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A boolean spider monkey optimization based energy efficient clustering approach for WSNs

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Abstract Wireless sensor network (WSN) consists of densely distributed nodes that are deployed to observe and react to events within the sensor field. In WSNs, energy management and network lifetime optimization are major issues in the designing of cluster-based routing protocols. Clustering is an efficient data gathering technique that effectively reduces the energy consumption by organizing nodes into groups. However, in clustering protocols, cluster heads (CHs) bear additional load for coordinating various activities within the cluster. Improper selection of CHs causes increased energy consumption and also degrades the performance of WSN. Therefore, proper CH selection and their load balancing using efficient routing protocol is a critical aspect for long run operation of WSN. Clustering a network with proper load balancing is an NP-hard problem. To solve such problems having vast search area, optimization algorithm is the preeminent possible solution. Spider monkey optimization (SMO) is a relatively new nature inspired evolutionary algorithm based on the foraging behaviour of spider monkeys. It has proved its worth for benchmark functions optimization and antenna design problems. In this paper, SMO based threshold-sensitive energy-efficient clustering protocol is proposed to prolong network lifetime with an intend to extend the stability period of the network. Dual-hop communication between CHs and BS is utilized to achieve load balancing of distant CHs and energy minimization. The results demonstrate that the proposed protocol significantly outperforms existing protocols in terms of energy consumption, system lifetime and stability period.

Keywords SMO · binSMO · WSN · Network lifetime · Stability period

1 Introduction

Wireless sensor network (WSN) is an infrastructure which consists of densely distributed nodes that support not only sensing, but also data processing, computing and communicating capabilities. WSNs have a range of capabilities, functionalities and applications such as atmospheric monitoring, video surveillance, or virtually any task that involves sensing and communicating information [1]. These may be deployed in an open space, in the streets or roadsides, in the battlefields [2], in the interior of industrial machineries [1], in commercial buildings, and in or on a human body. The field is now progressing with the advancements in technology and its various potential applications are growing at a fast pace.

Wireless networks generally transmit the sensed information to base station (BS) that aggregate some or all of the information [1]. Clustering is a widely used technique in WSN that effectively reduces the energy consumption of sensor nodes [1]. In cluster-based routing protocols, the main task of cluster head (CH) is the collection of periodic data from its cluster members (CMs) and to transmit aggregated data to BS. For a CM, the energy consumption is considerably lower to reach the CH than to transmit directly to BS. A cluster based WSN reduces energy consumption significantly as only CH per cluster involves in data aggregation and routing process.

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Clustering has been widely investigated and a number of research proposals [2] have been reported in the literature for energy saving in WSNs. Among these, low energy adaptive clustering hierarchy (LEACH) protocol is a popular clustering protocol [3]. It is an adaptive clustering algorithm for homogeneous WSN that uses stochastic self CH election. The decision for CH selection relies on the predetermined percentage of CHs and when the node served as a CH last time. LEACH is capable of increasing the network lifetime in comparison to direct transmission and minimum transmission energy protocols [3]. Stable election protocol (SEP) [4] and SEP-extended (SEP-E) are two level and three level heterogeneous variants of LEACH. Smardakis et al. proposed SEP for clustered heterogeneous WSNs (HWSNs). The objective is to prolong network stability period essential for some applications. In order to achieve the increased stability period, SEP tries to balance energy consumption among different nodes. In this protocol, some sensor nodes are provided with additional energy than normal nodes termed as advanced nodes. Advance nodes have higher chance to become CH to ensure enhanced stability by using heterogeneity. SEP ensures that the CH election process is suitably adapted to deal with heterogeneity of nodes. An enhancement of SEP (SEP-E) considers three level of heterogeneity. SEP-E extends the network lifetime as well as stability period in comparison to LEACH and SEP. A number of variants to LEACH protocol are reported in literature that differ from it on the basis of node heterogeneity [3–7], distance-based thresholds [8], multi-hopping concept [7, 9, 10], deterministic clustering [11] and query-based reactive protocol [12–14].

Recently, Mittal and Singh [13] proposed a clustering algorithm named distance-based residual energy-efficient SEP (DRESEP) for heterogeneous sensor networks. It is a reactive algorithm optimal for event driven applications like forest fire detection. DRESEP considers the residual energy of nodes and their distances from BS as parameters for CH selection. In order to balance the load of distant CHs, a dual-hop communication between distant CH and BS is used. DRESEP improves the energy utilization and operational network lifetime significantly in comparison to LEACH and SEP-E. Mittal et al. [14] also proposed a stable version of DRESEP named stable energy efficient clustering protocol (SEECP). The key idea of SEECP is to select the CH in deterministic fashion. In SEECP, a predetermined number of CHs are selected on the basis of residual energy of nodes. The focus is to balance the load among nodes and provide full network coverage. SEECP favors higher stability period in lieu of overall network lifetime.

Bio-mimic optimization algorithms have also been successfully applied to design clustering-based routing protocols [15–22]. The aim of such optimization algorithms is to select CHs dynamically to efficiently manage the overall energy consumption of WSN. A genetic algorithm (GA) based hierarchical cluster-based routing (HCR) protocol [17] is designed to find CHs that minimizes communication distance in sensor networks. To evaluate the fitness, few parameters are considered: residual energy of each sensor node, distance of node from BS, distance of node from CHs, uniform spatial distribution of node by calculating the standard deviation in terms of cluster distance, and number of transmissions at each stage. The fitness function is evaluated by combining all above said parameters. Though HCR prolongs the network lifetime in comparison to LEACH, but it failed to ensure a longer reliability period.

Khalil and Attea proposed an energy-aware evolutionary routing protocol (EAERP) [18] that aims to minimize the total energy dissipation in the network. EAERP is more energy efficient in comparison to LEACH. Khalil and Attea proposed another evolutionary based clustering routing protocol (ERP) [19] that focused on minimization of intra-cluster-distance between CHs and its associated CMs along with maximization of the minimum distance between CHs. The fitness function for CH selection considers parameters like cohesion and separation error for improved cluster quality. ERP improves operational lifetime as well as network stability in comparison to LEACH.

Rao et al. proposed a novel chemical reaction optimization (nCRO) algorithm based energy efficient clustering approach [20]. To achieve better energy efficiency, various parameters such as intra-cluster distance, sink distance and residual energy of sensor nodes are considered in the CH selection phase. To mitigate the hot spot problem, Rao et al. proposed an unequal clustering and routing protocol based on nCRO algorithm [21]. In clustering, the network is partitioned into unequal clusters such that smaller size clusters form near to BS and larger size clusters are relatively far away from BS. For this purpose, the CH selection algorithm is developed based on nCRO paradigm and assign the non-CH nodes to the CHs depending on cost function. Routing is also performed using nCRO based approach. Rao et al. [22] also proposed an energy efficient particle swarm optimization (PSO) based CH selection algorithm. The algorithm is developed with an efficient scheme of particle encoding and fitness function. For optimal selection, one of the objectives is to minimize average intra-cluster and sink distance of all the CHs. Another objective is to maximize the total current energy of all the selected CHs. The simulation results show that it performs better than the existing algorithms in terms of total energy consumption, network lifetime and the number of data packets received by BS.

Shokouhifar and Jalali [23] designed an application-specific routing protocol to prolong the operational lifetime of WSN according to the application. CH selection is performed on the basis of remaining energy, distance of node from BS and distance between node and respective CH. Tuning of controllable parameters is performed using GA-SA hybrid approach to achieve better performance. The proposed algorithm efficiently balances the energy consumption of nodes, improves operational lifetime and received more data packets at BS.

The literature reveals that the key objective of the above said clustering protocols is to prolong the network lifetime by applying efficient clustering algorithms. However, in cluster based WSNs, CHs bear additional workload contributed by their CMs. Moreover, the CHs are normally elected randomly which can die quickly due to this additional workload. Also, most existing clustering solutions are unable to support load balancing among nodes as these either consider direct transmission or multi-hop communication between CHs and BS. Direct transmission leads to unbalancing the energy distribution to the nodes which are far from BS, whereas multi-hopping causes overburden to the nodes near to BS. Therefore, there is a requirement to consider an alternate way to eliminate the effects of direct transmission and multi-hopping. In addition, most of the clustering protocols employ proactive methods for periodic transmissions. However, a number of WSN applications require reactive methods, e.g., military applications in which nodes transfer their data only on the detection of an intruder. Therefore, designing clustering protocols for event-driven networks is of prime consideration.

Various studies have used the meta-heuristics optimization schemes to solve clustering in WSN that are reported in [17–23]. The reported results show the efficiency and flexibility of such techniques in solving complex problems. The spider monkey optimization algorithm (SMO), which is not well known to the WSN clustering community, will be presented in this paper. The main goal of this paper is to demonstrate its effectiveness to allow this algorithm to join other popular evolutionary optimization techniques as a useful tool for clustering problems in WSNs. SMO algorithm is recently developed heuristics that mimics the foraging behaviour of spider monkeys [24] and has been successfully applied for antenna design problems [25–27]. SMO shows its superiority or competitiveness over the existing popular meta-heuristics such as GA and PSO in the electromagnetics and antennas [27].

