Load balanced clustering scheme using hybrid metaheuristic technique for mobile sink based wireless sensor networks

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Abstract

Fundamental design goal of a typical wireless sensor network is to optimize energy consumption. Recent studies have confirmed that node clustering mechanism efficiently utilizes energy resource of the network by organizing nodes into a set of clusters and helps in extending the network lifetime. Most of the existing node clustering schemes suffers from non-uniform distribution of cluster heads, unbalanced load problem among clusters and left-out node issues. In order to solve these issues, we have focused on to design a load-balanced clustering scheme which also resolves the left-out nodes problem. This study proposes a hybrid meta-heuristic technique where best features of Artificial Bee Colony and Differential Evolution are combined to evaluate the best set of load-balanced cluster heads. For energy efficient and load-balanced clustering, a novel objective function is derived based on average energy, intra-cluster distance and delay parameters. Following this, Artificial Bee Colony based meta-heuristic algorithm is proposed for the dynamic re-localization of the mobile sink within a cluster-based network infrastructure. Performance comparison of the proposed scheme with the existing three well known schemes is evaluated under different network scenarios. Simulation results validate that the proposed scheme performs better in terms of average energy consumption, total energy consumption, residual energy, and network lifetime.

1 Introduction

A typical Mobile Sink based Wireless Sensor Network (*MSWSN*) has a set of sensor nodes that are deployed to the area of interest for sensing and monitoring of the physical phenomenon of the environment (Akyildiz et al. 2002; Akkaya et al. 2007; Alsalih et al. 2007; Abbasi and Younis 2007; Anastasi et al. 2009). In *MSWSN*, one or more mobile sinks are deployed that has locomotive capability to move within the network. Each sensor node is generally equipped with a microcontroller unit, radio unit, storage unit, power unit and one or more sensors. Due to low-cost and small size, a sensor node generally has limited energy reserve which is supplied by 2AA battery (Kaur et al. 2018). In order to provide longevity of the deployed sensor network, smart uses of the energy resource of any sensor nodes are

paramount requirement (Akyildiz et al. 2002; Akkaya et al. 2007; Anastasi et al. 2009).

Recent studied (Anastasi et al. 2009; Alsalih et al. 2007; Abbasi and Younis 2007; Heinzelman et al. 2002; RejinaParvin and Vasanthanayaki 2015; Srinivasa Rao and Banka 2015; Mann and Singh 2016; Rao et al. 2016; Gupta et al. 2018a; Sarkar and Senthil Murugan 2017) have confirmed that node clustering mechanism efficiently utilizes energy of the network by organizing nodes into a set of clusters and helps in extending the network lifetime. Most of the existing node clustering schemes (Alsalih et al. 2007; Abbasi and Younis 2007; Heinzelman et al. 2002; RejinaParvin and Vasanthanayaki 2015; Srinivasa Rao and Banka 2015; Mann and Singh 2016; Rao et al. 2016; Sarkar and Senthil Murugan 2017) suffers from non-uniform distribution of cluster heads, unbalanced loads problem among clusters and left-out node issues. Due to non-uniform distribution of the cluster heads, some cluster heads become overloaded and die early which causes poor network lifetime. In addition, existing clustering scheme also suffers from left-out nodes problem where some remote nodes would not able to join any clusters, due to

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its communication unreachability with the nearby cluster heads and not able to transmit its sensed data to any cluster heads. In order to solve these issues, this work focuses on to design a load-balanced clustering scheme which also considers the left-out nodes problem.

There are various techniques are proposed in the literature for enhancing the longevity of the deployed sensor network such as duty cycling, clustering, use of mobile sink and so on. In this research work, we focus on a hybrid technique which incorporates best features of clustering and mobile sink based techniques in order to enhance the network lifetime. In the clustering technique, sensor nodes are organized into a set of clusters where each cluster has a cluster coordinator node, called cluster head (*CH*) and remaining nodes of the cluster, called cluster members (*CMs*) (Abbasi and Younis 2007; Heinzelman et al. 2002). Clustering technique offers various advantages such as reduction of inter-cluster traffic, load-balancing within the network, increases the scalability and network lifetime. In addition, mobile sink (*MS*) based various solutions are also available in Shi and Hou (2008), Cayirpunar et al. (2013a, b, 2015), Abdul Latiff et al. (2011) and Singh and Kumar (2019) for enhancing the network lifetime. Since, placement of the *MS* and its movement affects the performance of the network in terms of network lifetime (Shi and Hou 2008; Cayirpunar et al. 2013a, b, 2015; Abdul Latiff et al. 2011; Singh et al. 2013; Alia 2017; Singh and Kumar 2019). Movement of the *MS* near to each node for data collection, can save the energy, spent in transferring a data packet from sensor node to the static sink via multi-hop communication. But, it introduces latency in data gathering from the network. In order to overcome trade-off between energy saving and latency parameter, smart repositioning of the mobile sink within the network to balance the energy uses of all transmitting *CHs* is a challenging research problem (Shi and Hou 2008).

This article presents a hybrid method which integrates the clustering technique with the mobile sink and proposed a novel scheme for the formation of a scalable network infrastructure. The noteworthy contributions of the proposed research work are as follows:

- To provide load-balanced node clustering, a novel hybrid of Artificial Bee Colony (*ABC*) with Differential Evolution (*DE*) based meta-heuristic technique, named as *ABC-DE* based clustering scheme, is proposed.
- For selection of load balanced *CHs*, a novel objective function and efficient encoding technique are formulated.
- In order to resolve the trade-off between energy consumption and latency, Artificial Bee Colony based meta-heuristic algorithm is proposed for dynamic repositioning of the mobile sink within the network.
- Performance evaluation of the proposed scheme is evaluated and compare with the state-of-art schemes in terms

of energy consumption, residual energy and network lifetime.

The remaining parts of the paper are organized as follows: Sect. 2 provides a brief overview of the related work. In Sect. 3, network model and various assumptions are discussed. Section 4 presents the formulation of the objective function, and proposed meta-heuristic based scheme for clustering and repositioning of the mobile sink. Section 5 presents performance evaluation of the proposed scheme and its comparative studied with the state-of-art scheme. Finally, Sect. 6 concludes the proposed scheme and its performance.

