



# A multiple pheromone ant colony optimization scheme for energy-efficient wireless sensor networks

Vishal Kumar Arora<sup>1</sup> · Vishal Sharma<sup>2</sup> · Monika Sachdeva<sup>3</sup>

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## Abstract

Ant colony optimization (ACO) is a well-applied technique to solve the real-time problem of discovering the energy-efficient routes to transmit the sensing information to the base station (BS). Traditionally, ACO incorporated wireless sensor networks used only one pheromone, i.e., minimum distance between the sensor nodes to discover the optimum route to the BS. The authors illustrated a multiple pheromone-based ACO technique known as multiple pheromone ant colony optimization (MPACO), for instance, distance between sensing nodes, their residual energy and number of neighbor nodes to ascertain an efficient route. MPACO enables the sensing nodes to transmit the sensing data to BS over optimal routes with economical energy consumption to achieve a prolonged network life span. The comprehensive evaluation reveals that MPACO proffers 20% more network lifetime than the current existing ACO technique, i.e., improved ACO. Moreover, MPACO shows a significant improvement of 300% in network life span than another existing fuzzy-based strategy, i.e., multi-objective fuzzy clustering algorithm.

**Keywords** Energy-aware routing · Wireless sensor networks · Swarm intelligence · Ant colony optimization

## 1 Introduction

Wireless sensor networks (WSNs) are being designed for a number of monitoring applications, for instance, to detect the water level in the dams, observing air quality to detect dangerous gases, to control pollutant in water and many other consumers/industrial areas (Qiu et al. 2017; Duan et al. 2017). Generally, WSN comprises of spatially dedicated sensor nodes for monitoring, aggregating and forwarding the collected data to a central location, i.e., BS. The sensor nodes are randomly deployed, left unattended and are expected to perform efficiently. Each sensor node consumes a certain amount of energy to sense, process and to transmit the processed data to the BS. These sensor nodes are battery operated

and difficult to replace or recharge. Moreover, each sensor node has a range of detection and estimates its distance from the source node by accessing the intensity of the received signal. This received signal is attenuated with an increase in distance between the destination node and the source node.

In couple of decades, a number of issues including energy consumption, clock synchronization techniques, secure data aggregation and efficient routing techniques have been analyzed and investigated by the researchers for improving the performance of such networks (Dehkordi and Schmaltz 2012; Labraoui et al. 2013). However, an energy-efficient routing technique is a challenging issue till date. Generally, energy-efficient routing reduces the power consumption by distributing load uniformly among the sensor nodes and is classified in two categories: flat and hierarchical routing protocols (Al-Karaki and Kamal 2004). In flat-based routing, each sensor node has its unique global address and at the same level. Alternatively, flat-based routing is further categorized as proactive, reactive and hybrid routing strategies (Pantazis et al. 2013). In proactive, each sensor node maintains its own routing table to evaluate a route to the destination. So, each sensor node transmits its own data to the destination node through the pre-defined route, for instance, the Wireless Routing Protocol (WRP), and Topology Dissemi-

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✉ Vishal Kumar Arora  
vishal.fzr@gmail.com

<sup>1</sup> IKG PTU, Kapurthala, Punjab, India

<sup>2</sup> Department of Electronics and Engineering, Shaheed Bhagat Singh State Technical Campus, Ferozepur, Punjab, India

<sup>3</sup> Computer Science and Engineering Department, IKG PTU, Kapurthala, Punjab, India

**Table 1** Comparison between the proactive and reactive protocols

| Parameters  | Proactive protocols | Reactive protocols |
|---|---------------------|--------------------|
| On demand   | No                  | Yes                |
| Route updation                                    | Continuously        | On demand          |
| Route setup delay                                 | No                  | Yes                |
| Need to send update message when topology changes | Yes                 | No                 |
| Handle bursty traffic                             | No                  | Yes                |
| Handle heavy load                                 | Yes                 | No                 |
| Messaging overhead                                | Yes                 | No                 |
| Maintain routing information of all the nodes     | Yes                 | No                 |

nation based on Reverse Path Flooding (TBRPF) technique. In reactive strategy, a sensor node reacts only if the sensed value changes beyond a certain pre-defined threshold, e.g., Threshold-sensitive energy-efficient sensor network (TEEN) and are used mainly for time-critical applications. Table 1 shows the comparison between the proactive and reactive protocols. Further, hybrid protocols combine the advantages of both proactive and reactive protocols, for instance, Adaptive Periodic TEEN (APTEEN). This strategy, initially, defines all the possible routes among the sensing nodes to the BS and updates them periodically. Alternatively, in hierarchical routing protocols such as LEACH, C-LEACH and TBC the sensing nodes compute the different routes in their clusters for managing network energy consumption efficiently to increase the network life span. However, for a specific network topology, there is no deterministic polynomial algorithm that can partition the network into uniform clusters (Avril et al. 2014). Moreover, routing algorithm must produce a set of low-cost paths among a number of possibilities.

To combat with this situation, clustering and routing techniques are developed by implementing swarm intelligence-based algorithms (Saleem et al. 2011). Swarm intelligence can be seen as analogies between computing methods and biological behavior of swarms in which the collective intelligence is emerged. The considered swarms are colonies of social insects, bird flocking and fish schooling. Each swarm is an autonomous individual, which cooperate with each other to achieve some tasks necessary for the survival of the colony. In the context of WSNs, these simple and robust behaviors have been successfully applied by identifying and modeling some analogies between the two systems. ACO, one of the swarm intelligence-based optimization technique uses the stimulus to discover the shortest path, becomes an attractive alternative recently in WSN networks (Dorigo and Birattari 2011). During traversing, ants took the decision based on trail information and attractiveness. Every ant secretes certain amount of pheromone on the traversed path, and this substance is used by the future ants to discover the optimal path. The authors have extended the work of Lee et al. (2011) to discover an optimized path from the sensor nodes to the BS.