In this paper, dual hop inter-cluster communication is employed to overcome the load balancing shortcomings of both the direct and multi-hopping protocols. For intra-cluster communication, CMs use threshold decision based reactive strategy for data transmission to CH. Designing energy efficient clustering algorithm is an NP-hard problem. In this paper, SMO based clustering algorithm is proposed to solve the above load balancing problem.

This paper is organized as follows. Section 2 gives an overview of SMO and boolean SMO algorithms. Section 3 presents the proposed protocols in detail. Section 4 exhibits and analyses our simulation results. Section 5 concludes the paper with possible future directions.

2 Boolean spider monkey optimization algorithm

SMO is a swarm intelligent metaheuristic algorithm inspired from the social structure of spider monkeys [24]. The algorithm mimics the foraging behaviour of spider monkeys. This behavior can be classified in four steps based on the concept of fission–fusion social structure (FFSS) of spider monkeys. First, the group evaluates the distance from the food and then starts food foraging. In the second step, the positions of group members and the evaluated distance from the food sources is updated. In the next step, the local leader updates its best position within the group. All the group members start searching the food in the case of the lack of best position updation by the local leader. In fourth step, the global leader updates its ever best position. The group is splitted into smaller subgroups in the case of stagnation (no updation in global leader position for a specified time).

The local leader limit (LLL) is applied to reduce the occurrence of stagnation by redirecting the group to alternate direction for foraging. On the other hand, the group is splitted into smaller subgroups if the global leader is unable to update the position for global leader limit (GLL). Negative feedback is received from LLL and GLL for the local and global leaders to take their decisions.

CH selection in WSNs is a binary-coded problem, therefore, the basic SMO algorithm cannot be used to tackle this problem. Inspired from the basic SMO algorithm, boolean SMO is used for binary optimization problems. This boolean SMO approach has been named as binSMO and uses logical operators for position update [26]. Logical operators are incorporated in the basic equations of SMO algorithm in order to work in binary space. Similar to SMO [24], binSMO has several phases and each phase is explained as below:

Initialization phase

In the first phase of binSMO algorithm, a population of N spider monkeys (SM) is initialized randomly using Bernoulli process and is given by

$$SM_{i,j} = \begin{cases} 1, & a < prob \\ 0, & otherwise \end{cases} \tag{1}$$

where $SM_{i,j}$ is the jth dimension of ith spider monkey, $prob$ is probability taken as 0.5 and a is a uniformly distributed random number in the range of [0,1]. The fitness of randomly generated solution SM_i (for the minimization problems) is calculated as:

$$fit_i = \begin{cases} 1 + |f_i|, & f_i \leq 0, \\ \dfrac{1}{1+f_i}, & f_i \geq 0 \end{cases} \tag{2}$$

where f_i is the fitness function of the problem under consideration.

Local leader phase:

The second phase uses the experience of local leader and group members to update the solution. For a binary optimization problem, logical AND, OR and XOR operators have been used. The position update equation is given as:

$$SMnew_{i,j} = \begin{cases} SM_{i,j} \oplus \left(\left(b \otimes \left(LL_{k,j} \oplus SM_{i,j} \right) \right) + \left(d \otimes \left(SM_{r,j} \oplus SM_{i,j} j \right) \right) \right), & rand \geq pr \\ SM_{i,j}, & otherwise \end{cases} \tag{3}$$

where $SM_{i,j}$ and $SMnew_{i,j}$ is the previous and updated position of ith SM in the jth dimension, $LL_{k,j}$ represents the local leader of kth group in the jth dimension, b and d are binary random integers in the range [0, 1] and $\oplus$, $\otimes$, $+$ are logical XOR, AND and OR operators respectively, and pr is the perturbation rate.

Global leader phase

In the third phase, all SMs update their velocity update equation or positions based upon the experience of global leader and members of global group. The positions are updated based upon some probability given by:

$$P_i = 0.9 \times \frac{(fit_i)}{\text{max\_fit}} + 0.1 \tag{4}$$

where P_i is the probability, fit_i is the fitness of ith SM and max_fit is the maximum fitness of the group. The position update equation for this phase is given by:

$$SMnew_{i,j} = SM_{i,j} \oplus \left(\left(b \otimes \left(GL_j \oplus SM_{i,j} \right) \right) + \left(d \otimes \left(SM_{r,j} \oplus SM_{i,j} \right) \right) \right) \tag{5}$$

where GL_j is the global leader in the jth dimension.

Local leader learning phase

In this phase, each group member updates its position and best among them is considered the local leader. This process continues until the local leader stops updating. The local leader count is then incremented by 1, if local leader is not updated after some predefined number of times.

Global leader learning phase

The position of global leader is updated and best among them is considered the local leader. This process continues until the global leader stops updating. The global leader count is then incremented by 1, if global leader is not updated after some predefined number of times.

Local leader decision phase

In this phase, if the local leader count exceeds a predefined threshold LLL, then the position of all group members is updated as follows:

$$SM_{i,j} = \begin{cases} SM_{i,j} \oplus \left(\left(b \otimes \left(LL_{k,j} \oplus SM_{i,j} \right) \right) + \left(b \otimes \left(GL_j \oplus SM_{i,j} \right) \right) \right), & rand \geq pr \\ \text{use equation 1}, & otherwise \end{cases} \tag{6}$$

Global leader decision phase

In the final phase of binSMO algorithm, if the global leader count exceeds a predefined threshold GLL, the group is divided into sub groups. When the maximum number of groups is formed, the global leader combines to form a single group and position of local leader is updated.

The flow code for Boolean SMO algorithm is given in Fig. 1.

3 Proposed protocol

In this work, SMO based threshold-sensitive energy-efficient delay-aware routing protocol (SMOTECP) is proposed to design efficient clustering solutions in sensor networks. SMOTECP attempts to increase the overall operational lifetime of WSN. The proposed protocol is distributed, threshold-sensitive, energy-efficient and delay aware.

The operation of the protocol is divided into rounds, each consists of set-up phase and steady-state phase. The steady-state phase is similar to as in DRESEP [13], but the CH selection procedure in set-up phase is modified. In setup phase, BS uses binSMO as a tool for creating energy efficient clusters for a given number of alive sensor nodes and network residual energy. Steady-state phase solves the problem of load balancing by using the threshold based intra-cluster data transmission and dual-hop inter-cluster communication algorithm.

The set-up phase consists of the following steps:

CH Election In the election phase, sensor nodes exchange their information for the network control to BS as shown in Fig. 2(a). Based on the information received from sensor nodes, CH nodes are chosen using binSMO as shown in Fig. 2(b). It handles a population of several individual solutions. A complete solution determines the location of CHs and their members in WSN. Alive regular sensor nodes and CHs are represented by 0 and 1 respectively. The phase begins by generating initial population and the fitness for each individual is calculated based on the estimated energy consumption, which is determined by