2 Related work

In the last decade, several studies are published in the literature for improving the performance of the *WSNs* by adopting mobile sinks (*MS*). In this section, we have reviewed some of the pertinent studied related to node clustering and mobile sink based schemes. Heinzelman et al. (2002) have proposed a clustering protocol for *WSN*, called as *LEACH*. In this protocol, cluster heads are selected using probabilistic formula of energy and number of rounds as parameters. Practically, this protocol suffers from many problems such as low-scalability, unbalanced load assignment to *CHs* and left-out nodes problem. In RejinaParvin and Vasanthanayaki (2015), a *PSO*-based cluster heads and clustering protocol, known as *E-OEERP* has been proposed. This research work concerns about the left-out nodes problem, but, it suffers from non-uniform placement of *CHs* as well as unbalanced load problem at *CHs*.

In Srinivasa Rao and Banka (2015), a clustering scheme using chemical reaction optimization (*CRO*) based meta-heuristic was proposed. This scheme also does not ensure uniform distribution of cluster heads that creates energy hole near to the base station. Mann and Singh (2016) have proposed artificial bee colony meta-heuristic based scheme for clustering and routing problem. This work also does not consider node-left out problem and load-balancing at *CHs*. In Rao et al. (2016), *PSO*-based cluster head selection algorithm is given, known as *PSO-ECHS*. This algorithm uses three parameters such as remaining energy, distance between *CH* and *CMs*, and distance between *CHs* and base station, to design fitness function. The main limitations of this scheme are that it suffers from non-uniform placement of *CHs* and does not consider load-balancing and left-out nodes problem.

In Sarkar and Senthil Murugan (2017), a firefly meta-heuristic technique based cluster heads selection scheme has been proposed where energy and delay parameter are considered to decide the selection process. This scheme neither considers left-out nodes problem nor load balancing

problem. Gupta et al. (2018a) have proposed Cuckoo Search based meta-heuristic scheme for selection of cluster heads and Harmony Search based scheme for routing of the collected sensed data from *CHs* to base station.

In Wang et al. (2005), application of a controlled mobile sink was discussed for the improvement of the network lifetime of the *WSN*. This work has formulated the network lifetime maximization problem by using integer linear programming based optimization scheme in order to get optimal location of the mobile sink and its stopover time. This paper also proposed centralized algorithm for determining the routes of the mobile sink and its stopover time by using mixed-integer linear programming. In Shi and Hou (2008), authors have proposed a mobile sink based scheme for extending the network life time by moving a mobile sink at different locations of the network. In this work, it is assumed that *MS* has inexhaustible energy resource and to balance the power consumption of the sensor nodes, sinks are moved to different locations. The authors in Shi and Hou (2008) use two different cases such as when number of *MS*'s location is finite and when it is infinite for solving this problem.

Abdul Latiff et al. (2011) have proposed a novel scheme for delay-tolerant *WSN* for improving its lifetime by repositioning the mobile sink. The main objective of this work was to determine optimal path and stop location of the *MS* in order to gather the sensed data from the network. This scheme also uses clustering scheme to organize the sensor nodes into a set of clusters. A *PSO*-based algorithm is proposed for repositioning of the *MS* within the network. The work proposed in Abdul Latiff et al. (2011) known as *PSO-BSP*. In this work, two main limitations were observed. First, selection of *CHs* is based on only residual energy of the eligible nodes however authors have not consider other factor such as coverage of *CHs*, delay and load balancing factor that may improve the network lifetime. Second, distribution of *CHs* is not uniform and also once *CHs* are selected, they are remained fixed during the lifetime of the network. This may generally cause unbalanced energy consumption problem. In Singh et al. (2013), authors have studied impact of the *MS* in a cluster based *WSN* where two type of *MS* itinerary were considered such as circular itinerary and cross-shaped itinerary. For controlling the movement of the *MS*, a fuzzy inference system was designed which guides movement of the *MS* for visiting the *CHs* for data collection. For the fuzzification process, two input parameters were considered such as residual energy of the *CH* and its distance with the *MS*. This scheme is also suffered from latency problem.

Cayirpunar et al. (2013a) have studied effects of the *MS* repositioning and proposed a novel optimization algorithm. This proposed optimization algorithm was evaluated under three different mobility patterns such as spiral, random and grid. This work has also modeled the problem using mixed integer programming to illustrate the effects

of *MS* mobility over the network lifetime of the *WSN* (Cayirpunar et al. 2013b). Experimental results of the proposed work claimed that spiral mobility enhances 35% network lifetime compare to random mobility and 25% compare to the grid mobility followed by *MS*. In Cayirpunar et al. (2015), authors have focused on the optimal mobility pattern problem for the *MS*. For repositioning of the *MS*, two mobility patterns are proposed such as Gaussian mobility as well as optimized spiral patterns. A mathematical analysis of the proposed mobility patterns is also discussed.

In Alia (2017), harmony search based meta-heuristic algorithm is proposed for clustering of sensor nodes and also for dynamic repositioning of the *MS* for *MSWSNs*. In this work, for selection of *CHs*, a fitness function is derived based of three parameters such as residual energy of the competing node and its distance from cluster member as well as base station. There are two main drawbacks are observed in this work. First, proposed scheme does not ensure uniform distribution of *CHs*. This is due to fact that one of the components of the fitness function was distance between *CH* and base station and proposed scheme try to minimize this factor which causes selection of the *CHs* near to the base station. Second, proposed scheme does not consider some very important factor such as delay and coverage of the *CHs* during *CHs* selection. There are few survey papers available in the literature such as Younis and Akkaya (2008), Saleem et al. (2011), Yang and Karamanoglu (2013), Silva et al. (2014), Yurtkuran and Emel (2015) and Siddique and Adeli (2015), interested readers may refers these paper for further studies in the area of mobile sink based *WSNs* and its various challenges. In Dattatraya and Rao (2019), a hybrid of *GSO* and Fruitfly Optimization i.e. *FFOA* is used for selection of *CHs*. This scheme does not consider optimization of sink node location within the network so that energy consumption will be balanced for all CHs.