## 1.1 Major contributions

Traditionally, ACO technique used only one pheromone to discover the optimum route efficiently (Camilo et al. 2006; Liu 2016, 2015; Malik et al. 2017). The authors have extended the work further by demonstrating a multiple pheromone, for instance, distance between sensing nodes, their residual energy and number of neighbor nodes-based ACO technique, termed as MPACO to ascertain an optimized/energy-efficient route among the available routes to arrive at BS with economical use of node energy. The authors illustrate a contrast of the demonstrated MPACO strategy with the traditional strategies like LEACH, TBC, PEGASIS and the recently reported schemes, for instance, IACO and MOFCA to demonstrate the robustness of MPACO to realize a prolonged network lifetime. The first pheromone, i.e., distance between sensing nodes, helps to discover the available neighbors of every sensor node in the network and stores their information in the one-dimension matrix. The second pheromone stores the information about the residual energy of the neighbor nodes, and third pheromone determines an optimum number of required sensor nodes to participate actively in transmission to BS in a tree-like structure using probability density distribution function. Unlike earlier ACO-based techniques, MPACO is independent of using the heuristic values, i.e.,  $\alpha$  and  $\beta$  (Dorigo and Birattari 2011; Liu 2016) and makes the process quite simple.

Rest of the paper is organized as follows: Sect. 2 presents an overview of earlier distributed and meta-heuristic routing approaches to define the research gaps. The detail description of the developed network model is well described in Sect. 3. Section 4 defines the performance metrics used for evaluation of the MPACO followed by its outcomes and conclusion in Sects. 5 and 6, respectively.

## 2 Related works

Several cluster-based energy-efficient routing algorithms have been proposed to reduce the energy consumption of

WSN nodes in Heinzelman et al. (2000, 2002), Wu et al. (2017), Sajwan et al. (2018), Li et al. (2018a) and Chang and Ju (2014). LEACH, one of the traditional schemes, organized the whole network into clusters with the varied number of sensor nodes (Heinzelman et al. 2000). Each cluster has one elected node called cluster head (CH), selected either by sensor nodes themselves or by a centralized device. CH aggregates the sensed data of its cluster and forwards to the BS via single hop. However, LEACH protocol does not offer any guarantee about the location and number of CHs. Centralized LEACH (C-LEACH) uses a centralized algorithm to form better clusters by dispersing CHs throughout the network (Heinzelman et al. 2002). During setup phase of C-LEACH, BS collects the information about all the position and the remaining energy of sensor nodes in the network. Based on collected information, BS determines the number of CHs, discriminates their boundaries, organizes the network into clusters and thus broadcasts this information to the network. CHs wait for other nodes to join their respective CHs, while member nodes discover their transmitting schedule as per their allotted TDMA slot. A non-autonomous CH selection is the main disadvantage of C-LEACH. Further, LEACH with deterministic CH (LEACH-D) selection prolongs the network lifetime by considering the residual energy of sensor nodes independent of their location (Handy et al. 2002). However, LEACH, C-LEACH and LEACH-D allow nodes to communicate directly with the BS irrespective of the distance between the sensor node and their respective CH. Moreover, CH also transmits aggregated data directly to the BS over a single-hop approach that leads to increase the energy requirements. Power-Efficient Gathering in Sensor Information System (PEGASIS) protocol is a chain-based protocol in which each sensor node communicates with its neighbor node only (Lindsey and Raghavendra 2002). Unlike LEACH, PEGASIS avoids cluster formation and makes only a single node in the chain to transmit data to the BS. PEGASIS increases the lifetime of the network more than 200% as compared to LEACH. To avoid this direct communication between a CH and the nodes, a Tree-based Efficient Protocol for Sensor Information (TREEPSI) is proposed in which a root node is selected before the transmission of data (Satapathy and Sarma 2006). In TREEPSI, either the BS constructs a route to the selected root node or each sensor node implements their own algorithm to define their path to the root node. This reduces the transmission distance among the sensor nodes and hence decreases the energy consumption by 30% in contrast to PEGASIS. Earlier routing protocols fail to consider traffic and energy heterogeneity crucial for application heterogeneity and event-driven scenarios. Traffic and energy-aware routing (TEAR) considers sensor node traffic requirements along with its energy levels to improve CH selection criteria and performs better than LEACH, SEP and DEEC in terms of network lifetime for heterogeneous

network (Sharma and Bhondekar 2018). Node deployment is another challenging issue in WSNs. The main objective of node placement is to achieve desired coverage, i.e., every Point of Interest (PoI) is monitored by sufficient number of sensor nodes and has sufficient routing paths. Node Deployment Scheme based on Path Creation (NDSPC) proposed a novel node deployment scheme for mountain roads (Liu 2017). NDSPC avoids energy hole problem and reduces transmission delay by achieving data diversion through construction of extra paths.

Recently, tree-based cluster-based networks, also known as multi-hop networks, become more popular due to their adaptability, energy efficiency and fault-tolerant properties like tree-based clustering (TBC) strategy. It divides every cluster into different levels with CH at the center of the cluster (Liu 2012; Kim et al. 2010; Wang et al. 2016). Each sensor node looks for an intermediate node in the immediate next level that reduces its distance to the root node to prolong the network lifetime. However, it dissipates considerable amount of energy for the isolated/distant CHs. Furthermore, General Self-Organized Tree-Based Energy-Balance (GSTEB) extends TBC in which the BS has all information about the residual energy and location of all sensor nodes (Han et al. 2014). BS alleviates the highest energy sensor node as a root node. Each sensor node selects its parent node based on the distance and energy level and results in the construction of a tree-like structure to the root node. GSTEB claims 100% improvement over HEED and 100–300% than PEGASIS. Further, to minimize the delay and energy consumption, an optimal value for the cluster radius has been computed through theoretical analysis (Li et al. 2018b). To prolong the network lifetime, the number of state transitions was reduced by scheduling the sensor nodes in a consecutive time slots.