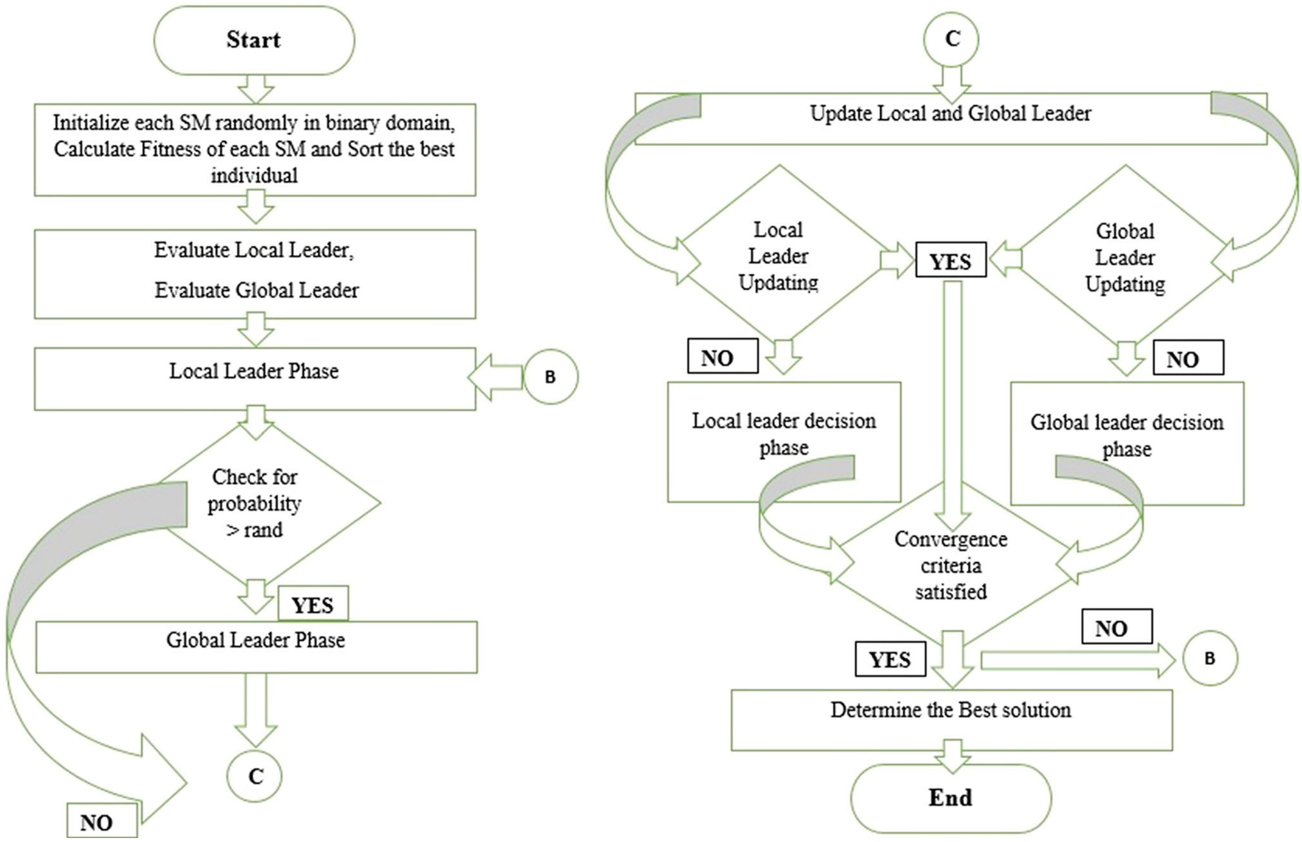


Fig. 1 Flow code for Boolean SMO algorithm

the proposed fitness parameters. After that, the population goes through several operators to create an evolved population. These operations are iterated for until the termination criterion is satisfied. Then, the fittest individual is used to seed the next phase where the non CH nodes are associated to their CHs to form clusters. The cluster formation and CH selection in SMOTECP is given in Algorithm 1.

CH Advertisement and Cluster Setup The elected CHs broadcast their status by an advertisement message to the sensor nodes that contains CH's ID as shown in Fig. 2(c). The node replies the join request to the CH nearest to it using CSMA MAC protocol as shown in Fig. 2(d).

TDMA Schedule Creation CH creates a TDMA schedule for CMs to allow their intra-cluster communication. This schedule specifies the time slots during which CMs are authorized to transmit the data.

In the *steady-state phase*, being reactive protocol a non-CH node transmit its data to respective CH only when an event is triggered [13], shown in Fig. 2(e). CHs send the aggregated data to BS using either direct or dual-hop routes depending upon the distance between them as shown in Fig. 2(f) [13, 14]. If the distance between CH and BS is higher than *R*, it looks for another CH as relay to forward the data to BS; otherwise data is forwarded to BS in a single hop [28].

Fitness Evaluation Consider a WSN of *n* sensors randomly deployed in the sensing field. For CH election, SMOTECP uses a population of spider monkeys that evolves toward forming appropriate clusters and maintaining the minimum energy consumption of the network. Each spider monkey is represented as a fixed-length list of size equal to the total number of nodes in the WSN.

Let $SM = (SM_1, SM_2, \ldots, SM_n)$ denote the population vector of a WSN with *n* sensors, where $SM_i(j) \in \{0, 1\}$. CH and regular nodes are denoted by values 1 and 0 respectively. Consider the example:

SM_1	SM_2	SM_3	SM_4	SM_5	SM_6	SM_7	SM_8	SM_9	SM_{10}
1	0	0	0	1	0	0	1	0	0

In this, sensor nodes SM_1, SM_5 and SM_8 are CHs. The remaining nodes are regular sensors. The initial population consists of randomly generated individuals. SMO is used to select CHs. The initial population of *N* individual solutions is randomly initialized in terms of 0 s and 1 s according to desired percentage of CHs and is given by

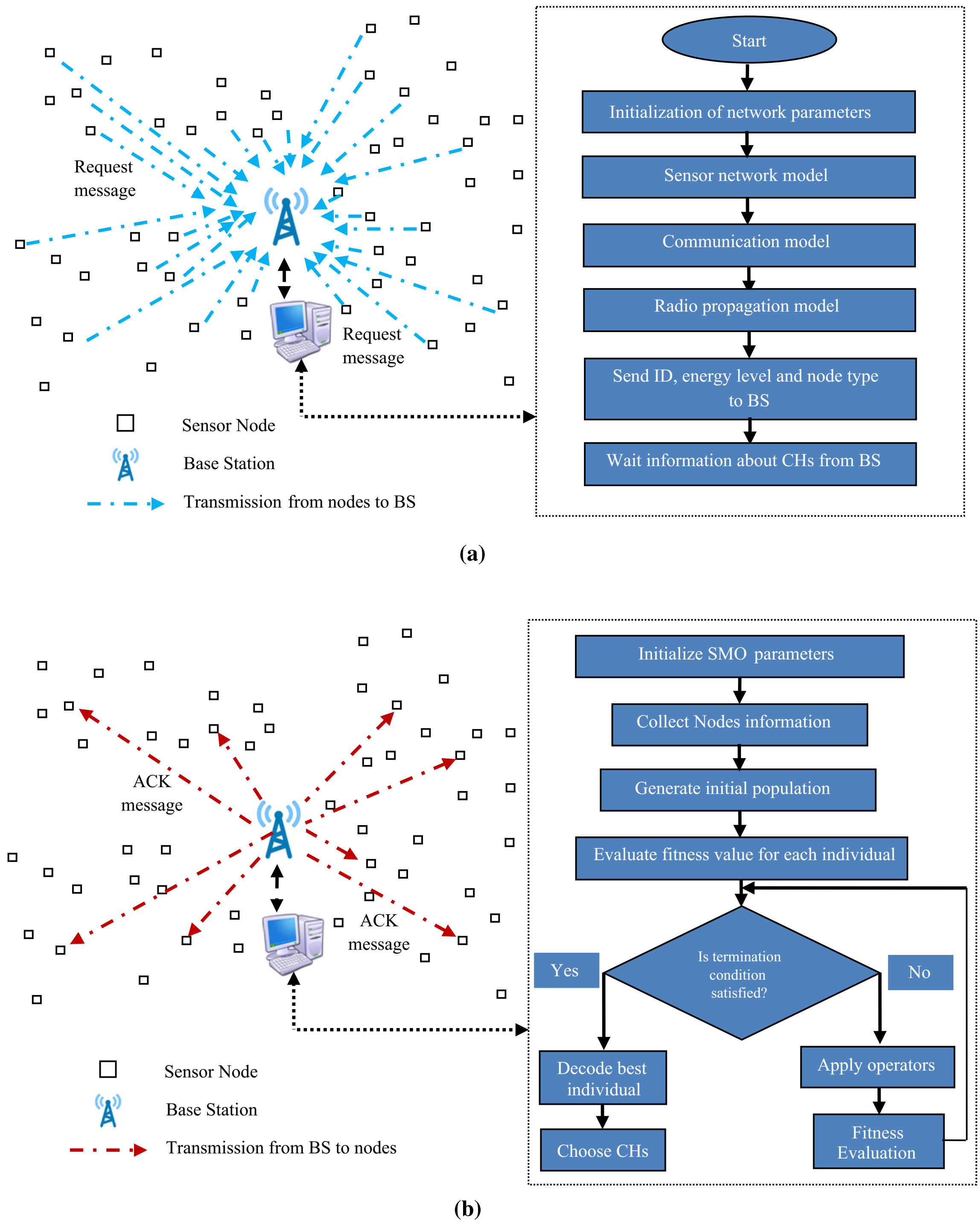
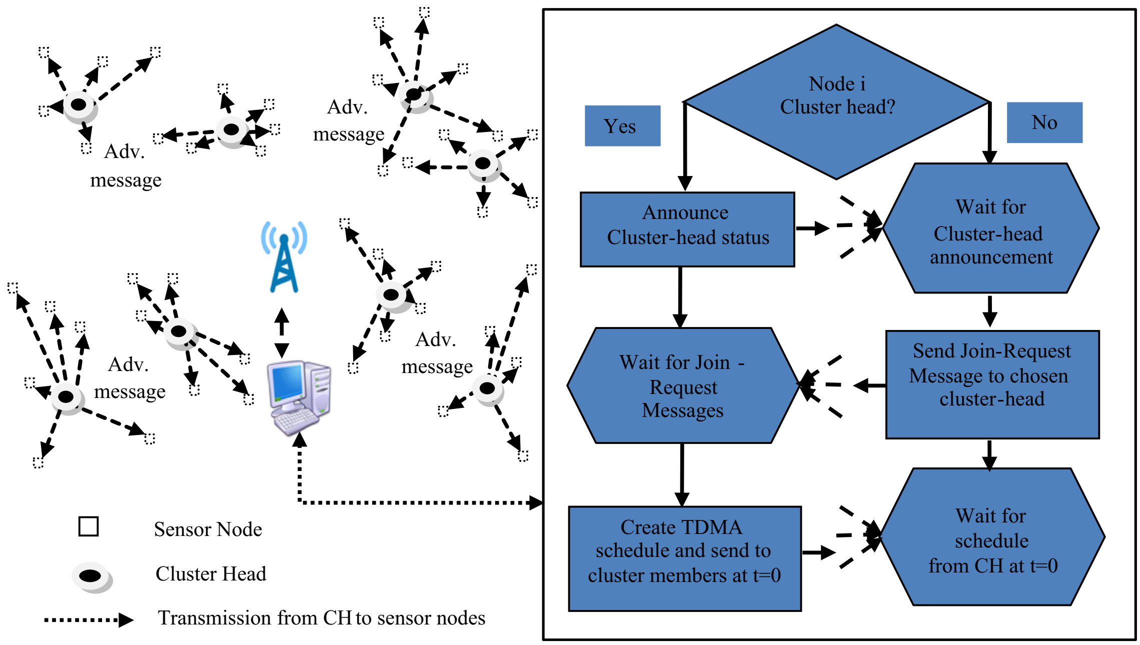
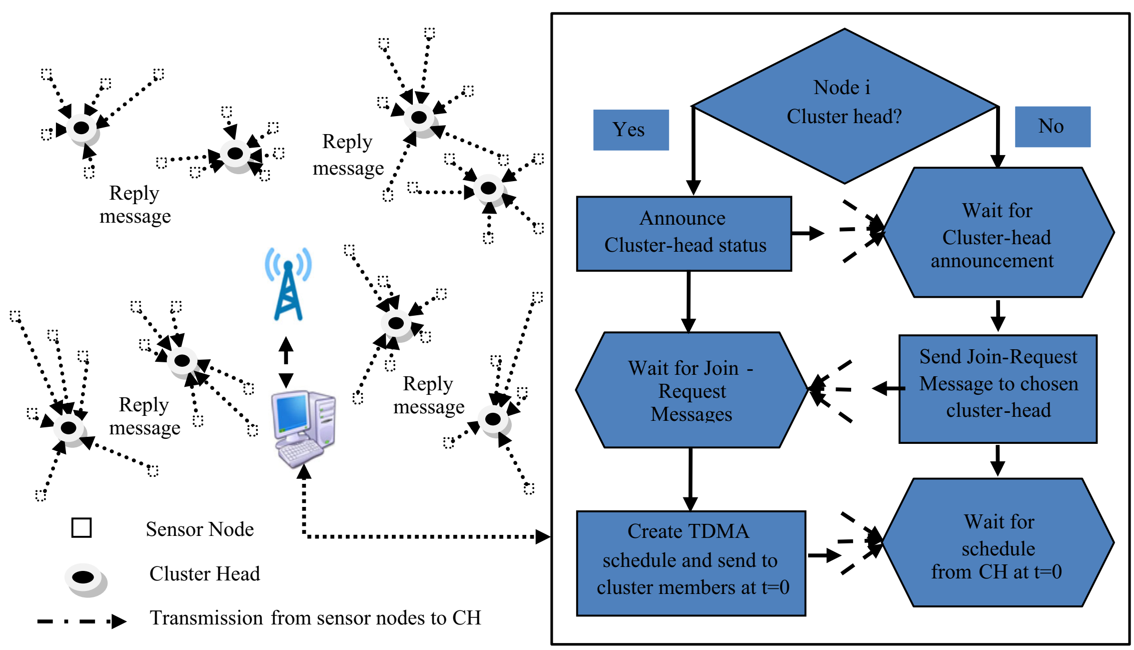