In Arora et al. (2019), an ACO-based routing scheme is proposed for intra-cluster communication. In this scheme, ACO is used for discovering the multiple paths between CH and CMs. Similarly, in Zou and Qian (2018), an improved ACO-based adaptive routing scheme is proposed where transfer function for each sensor node is constructed to select a dynamic route. Kumar and Dash (2019) have proposed a network flow approach based data transmission scheme from sensor nodes to the mobile sink. This scheme used two different data model for receiving the data packets from SNs nodes to MS. These schemes do not consider optimization of sink node location within the network so that energy consumption will be balanced for all CHs. Similarly, in Mehra et al. (2020), fuzzy based balanced *CHs* selection scheme is proposed where three parameters are considered such as energy node density and distance from sink node. The main limitation of this approach is that nodes nearest to the sink

will get priority which results in non-uniform distribution of *CHs* within the network.

Most of the existing node clustering scheme as reviewed in this section, do not consider various issues such as non-uniform distribution of cluster heads, load-balancing and left-out nodes issues. These issues severely affect the performance of the network in terms of network lifetime. In order to solve these issues as mentions above, we have proposed a novel hybrid meta-heuristic optimization technique by combining the best features of Artificial Bee Colony and Differential Evolution meta-heuristic algorithms for selecting the load-balanced cluster heads. The proposed scheme not only provides evenly distribution of *CHs* and inclusion of the left-out nodes but also optimizes the placement of the mobile sink within the network to further save the energy consumption during communication between *CHs* and *MS* and thus, enhances the network lifetime.

3 System model and assumptions

In this research work, we have used a system model similar to model used in Heinzelman et al. (2002), Alia (2017) and Gupta et al. (2018b) which possesses following properties.

- Sensor nodes are stochastically and evenly distributed over a two dimensional area of interest and their location is static after deployment.
- All sensor nodes are homogeneous and have equal initial energy.
- Data sensed by the sensor nodes can be transported to its neighboring sensor nodes that are in their communication range.
- Each sensor node has limited energy and it decreases when node is involved in transmission and receiving activities of the packet.
- There is a mobile sink which has sufficient energy resource.

In *WSN*, sensor nodes are generally operated with help of *2AA* battery. Hence, we need an energy model in order to estimate energy consumption of the sensor node during its different functioning. In this work, we consider an energy model similar to the energy model used in Heinzelman et al. (2002), Singh et al. (2013), Alia (2017) and Gupta et al. (2018b).

For transmitting a packet of '*L*' bits from a sender node to a receiver node of distance *d*, energy spent in transmission is estimated using Eq. (1).

$$E_{T_x}(L, d) = \begin{cases} L * E_{elec} + L * \epsilon_{fs} * d^2 & if \ d \leq d_0 \\ L * E_{elec} + L * \epsilon_{mp} * d^4 & if \ d > d_0 \end{cases}. \quad (1)$$

Here E_{elec}. is energy dissipation of node circuit and $d_o = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}$. ϵ_{fs} and ϵ_{mp} are amplifier energy in a free space and multipath propagation model, respectively. And for receiving a packet of '*L*' bits, energy consumption is estimated using Eq. (2).

$$E_{R_x}(L) = L * E_{elec} \quad (2)$$

4 Proposed load balanced clustering scheme using hybrid meta-heuristic technique

In this section, first linear programming formulation for the *CHs* selection is discussed. After this, a detail discussion on the proposed load balanced clustering scheme using Hybrid of Artificial Bee Colony (*ABC*) and Differential Evolution (*DE*) based meta-heuristic technique, named as *ABC-DE* based clustering scheme, is discussed. Next, Artificial Bee Colony (*ABC*) meta-heuristic based Mobile Sink re-localization algorithm is presented.

4.1 Linear programming formulation for cluster heads selection problem

The main goal of proposed scheme is to select a set of *CHs* that should be evenly distributed throughout network. For the selection of appropriate set of *CHs*, different parameters such as average energy, intra-cluster distance and delay are considered. Let f_1, f_2 and f_3 be the Intra-Cluster distance, Average Energy of *CHs* and delay factors, respectively. Therefore linear programming of optimal selection of the *CHs* is expressed as follows:

$$Minimize : F = \omega_1 \times f_1 + \omega_2 \times f_2 + \omega_3 \times f_3 \quad (3)$$

Subject to

$$dis(CM_i, CH) \leq d_{max} \quad (constraint - 1)$$

$$E_{CH_j} > E_{TH}, \quad 1 \leq j \leq m \quad (constraint - 2)$$

$$0 < \omega_i < 1 \quad 1 \leq i \leq 3 \quad (constraint - 3)$$

$$0 < f_i < 1 \quad 1 \leq i \leq 3 \quad (constraint - 4)$$

The constraint illustrated in (constraint-1) states that cluster members (*CMs*) must be in the communication range of *CH* nodes. The constraint illustrated in (constraint-2) states that energy of all *CH* must be greater than threshold energy. In constraint illustrated in (constraint-3), ω_i controls effects of each parameter of the

fitness function, since fitness function is represented as weighted sum of three parameters such that f_1, f_2 and f_3.

4.2 Formulation of the objective function

Our objective function contains three components such as average intra-cluster distance, average energy of *CHs* and delay. The description of individual components is described as follows:

(a) Average Intra-Cluster Distance (f_1): The main goal of this parameter is to minimize intra cluster distance by selecting *CH* which is closer to their cluster members.

$$Minimize \quad f_1 = \frac{1}{p} \times \sum_{i=1}^{p} \frac{\sum_{j=1}^{c_i} d(CH_i, CM_j)}{|c_i|} \qquad (4)$$

Here, $d(CH_i, CM_j)$ is the distance between the cluster heads and their respective cluster members and c_i is the total number of cluster members in the ith cluster and p is the number of *CHs*.