Optimization techniques sort out the efficient routing issues and are well examined by several bio-inspired clustering approaches, for instance, ACO meta-heuristic multi-path routing in Kuila and Jana (2014), Sun et al. (2017), Yang et al. (2010) and Dong et al. (2014), particle swarm optimization in Kennedy (2011), and artificial bee colony (ABC) in Mann and Singh (2017) and Karaboga et al. (2012). ACO-based clustering and routing algorithms perform the CH selection periodically, models a sensor node as an ant and routes as an ant foraging. Every sensor node dynamically computes the probabilities to select an optimal path to prolong the life of the network. In another ACO-based optimized routing strategy, the proposed fitness function enables an optimal selection of CHs and clusters to uniformly dispense energy amid sensor nodes (Ye and Mohamadian 2014). To solve the problem of Efficient-Energy Coverage (EEC) during WSN implementation, many algorithms have been proposed in the past. One such algorithm uses one local pheromone and two global pheromones to efficiently solve the problem of EEC. Local pheromone reduces the number of sensor nodes, and

**Table 2** Comparison of proposed scheme with existing energy-saving algorithms

| Scheme  | Energy model | Operation of network topology | Routing structure    | Principle of CH selection  | Requirement of powerful base station |
|---------|--------------|-------------------------------|----------------------|----------------------------|--------------------------------------|
| LEACH   | First order  | Distributed                   | Cluster              | Random                     | No                                   |
| C-LEACH | First order  | Distributed                   | Cluster              | Random                     | Yes                                  |
| PEGASIS | First order  | Distributed                   | Cluster              | Random and residual energy | No                                   |
| TBC     | First order  | Distributed                   | Cluster-tree         | Random                     | No                                   |
| TEEN    | First order  | Distributed                   | Cluster-tree         | Random                     | No                                   |
| GSTEB   | First order  | Centralized                   | Self-organizing tree | NA                         | Yes                                  |
| ABC     | First order  | Centralized                   | Cluster              | Artificial bee colony      | Yes                                  |
| MOFCA   | First order  | Distributed                   | Cluster              | Fuzzy logic                | No                                   |
| IACO    | First order  | Distributed                   | Cluster              | Ant colony optimization    | No                                   |
| MPACO   | First order  | Distributed                   | Self-organizing tree | Ant colony optimization    | No                                   |

global pheromones help to find the optimum number of sensor nodes per Point of Interest (PoI) (Lee et al. 2011). Further, another improved ACO (IACO) algorithm based on ACO extended the traditional ACO to discover an optimal path (Sun et al. 2017). IACO considers transmission distance, transmission direction and residual energy to enhance the network life span. Moreover, a multi-objective fuzzy clustering algorithm (MOFCA) uses fuzzy logic approach that uses a probabilistic model for selecting tentative CHs and uses fuzzy logic to handle uncertainties in the WSN (Sert et al. 2015). MOFCA outperforms the traditional schemes in terms of first node dies, half of the nodes alive and total remaining energy (TRE). A comparison of pre-reported pertinent energy-saving hierarchical- and tree-based strategies has been summarized in Table 2.

### 3 Multiple pheromone ant colony optimization (MPACO) model

For the proposed network, the following assumptions have been adopted:

- There are ‘ $N$ ’ numbers of sensor nodes that are randomly deployed, and there is only one base station (BS).
- BS is at a certain distance from the network area.
- Sensor nodes are energy constrained, whereas BS has unlimited energy.
- Sensor nodes and BS are immobile.
- All sensor nodes can communicate either directly or indirectly (through intermediate sensor nodes) with the BS.
- All sensor nodes have an irreplaceable battery.
- Every sensor node has a unique id.
- Assume ‘ $C$ ’ as a number of ants and  $\varepsilon$  is the minimum probability for selection of a sensor node.

- Radio channel used for transmitting and receiving a message is symmetric.

#### Algorithm 1 Selection of parent node.

```

1. Set
    $n \leftarrow$  number of nodes
    $e \leftarrow$  energy of node
    $min\_prob \leftarrow \varepsilon$ 
    $i, h \leftarrow 1$ 
2. while  $i < n$  do
3.   Compute the number of neighbor nodes, i.e.,  $A_{neigh}$ 
4.   while  $h < A_{neigh}$  do
5.     Compute residual energy of every neighbor node, i.e., RES
6.     Compute the minimum number of sensors required from
        $A_{neigh}$  and their probability, i.e., prob
7.     if  $prob > min\_prob$  then
8.       Set
          $parent \leftarrow h$ 
          $min\_prob \leftarrow prob$ 
9.     end if
10.    increment  $h$  and goto step 4.
11.   end while
12.  increment  $i$  and goto step 2.
13. end while

```

After assuming the above-mentioned basic model assumptions, the proposed scheme discovers the parent nodes as per Algorithm 1 and described as follows: Step I: Initially, a sensor node ‘ $a$ ’ broadcasts a data-packet consisting of information about its coordinates and residual energy within a circle of radius  $r_2$  during its own time slot in its preamble. Its neighbor node ‘ $b$ ’ will receive this data with following probabilities depending upon the distance between the sensor node ‘ $a$ ’ and ‘ $b$ ’:

$$P_{ab} = \begin{cases} 0, & \text{if } d_{ab} > r_2 \\ e^{-k(d_{ab}-r_1)^m}, & \text{if } r_1 < d_{ab} < r_2 \\ 1, & \text{if } d_{ab} < r_1 \end{cases} \quad (1)$$

where  $k, m$  are decay parameters, and  $d_{ab}$  is the distance between sensor nodes ‘ $a$ ’ and ‘ $b$ ’. The  $r_1$  and  $r_2$  are the minimum and maximum distance detected by a sensor node, respectively. The values of  $r_1, r_2, d$ , and  $k$  depend upon the features of sensor and environment factors.