Fig. 2 The operation of SMOTECP. **a** Setup phase: sensor nodes interested for CH selection send request message to BS. **b** Setup phase: BS selects CH using SMO and inform CH nodes with acknowledge message. **c** CH Advertisement phase: CH sends advertisement message to sensor nodes. **d** Cluster setup phase: Sensor nodes interested to join CH send reply message to CHs. **e** Intra-cluster data transmission phase: data packets are transferred from sensor nodes to the CH. **f** Inter-cluster data transmission phase: data packets are transferred from CH to the BS (either direct transmission or dual hop depending upon the distance between them)



(c)

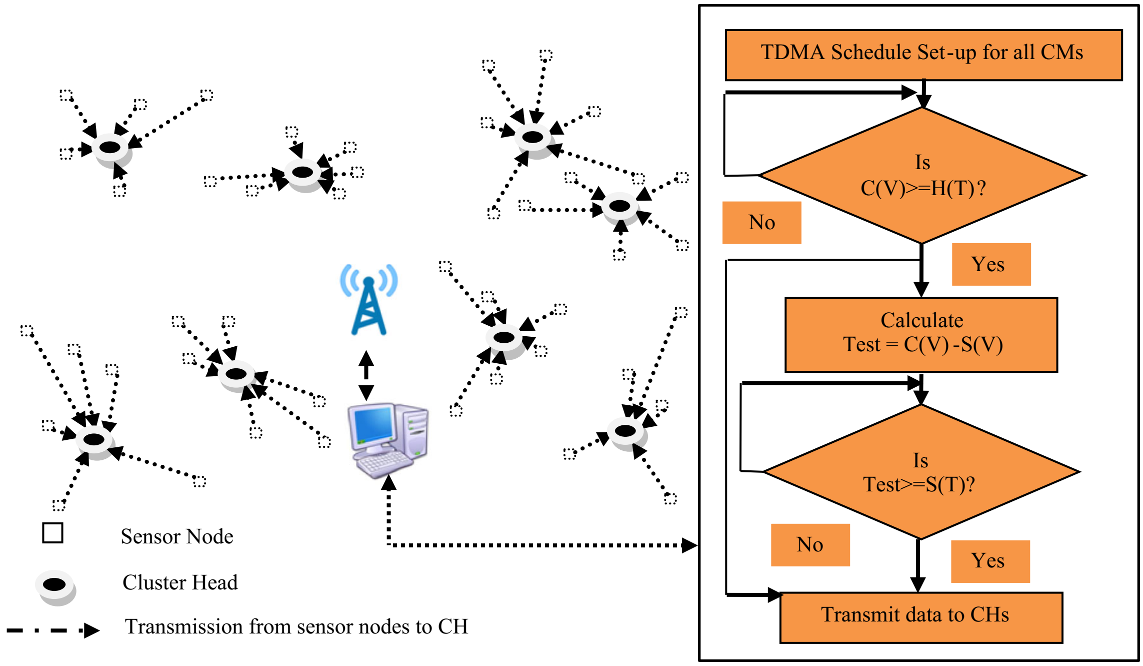


(d)

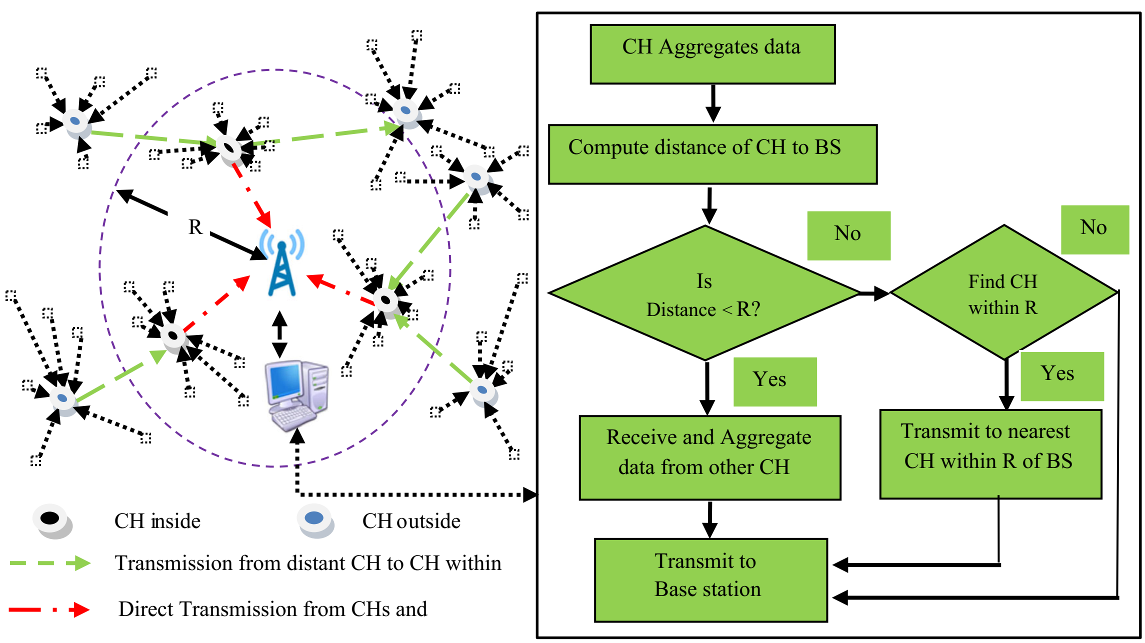
Fig. 2 continued

Table 1 Clustering objectives

Objective Name	Description
Energy consumption	Minimize the total energy consumption of the network
Cluster quality	Improve the quality of clustering by minimizing the cluster cohesion and maximizing the cluster separation
CH residual energy	Selection of a node as CH that has the higher residual energy with respect to member nodes
Scheduling time	Minimize the round trip delay in intra-cluster communication by reducing the size of cluster



(e)



(f)

Fig. 2 continued

$$SM_i(j) = \begin{cases} 1, & if(rand \leq p) \\ 0, & otherwise \end{cases} \qquad (7)$$

where p is the suggested percentage of CHs, and *rand* is a uniform random number in the range [0,1].