(b) Average Energy of Cluster Heads: This is defined as the sum of the ratio of residual energy of all cluster members in a cluster i with the residual energy of the cluster head of cluster i.

$$Minimize \quad f_2 = \sum_{i=1}^{p} \left(\frac{\sum_{j=1}^{c_i} E_j}{E_{CH_i}} \right) \qquad (5)$$

where E_j is the residual energy of cluster member, j and c_i is total number of cluster member in the ith cluster. E_{CH_i} is the residual energy of the ith *CH*. By minimizing f_2, it is expected that the *CH* selection and cluster formation process may be optimized in terms of energy consumption to enhance the network lifetime. In order to minimize f_2, numerator part of Eq. (5), $\sum_{j=1}^{c_i} E_j$, needs to be minimal, while the selected *CH* must have maximum residual energy. The node which is having greater energy level tends to become the *CHs*.

(c) Delay: The main goal of this parameter is to optimized data transmission delay. In a cluster based *WSN*, delay in data collection depends on the size of the cluster. In other words, it is proportional to the number of *CMs* in a cluster. So, size of the cluster should be optimal to minimize the delay parameter. Delay component f_3 can be described as follows:

$$Minimize \quad f_3 = \frac{max_{j=1}^{p}(c_j)}{n} \qquad (6)$$

Here c_j is the number of *CMs* in the jth cluster and p is the number of *CHs* and n is the total number of sensor nodes.

So the objective function F can be expressed as weighted sum of three components f_1, f_2, and f_3 as described in Eqs. (4), (5), and (6), respectively. Equation (7) illustrates the objective function (F) for evaluating the optimal number of *CHs*.

$$F = \omega_1 \times \frac{1}{p} \times \sum_{i=1}^{p} \frac{\sum_{j=1}^{c_i} d(CH_i, CM_j)}{|C_i|} + \omega_2$$
$$\times \sum_{i=1}^{p} \left(\frac{\sum_{j=1}^{c_i} E_j}{E_{CH_i}} \right) + \omega_3 \times \frac{max_{j=1}^{p}(c_j)}{n} \qquad (7)$$

where $\omega_1 + \omega_2 + \omega_3 = 1$ and $\omega_i \in [0, 1]$. The constant ω indicates the contribution of f_1, f_2 and f_3 in the objective function F.

4.3 Hybrid *ABC-DE* based meta-heuristic algorithm for load balanced node clustering

The proposed Hybrid *ABC-DE* based metaheuristic algorithm works in three phases such as Initialization phase, Employee bee phase and Onlooker bee phase. Description of each phase is described as follows:

(a) Initialization Phase: In this phase, an initial population which is represented as a matrix of dimension $S \times D$, is generated. Here D is dimension of solution vector and S is the number of solution vector. Each row of population matrix represents possible candidate of *CHs* for solution vector. Each solution vector is initialized randomly and the size of each solution vector is the number of required *CHs*. Each element of solution vector represents a sensor node. Representation of the initial population is illustrated in Eq. (8). In Hybrid *ABC-DE* based meta-heuristic algorithm, an employ bee phase uses first half of population matrix and onlooker bee phase uses second half of population matrix for its processing. In Eq. (8), $f(x_i)$ represent fitness estimation of solution vector x_i.

$$\begin{pmatrix} x_i^1 & x_i^2 & \cdots & x_i^D \\ x_{i+1}^1 & x_{i+1}^2 & \cdots & x_i^D \\ & & \vdots & \\ x_s^1 & x_s^2 & \cdots & x_s^D \end{pmatrix} \begin{pmatrix} f(x_i) \\ f(x_{i+1}) \\ \vdots \\ f(x_s) \end{pmatrix} \qquad (8)$$

(b) Employed bee phase: In this phase, first we generate a random solution vector by using Eqs. (9) and (10).

$$v_{i,d}^x = x_{i,d}^{min} + r \times \left(x_{i,d}^{max} - x_{k,d}^{min} \right), \quad d = 1, 2, \ldots D \quad (9)$$

$$v_{i,d}^y = y_{i,d}^{min} + r \times \left(y_{i,d}^{max} - y_{k,d}^{min} \right), \quad d = 1, 2, \ldots D \quad (10)$$

where $v_{i,d}^x$, represents x component of solution vector and $v_{i,d}^y$, represents y component of solution vector. Here x and y are the coordinate of a sensor node i. Here r is a uniform random number between $[-1, 1]$ and $x_{i,d}^{min}$, $x_{i,d}^{max}$ denotes the lower and upper bounds of the x coordinates of CHs position and $y_{i,d}^{max}$, $y_{k,d}^{min}$ denotes the lower and upper bounds of the y coordinates of CHs position. Next, a sensor node closest to the randomly generated sensor node position $(v_{i,d}^x, v_{i,d}^y)$ is selected. After this, fitness of this new solution vector v_i is evaluated. If fitness value of v_i is better than x_i, then v_i replace the old solution vector x_i in the population matrix.

(c) Onlooker bee phase: In this phase, a Differential Evolution (*DE*) (Yurtkuran and Emel 2015) based meta-heuristic algorithm is employed. Since the onlooker bee phase of the original *ABC* [26] algorithm endures lack of exploitation, i.e., incapable of applying available information to find better solution. Many researchers have analyzed this fact and observed that it will ultimately affect the *ABC* algorithm's convergence rate. In order to enhance the convergence speed of *ABC*, we have proposed a hybrid of *ABC* with *DE* (Yurtkuran and Emel 2015; Siddique and Adeli 2015) where onlooker bee phase is evaluated using *DE*-based meta-heuristic algorithm. *DE*-based metaheuristic generally contains three sub phases such as Initialization, Mutation and Crossover, working of each phase is described as follows:

(i) Initialization Phase: In initialization phase of the *DE*, an initial population is generated which is nothing but the second half of population matrix represented in Eq. (8).