All events that lie within the range  $r_1$  will be detected by a current sensor node ‘ $a$ ’ and beyond  $r_1$ , the probability of detection decreases exponentially. An event that occurs beyond the distance  $r_2$  will remain undetected. The neighboring nodes that are within the range of a current sensor node ‘ $a$ ’ as per equation 1 forms a set of sensor nodes. This set of sensor nodes are referred as a covered set  $A_{neigh}$ . Generally, each node similar to current sensor node ‘ $a$ ’ will maintain its covered set and is defined as:

$$RES_{ab}(t) = A_{neigh} * residualEgy_b(t) \tag{2}$$

where  $residualEgy_b(t)$  = residual energy of the  $b$ th sensor node of covered set  $A$ .

Step III: Further, every ant discovers the minimum number of neighbor nodes required for sensor node ‘ $a$ ’ from its covered set  $A_{neigh}$  using third pheromone denoted as  $MinSN_{ab}$ . The objective of this step is to determine the minimum number of sensor nodes required for each sensor nodes from their covered set, to complete the process of transmission. This is due to the fact that lesser the nodes involved in the transmission of the traffic data, the longer is the network lifetime. To achieve this goal, pheromone  $MinSN_{ab}$  is initiated as (Lee et al. 2011):

$$MinSN_{ab} = \begin{cases} \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-1}{2} \left( \frac{b - \mu_a}{\sigma} \right)^2}, & \text{if } b \leq n_a \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where  $n_i$  is the number of sensor nodes in the covered set of ‘ $A$ ’ and  $b = 1 \dots n_i$ .  $\sigma$  is a constant,  $\mu_i$  is initialized with zero, and its value increases with the number of times that the first ant of the first colony fails to organize the sensor set. This is carried out by evaluating the probability of selecting  $i$ th node as a neighbor node by ant ‘ $k$ ’ at any time ‘ $t$ ’ as:

$$SelProb_{n_i^k} = \begin{cases} \frac{MinSN_{in_i^k}(t)}{\sum_{m=1}^N MinSN_{im}(t)}, & \text{if } n_i^k \leq n_i \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where  $n_i^k$  is the number of nodes that have been identified out of the minimum number of nodes of covered set ‘ $A$ ’ by an ant ‘ $k$ ’. This probability is computed at the start of every round for every node. Nodes having probability more than the pre-defined minimum threshold  $\varepsilon$ , becomes the neighbor set for ‘ $a$ ’ sensor node.

Step IV: Further, MPACO will identify the required number of nodes defined in step III for current sensor node ‘ $a$ ’ by computing the probability of every sensor node of the neighbor set by an ant  $k$  (Lee et al. 2011). This is carried out by considering the residual energy (from step II) and the number of times a neighboring node is selected as the member of the neighboring set. Mathematically, it is computed as:

$$ParSel(sen_{a,j}^k) = \begin{cases} \frac{RES_{aj}(t) + V_j^k(t)}{\sum_{m \in n_j^k} (RES_{jm}(t) + V_m^k(t))}, & \text{if } a \in n_j^k \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where  $m$  is the identified neighboring nodes defined in step IV,  $V_j^k$  is another pheromone that computes the information about the number of times the  $j$ th neighboring node is selected to be acted as a parent node by an ant ‘ $k$ ’. The node having maximum probability  $ParSel(sen_{a,j}^k)$  is selected as a parent node for the current sensor node ‘ $a$ ’. After the selection of node  $j$  as an eligible parent node by ant  $k$ , the value of pheromone  $V_j^k$  for  $j$  sensor node is incremented as:

$$V_j^k(t + 1) = V_j^k(t) + \Delta V_{ja}^k \tag{6}$$

where

$$\Delta V_{ja}^k = \begin{cases} C_{aj}, & \text{if ant } k \text{ selects sensor } j \text{ for node } a \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where  $C_{aj}$  is a constant.

Like ant ‘ $k$ ,’ all other ants select their eligible parent node in this way, as shown in Figs. 1 and 2. The eligible parent node having the highest value of pheromone  $V_j^k$  is selected as a final parent node.

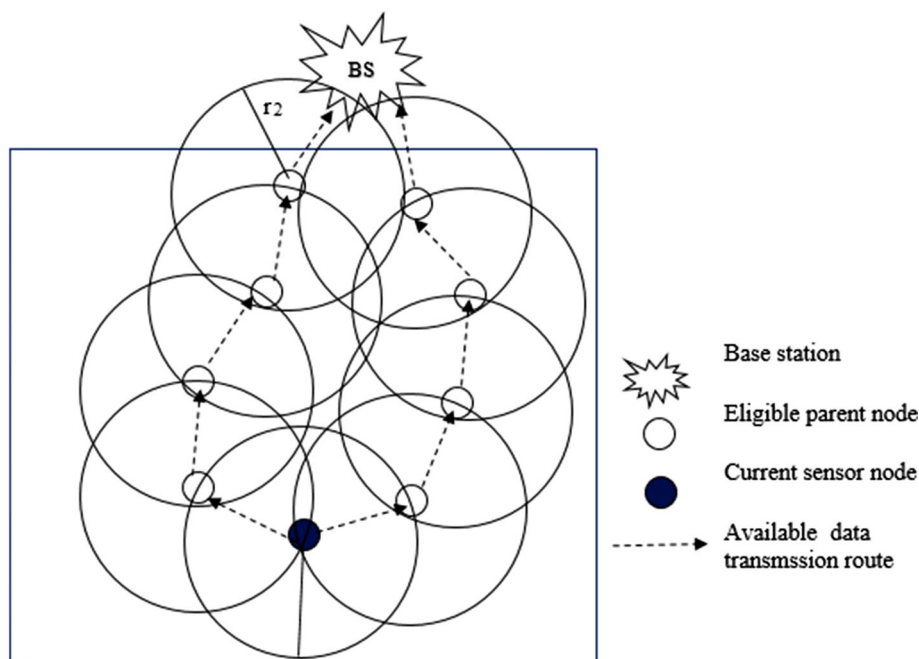
The flowchart of MPACO scheme is shown in Fig. 2.