These randomly deployed sensor nodes are organized into K clusters:$C_1, C_2, \ldots, C_K$. The CHs are selected such that they minimize the cost of the fitness function which is a function of minimum energy dissipation, minimum cluster cohesion and maximum cluster separation, residual energy of sensor nodes and scheduling time for data gathering process. These objectives are given in Table 1.

The fitness function may be defined as:

$$f_{\mathrm{obj}} = \sum_{\mathrm{i}=1}^{4} w_i \times f_i \tag{8}$$

with subject to: $\sum_{i=1}^{4} w_i = 1$.

The minimization of the total energy consumption of each node is of prime concern [18], and is given by

$$f_1 = \left(\sum_{k=1}^{K} \sum_{\mathrm{node_j} \varepsilon C_k} E_{TX_{\mathrm{node_j}, CH_k}} + E_{RX} + E_{DA} \right) + \sum_{k=1}^{K} E_{TX_{CH_k, BS}} \tag{9}$$

where K is the CHs count, $\mathrm{node_j} \varepsilon C_k$ is a CMs belongs to the kth CH, $E_{TX_{node_a, node_b}}$ is energy dissipated for forwarding data from $node_a$ to $node_b$.

The transmission costs for a l-bit message having transmitter–receiver separation d, is given by:

$$E_{TX} = \begin{cases} lE_{elec} + l\varepsilon_{friss\_amp} d^2, & if\ d < d_0 \\ lE_{elec} + l\varepsilon_{two\_ray\_amp} d^4, & if\ d \geq d_0 \end{cases} \tag{10}$$

The term E_{elec} designates the per-bit energy consumed in transmission. The transmission energy is proportional to d^4 when the distance is greater than threshold d_0, otherwise is proportional to d^2. The parameters ε_{friss_amp} and $\varepsilon_{two\_ray\_amp}$ are transmitter amplification parameters for free-space and multipath fading models respectively. The value of d_0 can be expressed as:

$$d_0 = \sqrt{\varepsilon_{friss\_amp} / \varepsilon_{two\_ray\_amp}} \tag{11}$$

The reception cost for the l-bit data message is given by:

$$E_{RX} = lE_{elec} \tag{12}$$

Table 2 Parameters used in MATLAB simulation

Parameter	Value
Number of nodes	100
Network size	100 m × 100 m
Location of BS	(50, 50)
Initial energy of normal node, E_0	1 J
Probability of CH selection	0.05
Radio electronics energy, $E_{Tx} = E_{Rx}$	50 nJ/bit
Energy for data-aggregation, E_{DA}	5 nJ/bit
Radio amplifier energy, ε_{friss_amp}	100 pJ/bit/m^2
Radio amplifier energy, $\varepsilon_{two\_ray\_amp}$	0.0013 pJ/bit/m^4

where E_{elec} denotes the per-bit energy dissipation during reception. E_{DA} is the data aggregation energy expenditure.

The second objective is concerned with the quality of clustering which is a function of cluster separation and cohesion [19]. If the ratio of cohesion to separation is small then the clustering is assumed to be good. Therefore, the objective is to minimize intra-cluster distance (cluster cohesion) between CHs and respective CMs; and maximize the minimum inter-cluster distance (cluster separation) between two distinct CHs. To achieve this objective, the fitness function is defined as ratio of total Euclidean distance of CHs to their CMs and minimum of Euclidean distance of two distinct CHs.

$$f_2 = \frac{\sum_{k=1}^{K} \sum_{\forall node_j \in C_k} d(node_j, CH_k)}{\underset{\forall C_c, C_k, C_c \neq C_k}{min} \{d(CH_c, CH_k)\}} \tag{13}$$

In clustering protocols, CHs assume the responsibility of gathering periodic information from their CMs, aggregating it and then transmitting it to distant BS. The failure of CH may degrade the performance of whole network. Therefore, the objective is to select the node as a CH that has higher remaining energy within the cluster. The third objective f_3 is defined as the sum of ratio of residual energy of alive sensors of a cluster to the remaining energy of respective CH in the current round. In order to minimize f_3, sum of residual energy of CMs needs to be minimal, while residual energy of CH must be maximized. Hence, minimizing f_3 ensures in the selection of higher residual energy CHs in the network.

$$f_3 = \sum_{k=1}^{K} \frac{\sum_{\forall node_j \in C_k} E(node_j)}{E(CH_k)} \tag{14}$$

In the proposed model, a round is completed when the whole data is gathered from CHs to BS. Since TDMA schedule is assigned by each CH for intra-cluster communication, the cluster having largest CMs will require the maximum scheduling time for data gathering process and hence, produces maximum delay. The next objective is to minimize the round trip delay in intra-cluster communication which is defined as:

$$f_4 = [max_{k=1,\ldots\ldots,K}(m_k + 1)] \tag{15}$$

where m_k is the total members in k^{th} cluster and K is cluster counts. The objective is to minimize the maximum time consumed by k^{th} cluster to transfer its data to BS which consists of m_k packets transmitted from CMs to CH and one aggregated packet from CH to BS.

Algorithm 1 Cluster Formation using SMOTECP

Define the fitness function: *f(x)*.
Set parameters:
(1) The number of population vectors: $\boldsymbol{N}$;
(2) The D-dimensional search space = number of sensor nodes: $\boldsymbol{n}$;
(3) The maximum number of rounds: $\boldsymbol{R_{max}}$;
(4) The maximum generation: $\boldsymbol{G_{max}}$;
(5) Global leader limit and local leader limit: ***GLL, LLL***;
(6) Maximum number of groups: ***MG***;
(7) Perturbation rate: $\boldsymbol{p_r}$**;**
(8) The probability of CH selection: $\boldsymbol{p}$;
while $\boldsymbol{r \le R_{max}}$
/* **Initialization phase:** Initialization of CHs with probability p *\
for *i* = 1 to *N*
for *j* = 1 to *n*
$$SM_i(j) = \begin{cases} 1, & if\ rand \le p \\ 0, & otherwise \end{cases}$$
end for
end for
\\ Count CHs
$CHcount = 0$
for *j* = 1 to *n*
if $SM_i(j) = 1$
$CHcount = CHcount + 1$
end if
end for
for *k* = 1 to $CHcount$
for *i* = 1 to *n*
Calculate distance $d(node_j, CH_k)$ between $node_i$ and all CHs CH_k.
Assign $node_j$ to the cluster C_k in which $d(node_j, CH_k)$ is minimum
end for
end for
Compute the value of fitness function given in (8)
for counter=1 to $\boldsymbol{G}_{max}$
Select Global and Local Leader by greedy search.
while termination criteria is satisfied **do**
/***Local leader phase***\
Generate new sol. based on equation 3.
Calculate fitness of new sol.
Select better sol. based upon fitness of new and old sol.
/***Global leader phase***\
Calculate probabilities based on equation 4.
Generate new sol. based on equation 5.
Calculate fitness of new sol.
Select better sol. based upon fitness of new and old sol.
Update local and global leader position.
/***Local leader decision phase***\
if local leader not getting updated
redirect all members for foraging using equation 6.
end if
/*Global leader decision phase*
if global leader not getting updated divide the group into two.
while maximum groups are formed.
Combine all groups to one.
Update Local leader.
end while
end if
update the CHs
end for
end while