(ii) Mutation Phase: In the phase, first two solution vectors x_{i_1}, x_{i_2} randomly selected from initial population matrix which is generated in initialization phase. Based on these randomly selected solution vector, a new solution u_i is generated by using following equation:

$$u_{i,d}^x = x_{best} + k \times \left(x_{i_1} - x_{i_2} \right) \quad (11)$$

$$u_{i,d}^y = y_{best} + k \times \left(y_{i_1} - y_{i_2} \right) \quad (12)$$

where $u_{i,d}^x, u_{i,d}^y$ indicate the coordinates of x and y of ith solution. x_{i_1}, x_{i_2} are the two randomly chosen vectors from the population matrix and

x_{best} and y_{best} is the component of a solution vector whose fitness is best among the initial population. k is a scaling factor whose value is taken as 0.3. It is observed that at the obtained value of u_i, it may be possible that there is no sensor node located. So, we choose a nearest node to the obtained value of u_i and take it as a new solution. This new solution u_i generated in this phase is called trial solution.

(iii) Crossover Phase: In this phase, a crossover operation is performed between the trial solution vector (u_i) and the parent solution vectors (x_i). Here parent solution x_i is the initial population vector of the *DE*. The crossover operation is performed by using expression as illustrated in Eq. (13). In the crossover operation, first a random value is generated between the range [0, 1] and compares its value with Crossover Rate (*CR*). If the generated value is less than equal to *CR* then corresponding element Offspring (x_{id}') will carry the corresponding element of trial solution u_{id} otherwise it wil carry the corresponding element of parent vector (x_{id}).

$$x_{id}' = \begin{cases} u_{id}, & \text{if } r \leq CR \\ x_{id}, & \text{otherwise} \end{cases} \quad (13)$$

Here the value of $r \in [0, 1]$ and *CR* is the crossover rate which is set to 0.4. Selection operator is applied for selecting the best solution. We have used greedy selection among the solution vectors, obtained in parent solution vectors and offspring solution vectors. In this way, we obtain a best solution vector for this iteration.

(d) Scout bee phase: If the present iteration round is less than the maximum iteration number, t_{max}, then this phase begin its processing. In this phase, the scout bee will search for a new set of solutions (i.e. set of *CHs*) by using Eqs. (11) and (12) again. In this way, we select the best sets of *CHs* from randomly deployed sensor nodes. After each iteration, the set of *CHs* will be replaced by a new set of *CHs* with better fitness values. Algorithm 1 described the steps of the proposed clustering protocol which is listed in Fig. 1.

4.4 Artificial Bee Colony (*ABC*)-based meta-heuristic algorithm for Re-localization of mobile sink (*MS*)

In this section, first, description of the fitness function used to determine the optimal location of the *MS*, is presented.

Fig. 1 Pseudo code of the pro-
posed hybrid ABC-DE based
clustering algorithm

Algorithm 1. Proposed Hybrid ABC-DE based Clustering Algorithm
Input: set of sensor nodes $S = \{s_1, s_2, ..., s_N\}$ and N is total number of sensor nodes
Output : Optimal position of *CHs*.
Phase 1: Initialization
1: Generate initial population X_i, $i = 1,...,SN$ where each individual of the solution vector is a possible candidate for becoming a *CH*.
2: First half of the initial populations are set as Employed bees. However, second half are set as Onlooker bees.
3: Evaluate the fitness of each individual solution.
4: round = 1;
5: **Repeat**
// **Phase 2 begin**
6. **for** (each **employed bee** solution x_i)
7:     create new solution v_i using Eq. (9) & Eq. (10)
8:     Calculate fitness of new solution v_i
9:     **if** ($F(v_i) < F(x_i)$)) // $F(x_i)$ represents fitness value of x_i
10:       $x_i = v_i$;
11:     **end if**
12: **end for**
//**Phase 3 begin**
13: **for** (each **onlooker's bee** solution x_i)
14:     Apply mutation operator using Eq. (11) & Eq. (12)) to create a trial solution u_i;
15:     Apply crossover operation using Eq. (13) to create an offspring x_i';
16:     **if** ($F(x_i') < F(x_i)$
17:       $x_i = x_i'$;
18:     **end if**
19: **end for**
20: store the solution vector with the best fitness value
21: round = round + 1
22: Goto step 6 if (round <= t_{max})
23: end

Next, Artificial Bee Colony (*ABC*)-based meta-heuristic algorithm is proposed for re-localization of the *MS* within the network.

4.4.1 Objective function used in *ABC*-based re-localization of the *MS*

This section discusses the derivation of the objective function used for selecting the best optimal location of the *MS*. Here, the best position of the *MS* is the centre position of all the *CHs*. The objective function is formulated as follows:

$$Minimize \quad MS_{obj} = \max_{\forall CH_j, 1 \geq j \geq p} \left\{ \|POS_{MS}, POS_{CH_j}\| \right\} \quad (14)$$

Here Pos_{MS} and Pos_{CH_j} are position coordinate of the *MS* and CH_j, respectively. The value of p is number of *CHs*. MS_{obj} is fitness function which intends to minimize the highest Euclidean distance between the *MS* and all

CHs with a specific end goal to reduce the energy utilization equally between the *CHs*. The position of the *MS* that can give the minimum effective value of the MS_{obj}, will be chosen as its new position.

4.4.2 Description of proposed re-localization algorithm

To balance the energy consumption of *CHs*, we have proposed an Artificial Bee Colony (*ABC*)-based meta-heuristic algorithm for the re-localization of the *MS* within the network. In the proposed algorithm, the *MS* relocate itself in order to balance energy consumption spent during the communication with *CHs*. For this purpose, optimal location of the *MS* needs to be estimated based on the location of all *CHs*. In this research work, we have utilized an Artificial Bee Colony (*ABC*) based meta-heuristic algorithm for re-localization of the *MS* with objective to find optimal position of the *MS* which minimizes the distance between *CHs* and *MS*. The proposed *ABC*-based *MS*-relocalization algorithm works in four phases such as initialization, employee bee

phase, onlooker phase and scout bee phase. Description of each phase is presented as follows:

