigma = M/75$ maintains less number of packet transmissions for all values of data accuracy. For $\sigma = M/5$, the packet transmissions increase significantly beyond the accuracy of 94%. This shows that the proposed algorithm can provide a data accuracy of $q = 0.94$ (94%) even with relatively large values of variances.

6.1.3 Comparison of Percentage Gain

To analyze the percentage gain for LEACH, the data obtained from Fig. 5 as given in the Table 2 are considered. The simulation is performed with homogeneous sensor nodes having probability of $CH = 0.1$. The percenatge gain in case of 100% node death is calculated as

$$\%\, gain = \frac{54 - 41}{41} \times 100 = 31\% \tag{30}$$

Hence, the result confirms that the proposed algorithm is 31% more efficient as compared with LEACH in case of node death of 100%.

To analyze the percentage gain for D-SEP the data obtained from Fig. 5 and presented in Table 3 are considered. The simulation is performed with two level heterogeneous nodes having $a = 0.1$ (10% advance nodes), $\alpha = 0.5$ (more energy then normal nodes), $\lambda = 0.2$ and accuracy $q = 0.9$ (90%). The percentage gain in case of 100% node death is calculated as

Table 2 Gain compare to LEACH

%Node death	Number of rounds in LEACH	Number of rounds in proposed method	Gain
100	41	54	31%

Table 3 Gain compare to D-SEP

%Node death	Number of rounds in D-SEP	Number of rounds in proposed method	Gain
100	580	640	10%

$$\%\ gain = \frac{640 - 580}{580} \times 100 = 10\% \tag{31}$$

Hence, the above result confirms that the proposed algorithm is 10% more efficient as compared with D-SEP in case of node death of 100% at $q = 0.9$. Thus, the simulation results prove that the proposed algorithm prolongs the network life.

7 Conclusions

An energy efficient algorithm based on game theoretic approach and ACO technique is proposed in this paper. The coalitions and their representatives are chosen on the basis of their energy, utility and the permitted accuracy. The coalition size is optimized on the basis of the pheromone deposited on individual nodes. The proposed algorithm works well to obtain the optimized set of coalitions by exploiting the spatial redundancies. The considered coalition representative communicates with its nearest cluster head on behalf of the coalition. The simulation confirms that due to reduced number of transmissions, the proposed algorithm prolongs the network lifetime while simultaneously satisfying the data accuracy constraints. The proposed algorithm results in a trade-off between the network lifetime and accuracy (QSS) parameter. The proposed algorithm also ensures that the coalitions formed have distributed energies resulting in uniform consumption of energy throughout the network. From the simulation results, it is proved that the energy consumption is uniform when compared with the LEACH protocol and the D-SEP protocol. It is worthwhile to note that the proposed method can find tremendous utility and applications in real and practical situation such as:

- Monitoring the temperature and others, inside the deep forest, especially where human intervention is difficult to achieve.
- In battlefield to gather data from the nodes deployed in the field.

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