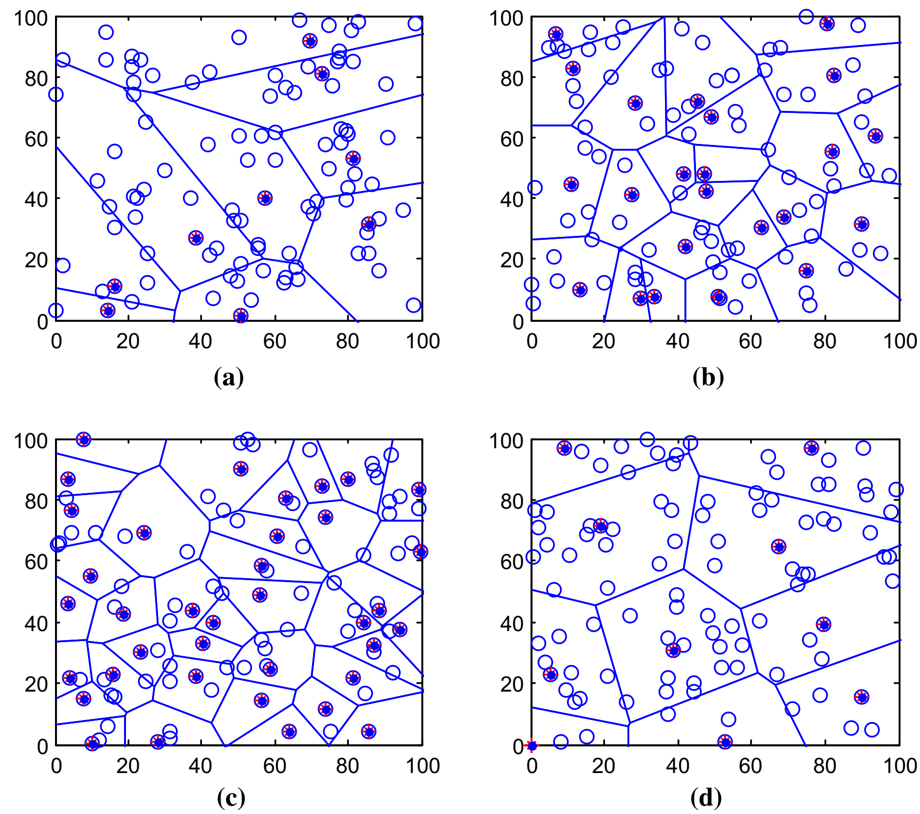


Fig. 3 Cluster formation voronoi diagrams of LEACH, HCR, ERP and SMOTECP for homogeneous setup. **a** Cluster formation of LEACH. **b** Cluster formation of HCR. **c** Cluster formation of ERP. **d** Cluster formation of SMOTECP

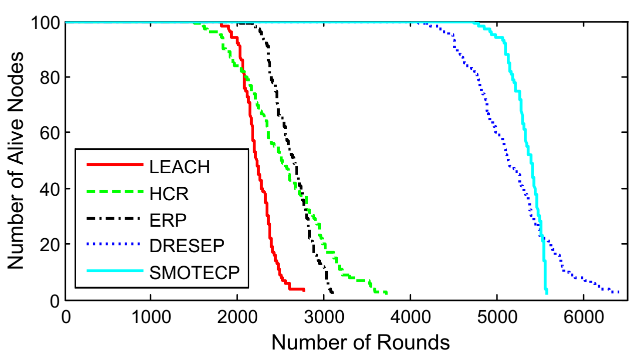


Fig. 4 Number of alive nodes per round for simulated protocols for homogeneous setup

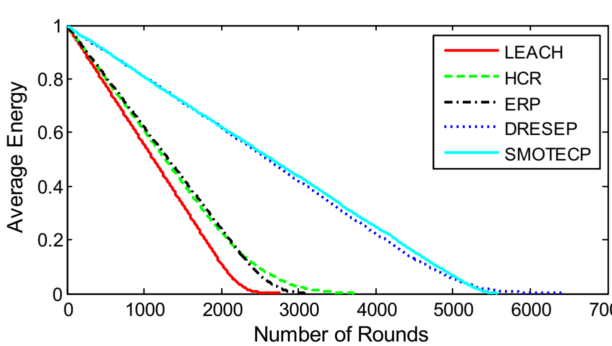


Fig. 5 Average remaining energy per round for simulated protocols for homogeneous setup

4 Simulation results

The performance of SMOTECP protocol has been analysed in terms of total energy remaining in the network, stability period and network lifetime against LEACH, SEP-E, HCR, ERP and DRESEP protocols using MATLAB. The network characteristics used for the protocol simulations are summarized in Table 2.

This study is carried out to analyse the effects of SMOTECP protocol in both homogeneous and heterogeneous setups. The simulations are performed with varying

Table 3 Round history of dead nodes for homogeneous setup

% Dead nodes	LEACH	HCR	ERP	DRESEP	SMOTECP
1 (FND)	1805.2	1726	2113.3	4101.6	**4833.3**
10	2022.8	2048.6	2276.3	4504.2	**5098.4**
20	2069.3	2189.6	2364.4	4769.9	**5228.5**
30	2141	2315.3	2438	4881.4	**5320.8**
40	2169.4	2420.2	2509.5	4983.5	**5400.7**
50 (HND)	2215.2	2524.6	2580	5126.7	**5485**
60	2280.1	2629.9	2648.9	5294.2	**5559.3**
70	2346.3	2752.2	2744.8	5395.4	**5627.7**
80	2394.8	2916.8	2837.3	5621.1	**5710.5**
90	2485.6	3107.1	2983.3	**5770.7**	5746.4
100 (LND)	2763.5	3574.3	3305.9	**6402.2**	5765.6

Bold values indicate the best value with respect to others temperature (randomly between 0 and 200 °F) in different regions for SMOTECP and DRESEP. The hard threshold and soft threshold values are set to 50 and 2 °F respectively [13, 14]. In SMOTECP, the weights in the fitness function of Eq. (8) are set to same value (i.e., $w_i = 1/4$). so that equal importance is given to each individual fitness parameters. For fair comparison, the evolutionary components of competitive HCR and ERP protocols are considered same as given in [18]. The initialization parameters for HCR and ERP are selected as crossover probability $(P_c) = 0.6$, mutation probability $(P_m) = 0.03$. The simulations are performed for 100 iterations for population size of 40. The parameters for binSMO are taken as follows:

Table 4 Total number of data packets received at BS for homogeneous setup

Protocol	FND	HND	LND
LEACH	66,545.7	78,217.3	84,356.2
HCR	64, 321.2	80,548.8	**89, 782.4**
ERP	**69,148.9**	**80,934.2**	88, 892.3
DRESEP	44,386.5	51,752.7	56,383.8
SMOTECP	48,786.3	54,367.8	57,642.2

Bold values indicate the best value with respect to others

- Swarm size = 40;
- maximum number of groups = 4.
- Perturbation rate, $pr = [0.1, 0.4]$ increasing linearly according to the relation:
  $pr_{G+1} = pr_G + (0.4 - 0.1)/maxiter$
  where G is the iteration counter and $maxiter$ is the maximum number of iterations.
- Global leader limit = 10
- Local leader limit = 20