(a) Initialization phase: In this phase, an initial population is generated. Here, we have generated S number of solution vector as initial population. Each solution vector is initialized randomly as illustrated in Eq. (15). Each row of population matrix represents possible x and y coordinate for the MS position. In ABC-based metaheuristic algorithm, Employ Bee phase uses first half of population matrix and the Onlooker Bee phase uses second half of population matrix for its processing. In Eq. (15), $f(Pos_{i.x}, Pos_{i.y})$ represent fitness value of solution vector $[Pos_{i.x}, Pos_{i.y}]$

$$
\begin{pmatrix}
Pos_{i.x}, Pos_{i.y} \\
Pos_{i+1.x}, Pos_{i+1.y} \\
. \\
. \\
. \\
Pos_{S.x}, Pos_{S.y}
\end{pmatrix}
\begin{pmatrix}
f(Pos_{i.x}, Pos_{i.y}) \\
f(Pos_{i+1.x}, Pos_{i+1.y}) \\
. \\
. \\
. \\
f(Pos_{S.x}, Pos_{S.y})
\end{pmatrix}
\tag{15}
$$

(b) Employed bee phase: In this phase, a new solution of the possible set of coordinates for locating the MS is generated. A new solution ($InitVec_j$) is generated by using Eqs. (17) and (18).

$$
InitVec_j = [Pos_{j.x}, Pos_{j.y}]
\tag{16}
$$

$$
Pos_{j.x} = rand() \times (Tp_x - Bot_x) + Bot_x
\tag{17}
$$

$$
Pos_{j.y} = rand() \times (Tp_y - Bot_y) + Bot_y.
\tag{18}
$$

Here $Pos_{j.x}$ and $Pos_{j.y}$ indicate the coordinates of x and y of jth vector. To load the ABC memory with logical value vectors with respect to the locations of the CHs, $rand()$ function is used which produces an arbitrary number $\in [0, 1]$. Tp_x and Tp_y are the topmost level of x-coordinate and y-coordinate of all CHs positions, and Bot_x and Bot_y are the bottommost level of the coordinates of x and y of all CHs positions. Then, we calculate fitness of the new solution vector $InitVec_j$. If fitness value of $InitVec_j$ is better then old solution, then $InitVec_j$ replace the old solution vector in the population matrix.

(c) Onlooker bee phase: In this phase, an onlooker bee chooses the coordinate of the MS based on a probability value as described in Eq. (19). Here, f_i. represent fitness of new solution and also performs a local search on new solution according to Eqs. (17) and (18) and the new solution has greater probability, then the new solution will overwrite old solution.

$$
p_i = \frac{f_i}{\sum_{n=1}^{S} f_i}
\tag{19}
$$

(d) Scout bee phase: If present iteration (t) is less than the maximum iteration (t_{max}), the process of Scout bee phase will start. In this phase, scout bee will search a new set of solutions (i.e. location of the MS) with help of Eqs. (17) and (18) again. In this way, we select the best coordinates of the MS from randomly deployed sensor nodes. After each round, the coordinates of the MS will be replaced by a new coordinates of the MS with better fitness values. Flowchart of the proposed Artificial Bee Colony (ABC)-based meta-heuristic algorithm for re-localization of the MS is illustrated in Fig. 2.
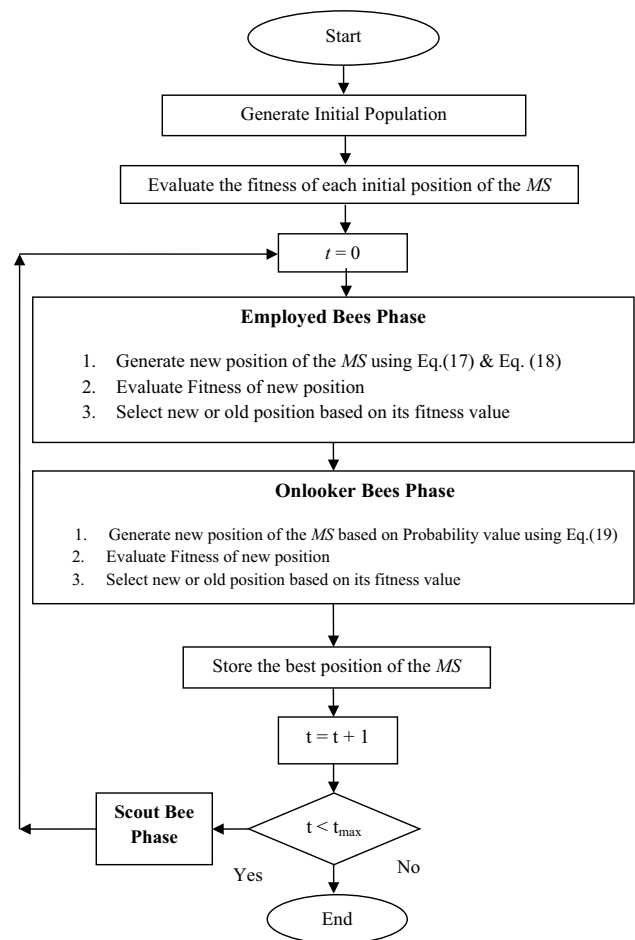

Fig. 2 Flow chart of ABC-based re-localization of the of mobile sink

5 Performance evaluation and result analysis

In this section, performance analysis of the proposed *ABC-DE*-based scheme and its comparative study with the state-of-art solutions such as *LEACH* (Heinzelman et al. 2002), *PSO-BSP* (Abdul Latiff et al. 2011) and *HS* (Alia 2017) are discussed. Simulation of the proposed scheme and the state-of-art solutions such as *LEACH* (Heinzelman et al. 2002), *PSO-BSP* (Abdul Latiff et al. 2011) and *HS* (Alia 2017) are done with help of custom simulator using MATLAB R2009 tool. The main objective of this paper is to design cluster based network model and also to determine optimal placement of the mobile sink within the network. Since a typical *WSN* is generally functions in a low duty cycle mode, impacts of the packet collisions perceive by *MAC* layer, over energy consumption should not be a big factor. Table 1 illustrates parameters list used in the simulation experiments. Simulation results shown in this paper were estimated by