All sensor nodes are assumed to have the same features, so the authors evaluate the complexity of the implementation of the proposed algorithm on one sensor node. During parent node selection process, the algorithm complexity of a sensor node is  $O(neigh)$ , where  $neigh$  is number of neighbor nodes for a sensor node and  $O(1)$  for sensor node that directly communicate with BS. During the tree formation process, the algorithm complexity of a sensor node is computed as  $O(m)$ , if the current sensor is a parent node, where  $m$  is the number of child nodes associated with a sensor node. Otherwise, it will be  $O(1)$  for a sensor node that does not have any associated child node. Once the tree formation is completed, followed by TDMA schedule, the data transmission phase begins.

### 4 Performance metrics

To evaluate the performance of the proposed MPACO, the following performance metrics have been evaluated:

**Fig. 1** Example of parent node selection



1. **First node dead (FND)** This metric depicts the number of rounds after which the first node dies. Usually, the death of the first node does not affect the performance of WSN; however, it becomes imperative in periodically deployed WSN scenarios.
2. **Half node dead (HND)** This parameter is used to denote the number of rounds in which half of the node dies and is considered in application areas of such networks where the coverage aspect is the primary area of interest.
3. **Network lifetime (LND)** Network lifetime is measured by the number of rounds after which all nodes die. However, most of the WSNs are useless in most cases where half of the node dies, but to measure the total network lifetime, it is an important parameter (Handy et al. 2002).
4. **Remaining energy** Each sensor has to expend some amount of energy to transmit its data that vary as per the routing strategy used. This is computed by subtracting energy spent by a sensor node from energy exhibit by the node itself after every round.