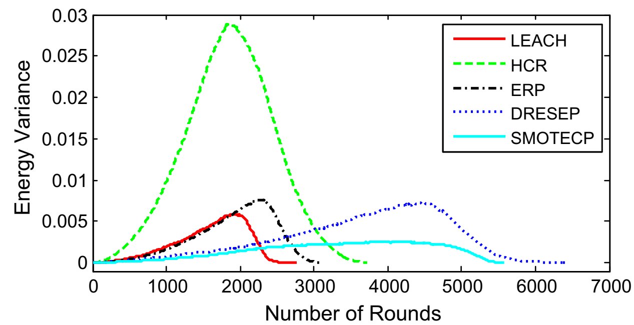


Fig. 7 Energy variance per round for simulated protocols for homogeneous setup

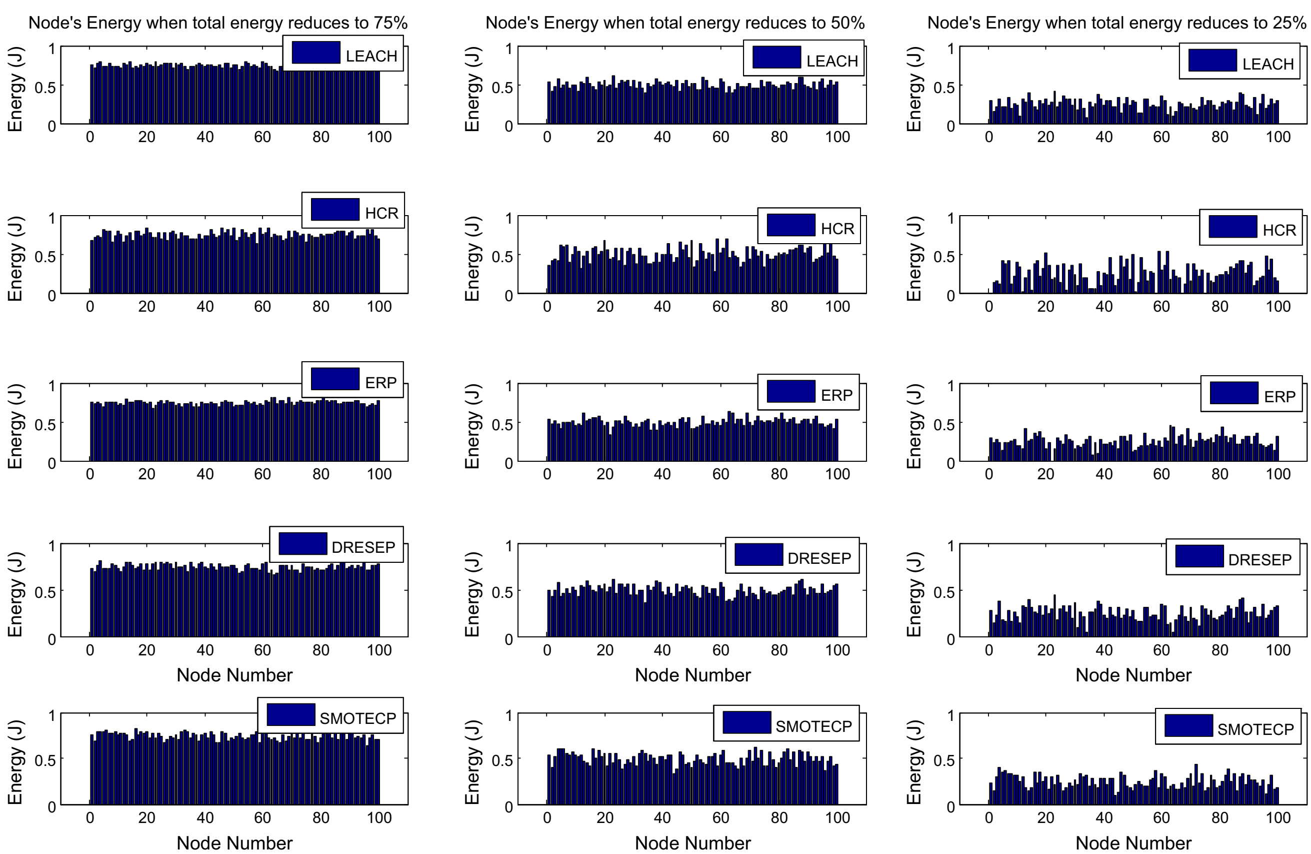


Fig. 6 Energy bar plot for simulated protocols for homogeneous setup

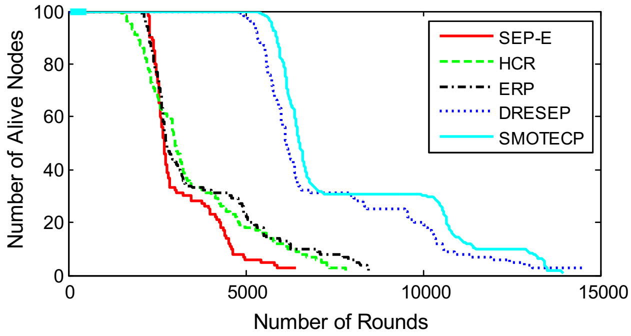


Fig. 8 Number of alive nodes per round for simulated protocols for heterogeneous setup

In homogeneous setup, 100 sensor nodes are randomly deployed in a 100 m × 100 m area with an initial energy of $E_0 = 1$ J. For a sensing field (X_{max}, Y_{max}), the circle of radius R $= \left(\sqrt{X_{max}^2 + Y_{max}^2}\right)/4$ m centred on BS defines the boundary for distant CHs to make a decision for direct or dual-hop communication with BS. In heterogeneous setup, the proportion of advanced and super nodes is set to 20 and 10% respectively of the total nodes. The initial energy of advanced and super nodes is set to 2 and 3 times that of normal nodes. The initial energy of a normal node is set to $E_0 = 1$ J.

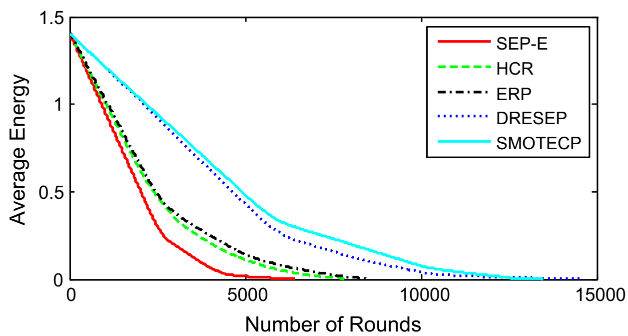


Fig. 9 Average remaining energy per round for simulated protocols for heterogeneous setup

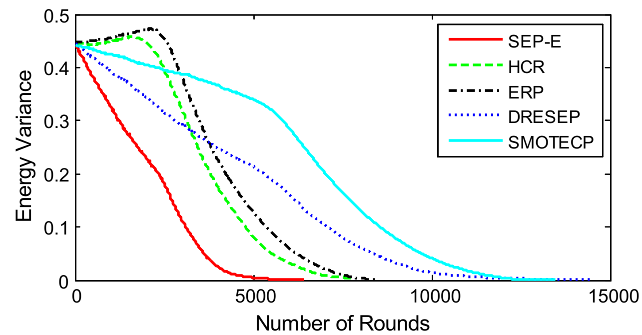


Fig. 11 Energy variance per round for simulated protocols for heterogeneous setup

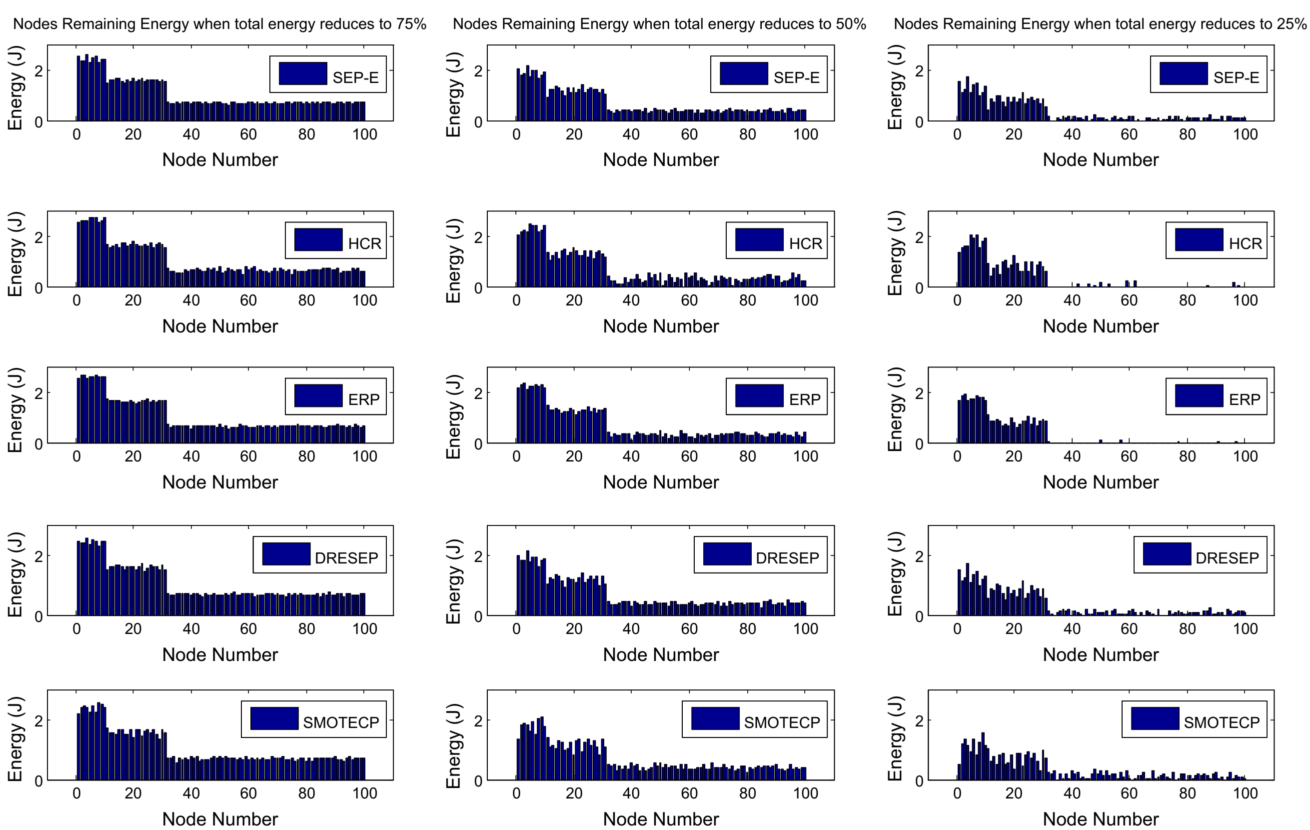


Fig. 10 Energy bar plot for simulated protocols in heterogeneous setup

The effectiveness of binSMO algorithm is first evaluated in the setup phase during cluster formation using voronoi diagrams shown in Fig. 3. The cluster formation of LEACH, HCR and ERP protocols are depicted in Fig. 3(a–c), respectively. The voronoi diagram indicates that the cluster formation in LEACH is not suitable. As shown in Fig. 3(a), some areas contain large clusters and other contain several smaller clusters; therefore, energy consumption in LEACH network is non uniform. On the other hand, HCR and ERP distribute the clusters across the network more evenly, although the number of clusters is more. This causes energy consumption in HCR and ERP to be higher to some extent. The energy consumption in the network increases when the size of cluster is not set properly. The voronoi diagram shows that in SMOTECP (Fig. 3(d)), the clusters are properly and uniformly distributed across the network using the objective function concerned with the quality of cluster as a function of cluster separation and cohesion. Therefore, energy consumption across all the clusters is fairly same because of almost similar sized clusters.