Table 1 Parameters list used in simulation experiments

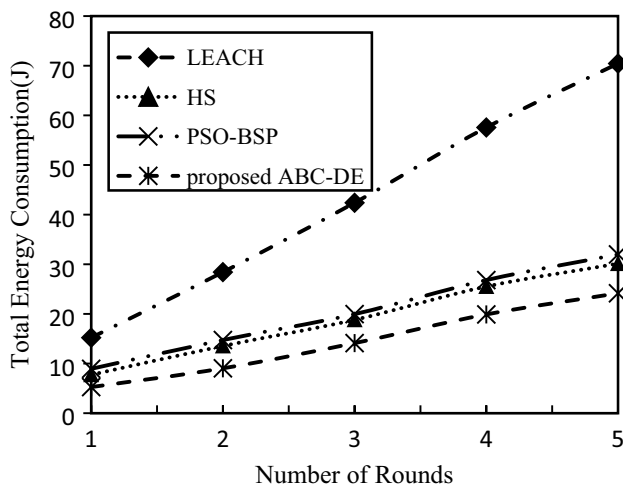| Parameters	Value
Size of network area	$200 \times 200 \text{ m}^2$
Number of sensor nodes	100–300
Initial energy	2 J, 200 J
% of CHs	10–15
E_{elec}	50 nJ/bit
E_{fs}	10 pJ/bit/m^2
E_{mp}	0.0013 pJ/bit/m^4
d_0	87.00
d_{max}	25 m
Packet length	4000 bits

Fig. 3 Total energy consumption versus the number of rounds
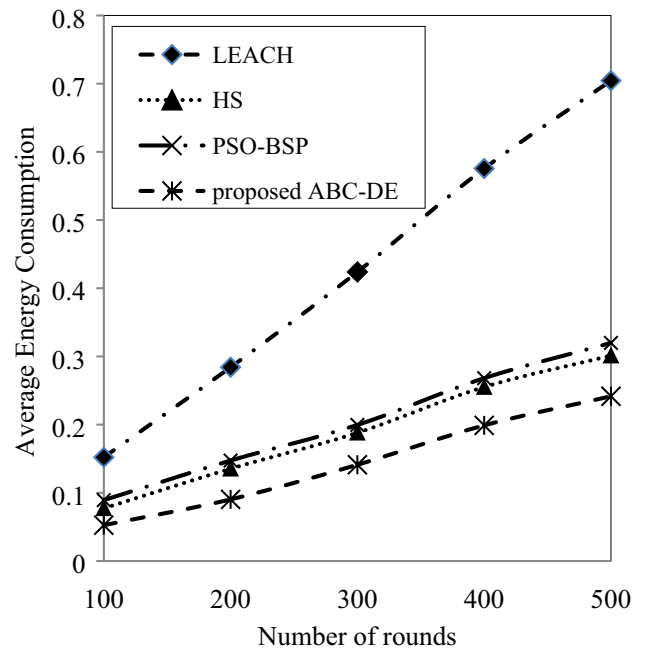

Fig. 4 average energy consumption versus the number of rounds

averaging 25 independent executions of the experiment. Confidence interval of the simulation results is 95%.

5.1 Result analysis in terms of energy consumption

In this simulation experiments, initial energy of each sensor node is set to 2 J and total 100 sensor nodes are randomly and uniformly distributed over a 200×200 monitoring area of interest. Figures 3 and 4 illustrates the performance comparison of the proposed *ABC-DE based* scheme with the state-of-art clustering solutions such as *LEACH* (Heinzelman et al. 2002), *PSO-BSP* (Abdul Latiff et al. 2011) and *HS* (Alia 2017) in terms of total energy consumption and average energy consumption, respectively. It can be examined from the Fig. 3 that the proposed Hybrid *ABC-DE* based scheme consumes notably less energy compare to the *LEACH* (Heinzelman et al. 2002), *PSO-BSP* (Abdul Latiff et al. 2011) and *HS* (Alia 2017). This is due to fact that *CHs* are selected uniformly from the whole network and its load is also balanced. However, *LEACH* suffers from an uneven distribution of *CHs* that causes more energy consumptions. Selection of the *CHs* determined by the proposed scheme is better than other three schemes, which results in better performance. Other factor which makes an impact in saving energy is the uniform energy consumption between *CHs* and the mobile sink.

Figures 5 and 6 noticeably illustrates the performance comparison of the proposed *ABC-DE* based clustering scheme by varying the node density within the network in terms of total energy consumption in the network and
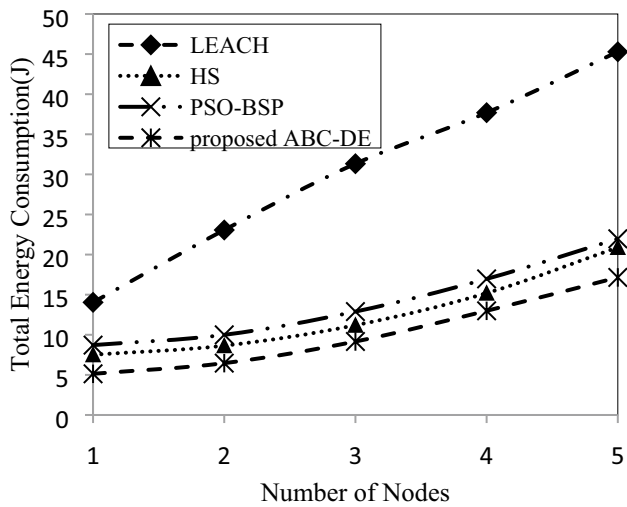
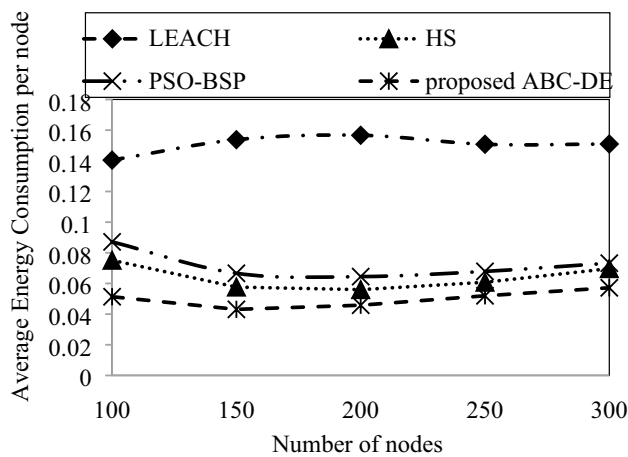**Fig. 5** Total energy consumption versus the number of nodes