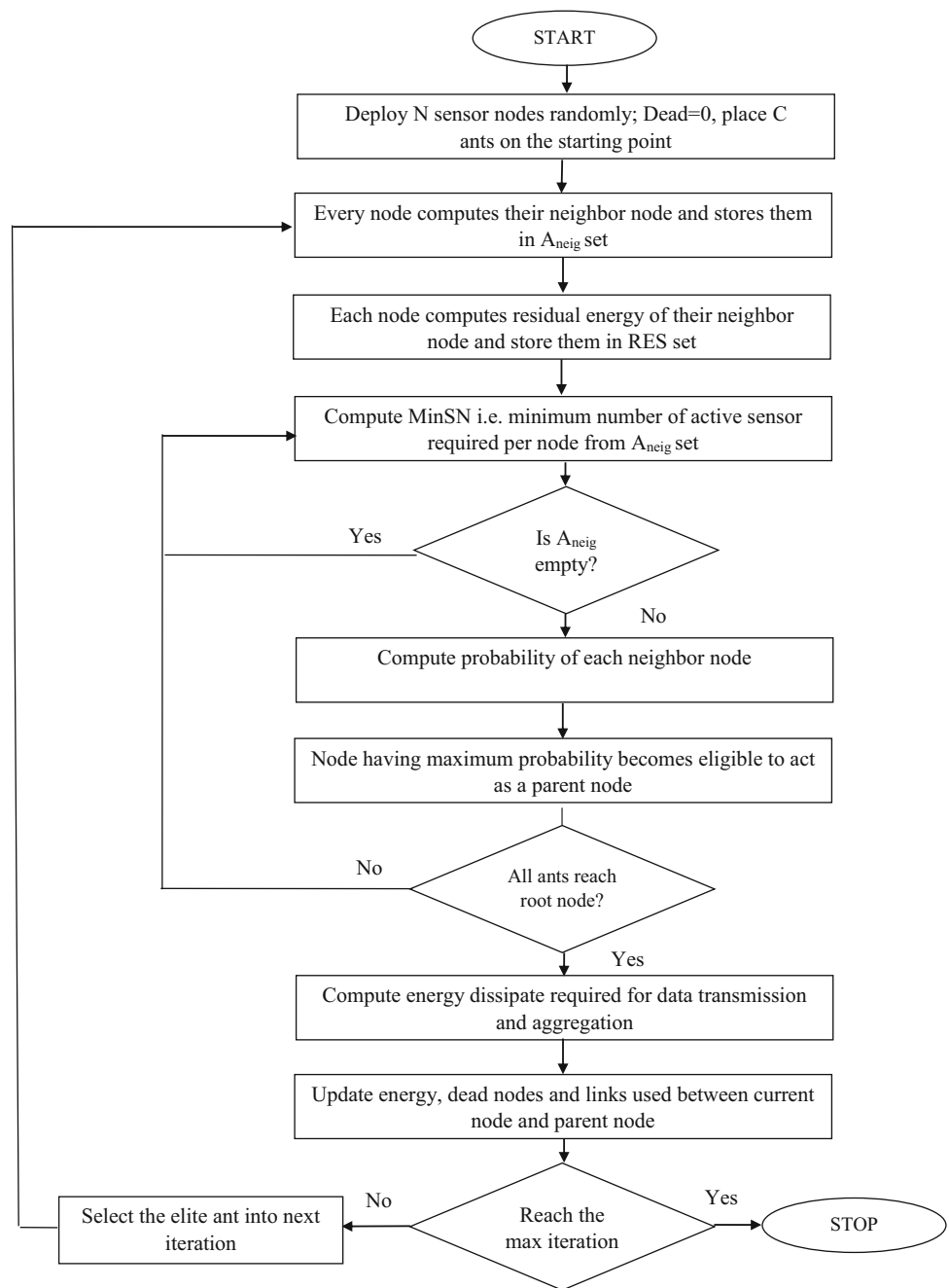
## 5 Result and discussion

The performance of the reported MPACO is evaluated by conducting a set of computer-based test bed with an iteration of 100 seeds. The demonstration is carried out with the varying number of stationary and randomly deployed sensor nodes equipped with an initial energy of 0.25 J. The sensing nodes transmit the sensing information in the form of data packets of 4000 bits in the network area of 100 m  $\times$  100 m. BS is located outside the network area with location coordi-

nates of BS is (50 m, 120 m). The other working parameters of the demonstrated test bed are depicted in Table 3.

Figure 3 shows the energy efficacy of the MPACO in terms of FND, HND, LND, and a contrast is drawn with the earlier reported schemes. The observation illustrates that MPACO outperforms the existing schemes, for instance, LEACH, PEGASIS, TBC, MOFCA and IACO by implementing the considered multiple pheromones to discover an optimized route between the sensor node and BS. MPACO enhances the network lifetime of the established network by more than three times of MOFCA, while it proffers an improvement of 20% in contrast with IACO. This is due to the fact that MOFCA considers the residual energy and node density for the selection of CHs. Like IACO, each sensor node in MPACO transmits its sensed data in a multi-hop manner (through best intermediate nodes) without any cluster formations. Alternatively, IACO selects its parent node by considering the distance only, i.e., the nearest node acts as the parent node to lead the shortest route-based transmission irrespective of the other pheromones like residual energy and the neighboring nodes. Moreover, IACO optimized the route using ACO technique to transmit the sensing data to the BS and performs better than TBC along with other traditional schemes. Furthermore, with each sensor node of 0.5 J, MPACO performs 25% better than IACO and 300% better than MOFCA as shown in Table 4. The outcomes of both the demonstrated scenarios, i.e., for initial energy of 0.25 J and 0.5 J, reveal here that MPACO ascertains the best available parent node among the deserving neighboring nodes to provide an energy-efficient route to reach BS by offering better load distribution among the current nodes. MPACO

**Fig. 2** Flowchart of proposed scheme



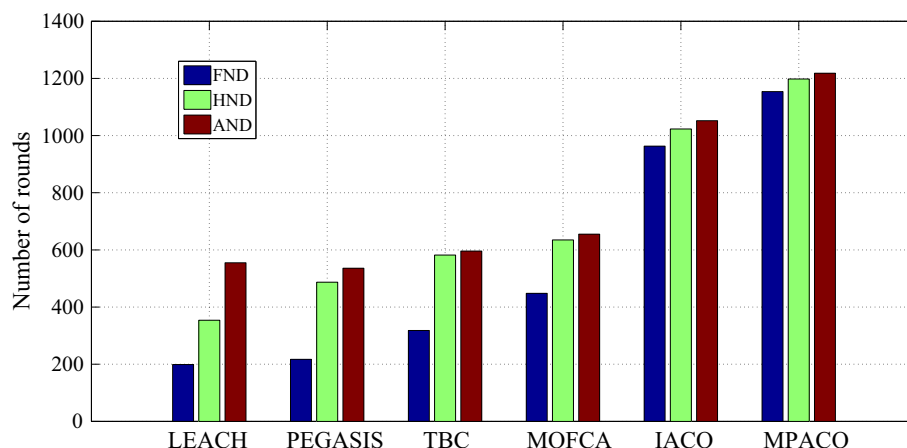
is further evaluated in terms of residual energy and number of alive nodes of a network of  $100 \times 100\text{m}^2$  with 100 randomly deployed sensor nodes as shown in Figs. 4 and 5. It is observed that the first node of MPACO died after 1200 rounds, i.e., after 200 rounds of IACO that confirms the enhancement of network life by 20% due to the capability of former strategy to select a parent node exhibiting minimum power consumption.

Furthermore, the ability to adjust large number of nodes that might not be predicted during the initial deployment stage of the network, termed as scalability is computed. It

**Table 3** MPACO test-bed parameters

| Parameter                                 | Value                        |
|---|------------------------------|
| Electronics energy                        | 50 nJ/bit                    |
| Initial energy                            | 0.25 J                       |
| Energy for data aggregation ( $E_{DA}$ )  | 5 nJ/bit/signal              |
| Communication energy ( $\epsilon_{fs}$ )  | 10 pJ/bit/m <sup>2</sup>     |
| Communication energy ( $\epsilon_{amp}$ ) | 0.0013 pJ/bit/m <sup>4</sup> |
| Sensing area ( $M \times M$ )             | 100 m $\times$ 100 m         |
| Number of sensor nodes (N)                | 100                          |