Fig. 6 Average energy consumption versus the number of nodes

Fig. 7 Total residual energy versus the number of rounds
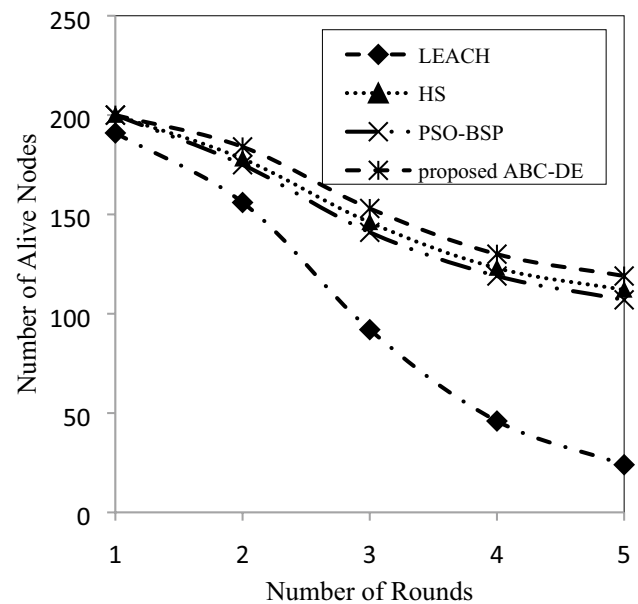
Fig. 8 Number of alive nodes versus the number of rounds

average energy consumption, respectively. In this experiment, nodes are varied from 100 to 300. It can be notably observed from the figure that the proposed *ADC-DE* based scheme outperforms the other schemes. This is because of the fact that the proposed *ABC-DE* based scheme offers a uniform distribution of the *CHs*, which balanced the load of the *CHs* and also due to re-localization of the *MS*, distance between the *CHs* and the *MS* is also optimized which save a lot of communication energy of the nodes. Hence, performance of the *ABC-DE* is better than the rest.

5.2 Result analysis in terms of residual energy

In this experiment, initial energy of each node is set to 200 J and total 100 sensor nodes are randomly and uniformly
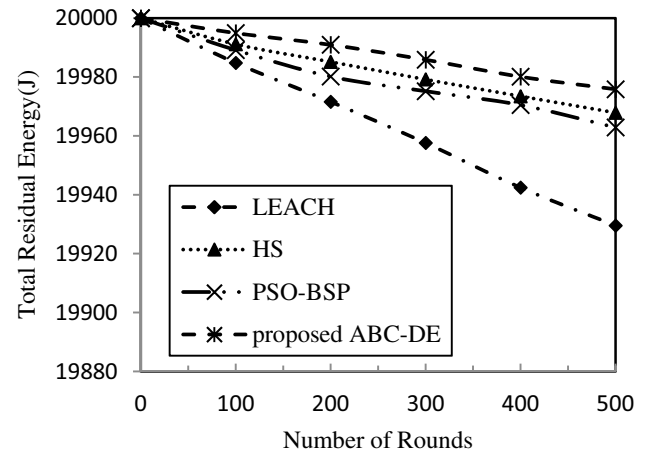
distributed over a 200×200 monitoring area of interest. Performance comparison of the proposed *ABC-DE* based scheme is illustrated in terms of total residual energy in Fig. 7. This figure shows that the proposed *ABC-DE* based clustering scheme outperforms the rest of the scheme in terms total residual energy consumption. This is due to facts that *CHs* are evenly selected and also dynamic re-localization of mobile sink is incorporated which reduce the traveling distance of data packet from *CHs* to the *MS*. However, other schemes such as *LEACH* (Heinzelman et al. 2002), *PSO-BSP* (Abdul Latiff et al. 2011) and *HS* (Alia 2017) do

not distribute *CHs* evenly which causes more uneven energy consumptions.

5.3 Result analysis in terms of network lifetime

Figure 8 demonstrates total number of alive nodes after a number of simulation rounds by each clustering scheme. In this experiment, total 200 sensor nodes are randomly and uniformly distributed over a 200×200 monitoring area of interest. Initial energy of each node is set to 2 J. From the Fig. 8, it can be observed that *ABC-DE* based scheme is more efficient that the other schemes. This is due to fact that for the *ABC-DE* based scheme, *CHs* are evenly distributed and data transportation distance between *CHs* and the *MS* is dynamically adjusted that save a lot of energy. Hence, the network lifetime of the proposed scheme is better compare to the other schemes.

6 Conclusions

In this research work, a novel hybrid meta-heuristic technique is proposed for node clustering problem where best features of Artificial Bee Colony and Differential Evolution are combined to evaluate the best set of load-balanced cluster heads in mobile sink based *WSN*. In addition, an Artificial Bee Colony based meta-heuristic algorithm is also proposed for dynamic placement of the mobile sink for the further optimization of the energy consumption and load balancing. A novel fitness function and population encoding method are devised for the optimization algorithm. Simulation experiments and its analysis was carried out to observed the performance of the proposed scheme in terms of total energy consumption, total residual energy and network lifetime. Simulation results confirm that the proposed scheme significantly save the network energy consumption by introducing uniform selection of *CHs* and load distribution among them. Moreover, dynamic adjustment of mobile sink placement within network also improves the performance of the network lifetime. In future, we plan to extend this work for underwater wireless sensor network with multiple sink nodes and also plan for performance analysis of the proposed scheme for cognitive radio based sensor networks.

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