**Fig. 3** Network life span versus diverse energy-saving schemes



**Table 4** Stability period of various energy-saving schemes

| Energy | Protocol | Number of nodes after which first node | Number of nodes which last node |
|--------|----------|--|---------------------------------|
| 0.25 J | LEACH    | 118                                    | 243                             |
|        | PEGASIS  | 246                                    | 568                             |
|        | TREEPSI  | 267                                    | 611                             |
|        | TBC      | 328                                    | 329                             |
|        | MOFCA    | 389                                    | 677                             |
|        | IACO     | 954                                    | 1079                            |
|        | MPACO    | 1171                                   | 1219                            |
| 0.5 J  | LEACH    | 208                                    | 435                             |
|        | PEGASIS  | 485                                    | 1067                            |
|        | TREEPSI  | 532                                    | 1123                            |
|        | TBC      | 589                                    | 1165                            |
|        | MOFCA    | 730                                    | 1330                            |
|        | IACO     | 1810                                   | 1952                            |
|        | MPACO    | 2375                                   | 2414                            |

is a major design issue of such networks to identify the network ability to accommodate additional sensing nodes up to a certain acceptable threshold without reorganizing the whole network. So, it is imperative that the routing protocols designed for a WSN network must be capable enough to offer the required network scalability to perform suitably. Consequently, the proposed work is further extended to evaluate the scalability of MPACO by varying the number of sensor nodes from 100 to 300 nodes by keeping all other designing metrics similar to the demonstrated test bed. The scalability is computed by measuring the first node dead after the number of rounds taken by each established scheme. The outcomes as shown in Fig. 6, disclose that MPACO endows with more scalability among the pre-reported algorithms due to the selection of the best available parent node by considering the multiple pheromones discussed in Sect. 3 that utilizes

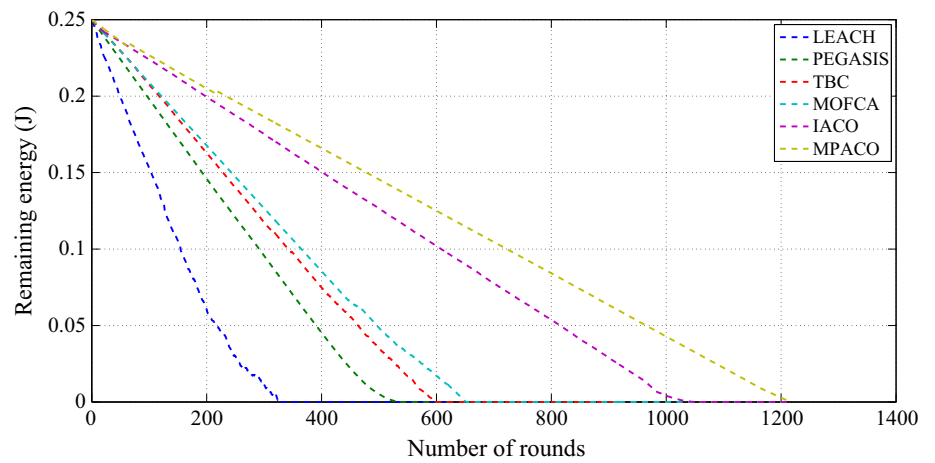
less node-energy consumption during transmission. Due to high energy consumption for transmitting data to BS via longer routes, IACO comes out as less-scalable approach than MPACO. The tree-based TBC clustering has also claimed low stability period because both the sensor nodes and CHs transmit their sensed data in a single-hop manner over long communication links. Similarly, the chain-based PEGASIS scheme is observed to be less scalable due to the isolated location of the elected leader from the BS which consumes a lot of energy during its communication. Further, it is also observed that while increasing the number of nodes from 100 to 300 (in the step-size of 50 nodes) in the terrain of size  $100 \times 100 \text{ m}^2$ , the stability period among all of the reported protocols increased by 5–10%. It can be accredited to the fact that with the increase in the number of nodes (keeping the network area constant), the inter-node distance decreased. Subsequently, it is worth to comment here that the demonstrated work performs better with increase in node density to be utilized for realizing an energy-efficient and scalable network.

Further, the total remaining energy (TRE) of reported network is computed over a varying number of sensor nodes to reveal out the robustness of the proposed scheme and depicted in Table 5. MPACO outperforms by asserting an improved network lifetime and residual energy in contrast with other demonstrated schemes. MPACO performs 11% better than IACO, 100% better than MOFCA, and 250% better than LEACH at node-density variation ranging from 100 to 300 nodes in terms of HND measurement.

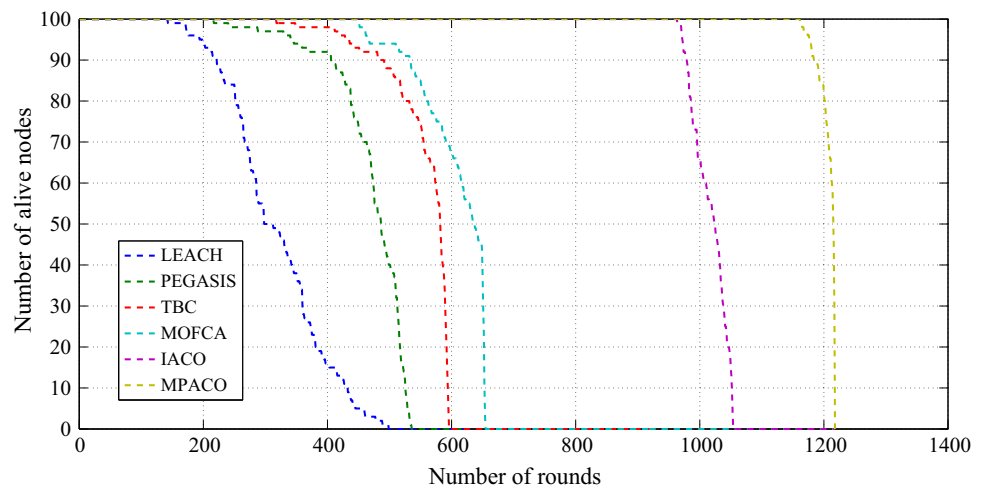
Further, this work evaluates the performance for the network scenario in which 1000 nodes are randomly deployed in the network size of  $1000 \times 1000 \text{ m}^2$ , equipped with 1 J initial energy, with the BS at a distance of (500 m, 500 m) amid packet size of 4000 bits. It has been observed that MPACO performs better for the tree-based routing topologies and Two-Tier Distributed Fuzzy Logic-Based Protocol (TTDFP) outperforms for the cluster-based energy-efficient



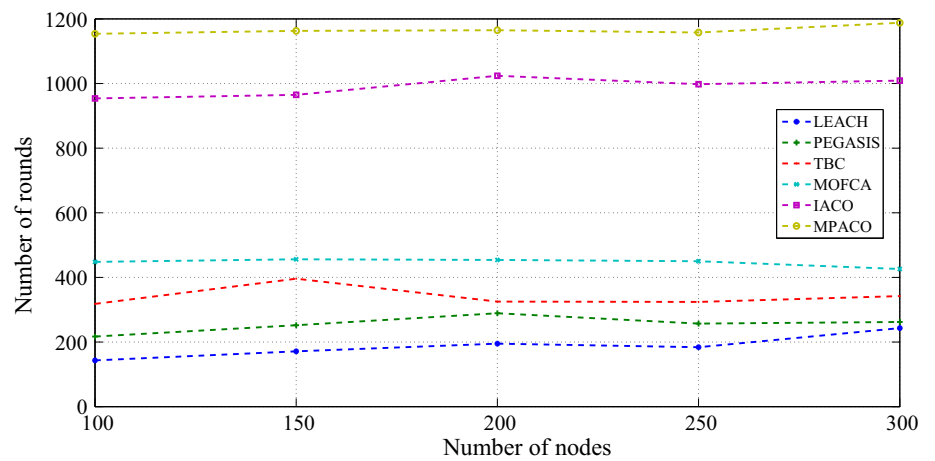
**Fig. 4** Energy depletion with respect to the number of rounds



**Fig. 5** Distribution of alive nodes with respect to the number of rounds



**Fig. 6** Stability period for 300 randomly deployed sensor nodes



multi-hop routing schemes by considering relative node connectivity, distance to the BS and the remaining node energy. Additionally, it uses average link residual energy and relative distance to select the most efficient routing path to prolong the network life.

## 6 Conclusion

This work demonstrates an energy-efficient multiple pheromone-based ant colony optimization (MPACO) scheme. MPACO considers the residual energy, node density and

**Table 5** Total remaining energy of various energy-saving schemes at various number of rounds

| Number of nodes | Number of rounds | LEACH | PEGASIS | TBC   | MOFCA | IACO  | MPACO |
|-----------------|------------------|-------|---------|-------|-------|-------|-------|
| 100 nodes       | 300              | 14.84 | 17.20   | 18.52 | 18.81 | 21.17 | 21.64 |
|                 | 400              | 12.20 | 14.65   | 16.31 | 16.75 | 19.96 | 20.63 |
|                 | 500              | 10.12 | 12.18   | 14.16 | 14.73 | 18.75 | 19.62 |
|                 | 600              | 9.18  | 11.32   | 12.16 | 12.81 | 17.55 | 18.60 |
| 150 nodes       | 300              | 23.81 | 26.46   | 28.05 | 28.37 | 31.85 | 32.53 |
|                 | 400              | 20.28 | 22.80   | 24.79 | 25.35 | 30.07 | 30.94 |
|                 | 500              | 17.17 | 19.21   | 21.60 | 22.35 | 28.30 | 29.39 |
|                 | 600              | 14.65 | 17.89   | 18.52 | 19.54 | 26.52 | 27.85 |
| 200 nodes       | 300              | 32.09 | 35.14   | 37.31 | 37.96 | 42.73 | 43.60 |
|                 | 400              | 27.28 | 30.28   | 33.00 | 33.96 | 40.42 | 41.52 |
|                 | 500              | 23.25 | 25.57   | 28.83 | 30.00 | 38.12 | 39.46 |
|                 | 600              | 19.88 | 22.89   | 24.84 | 26.26 | 35.81 | 37.40 |
| 250 nodes       | 300              | 40.44 | 44.32   | 46.87 | 47.52 | 53.23 | 54.52 |
|                 | 400              | 34.72 | 38.41   | 41.59 | 42.58 | 50.28 | 51.94 |
|                 | 500              | 29.74 | 32.61   | 36.49 | 37.69 | 47.35 | 49.37 |
|                 | 600              | 25.58 | 28.92   | 31.63 | 33.08 | 44.43 | 46.80 |
| 300 nodes       | 300              | 48.63 | 53.80   | 56.28 | 57.20 | 64.11 | 65.49 |
|                 | 400              | 41.88 | 46.82   | 49.93 | 51.28 | 60.64 | 62.39 |
|                 | 500              | 35.99 | 39.89   | 43.81 | 45.45 | 57.17 | 59.30 |
|                 | 600              | 31.13 | 35.28   | 37.96 | 39.93 | 53.71 | 56.22 |

distance among the sensor nodes to discover the most efficient route to the base station with less node-energy utilization that leads to high network life span. The outcomes reveal that for an initial node energy of 0.25 J, MPACO performs 20% better than IACO and ascertains a significant improvement of 300% in contrast with MOFCA in terms of network life span. Furthermore, MPACO is observed to have potential to accommodate additional sensing nodes, required in the later stage, without reorganizing the existing network in contrast with the pre-reported significant energy-saving hierarchical- and tree-based strategies.

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### Compliance with ethical standards

**Conflict of interest:** The authors declare that they have no conflict of interest.

**Ethical approval:** This article does not contain any studies with human participants or animals performed by any of the authors.

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