The simulation results of SMOTECP, LEACH, HCR, ERP and DRESEP for homogeneous set up are shown in Fig. 4. Figure 5 shows average energy remaining in the network per round. SMOTECP outperforms LEACH, HCR and ERP by increasing the network lifetime with a considerably higher number of rounds. Firstly, this is because SMOTECP considers residual energy of nodes for CH selection. Therefore, high energy nodes are always selected as CHs and hence it balances the load among nodes in a better way. Secondly, the proposed protocol is event driven protocols in that data transmission is possible when certain conditions are satisfied. Thirdly, the protocol balances the load of CHs by making dual-hop communication between BS and CH as a function of distance. In addition, the cluster formation in SMOTECP is much uniform in comparison to other protocols. In this way, SMOTECP balances the load among sensor nodes in a much better manner than LEACH, HCR and ERP. In comparison to DRESEP, SMOTECP improves the quality of clustering by minimizing the cluster cohesion and maximizing the cluster separation using its fitness function. Also, it attempts to find a better collection of clustered routes that minimizes the overall energy dissipated by the network. Therefore, with regard to the network lifetime, SMOTECP is found to be favorable against DRESEP to some extent.

The time span from initial time to first node dead (FND) is called the stability period of the network. Half node dead (HND) is another measure of network lifetime. It is defined as the time from start to the time when there is half number of nodes remaining in the network. Last node dead (LND) is the network lifetime from start to the time when no alive node remaining in the network. The time difference between FND and LND is termed as instability period. Table 3 presents the round history of dead nodes for homogeneous setup.

The statistics of total number of data packets received at BS for homogeneous setup is given in Table 4. The performance of SMOTECP and DRESEP lags behind LEACH, HCR and ERP with respect to number of packets received at BS. This is expected as SMOTECP and DRESEP only transmits time-critical data while sensing the environment continuously. So, based on the application and the energy constraints, the redundancy in the data transmission can be controlled to achieve higher network lifetime as is the case with SMOTECP and DRESEP.

The effectiveness of SMO algorithm to enhance the coverage in SMOTECP over other protocols can be explained using energy bar plots. The energy bar plots are used to provide the residual energy of each node [14]. For homogeneous setup, the energy-bar plots for simulated protocols are shown in Fig. 6. The energy bar plot for SMOTECP demonstrates more uniform energy depletion as compared to LEACH, HCR, ERP and DRESEP. By restricting CH election criteria to choose the higher energy node, the energy level of all nodes are uniformly preserved throughout the simulation. SMOTECP minimizes the

Table 5 Round history of dead nodes for heterogeneous setup

% Dead nodes	SEP-E	HCR	ERP	DRESEP	SMOTECP
1 (FND)	2269.2	1783.9	2102.5	4846.2	**5267.3**
10	2309.8	2127	2344.5	5331.7	**5875.1**
20	2452.3	2308.9	2473.9	5597.3	**6078.7**
30	2552.8	2469.6	2569.7	5789.4	**6193**
40	2607.1	2647.2	2668.2	5995.9	**6388.2**
50 (HND)	2701.2	2823	2788	6140.2	**6531.7**
60	2790.5	3131	2971.6	6376.4	**6698**
	3251.3	3931.4	4522.9	7920.3	**9984.3**
80	4272.7	4961.2	5203.7	9759.8	**10,666.7**
90	4605.6	6332.4	6310.8	10,568.5	**11,480.5**
100 (LND)	5872.8	8671.7	8306.5	**14,528.1**	13,867.9

Bold values indicate the best value with respect to others

Table 6 Total number of data packets received at BS for heterogeneous setup

Protocol	FND	HND	LND
SEP-E	72, 285.9	86,542.4	1,58,741.3
HCR	69,528.7	88,485.4	**1,67,425.8**
ERP	**75,269.2**	**89,126.9**	1,65,947.6
DRESEP	51,892.7	59,845.3	96,284.3
SMOTECP	53,963.6	61,849.3	97,834.6

Bold values indicate the best value with respect to others

Table 7 Comparison of network lifetime of simulated protocols together with stability and instability periods and number of packets received at BS

Setup No.	Protocol	FND	HND	LND	Stability Period	Instability Period	No. of packet received
Homogeneous Setup	LEACH	1805.2	2215.2	2763.5	1805.2	958.3	84,356.2
	HCR	1726	2524.6	3574.3	1726	1848.3	**89, 782.4**
	ERP	2113.3	2580	3305.9	2113.3	1192.6	88, 892.3
	DRESEP	4101.6	5126.7	6402.2	4101.6	2300.6	56,383.8
	SMOTECP	**4833.3**	**5484.5**	**5765.6**	**4833.3**	**932.3**	57,642.2
Heterogeneous Setup	SEP-E	2269.2	2701.2	5872.8	2269.2	**3603.6**	1,58,741.3
	HCR	1783.9	2823	8671.7	1783.9	6887.8	**1,67,425.8**
	ERP	2102.5	2788	8306.5	2102.5	6204	165,947.6
	DRESEP	4846.2	6140.2	14,528.1	4846.2	9681.9	96,284.3
	SMOTECP	**5267.3**	**6531.7**	13,867.9	**5267.3**	8600.6	97,834.6

Bold values indicate the best value with respect to others

energy variance of the WSN, and hence it provides flat variance plot compared to other protocols as shown in Fig. 7.

The behaviour of SMOTECP protocol for heterogeneous setup is shown in Figs. 8, 9, 10 and 11, and the statistics are given in Tables 5 and 6.

Table 7 presents the number of rounds taken for FND, HND and LND together with stability and instability periods of LEACH, SEP, HCR, ERP, DRESEP and SMOTECP protocols. There is an improvement of 167.74, 180, 128.70 and 17.83% in stability period for SMOTECP as against LEACH, HCR, ERP and DRESEP respectively. Also, the instability period reduces to 2.71, 49.55, 21.82 and 59.47% in comparison with LEACH, HCR, ERP and DRESEP respectively for homogeneous setup. Similarly, for heterogeneous setup, there is an improvement in stability period for SMOTECP in comparison to other protocols.

5 Conclusion

The major design challenges in the research of routing protocols for WSNs are energy management, network lifetime optimization and the stability period. The proposed SMOTECP is well suited for time critical applications like disaster relief applications, logistics and telematics. The protocol considers various parameters namely reduced energy consumption, node residual energy, distance of node to CH and distance between adjacent CHs, and minimum scheduling delay with the aim of optimizing the energy consumption using binSMO. The energy consumption of CHs is further reduced by threshold-based inter-cluster data transmission algorithm. Also, dual-hop communication is employed to improve the load balancing and to minimize the energy consumption of the distant CHs. The simulation results show that SMOTECP protocol can efficiently reduce the energy consumption of nodes and maximize the network lifetime.

Future research work needs to focus on more quality of service (QoS) requirements of WSNs. Furthermore, multi-objective optimization algorithms may be applied to provide higher network stability periods.

References

1. Afsar, M. M., & Tayarani-N, M. (2014). Clustering in sensor networks: A literature survey. *Journal of Network and Computer Applications, 46,* 198–226. doi:10.1016/j.jnca.2014.09.005.
2. Pantazis, N. A., Nikolidakis, S. A., & Vergados, D. D. (2013). Energy-Efficient routing protocols in wireless sensor networks: A survey. *IEEE Communications, Surveys and Tutorials, 15*(2), 551–591. doi:10.1109/SURV.2012.062612.00084.
3. Heinzelman, W. B., Chandrakasan, A., & Balakrishnan, H. (2000). Energy-efficient communication protocol for wireless microsensor networks. In *Proceedings of 33rd annual Hawaii international conference on system sciences* (HICSS-33), IEEE (p. 223). doi: 10.1109/HICSS.2000.926982.
4. Smaragdakis, G., Matta, I., & Bestavros, A. (2004). SEP: A stable election protocol for clustered heterogeneous wireless sensor networks. In *Proceedings of international workshop on SANPA*. http://open.bu.edu/xmlui/bitstream/handle/2144/1548/2004-022-sep.pdf?sequence=1.
5. Qing, L., Zhu, Q., & Wang, M. (2006). Design of a distributed energy-efficient clustering algorithm for heterogeneous wireless sensor network. *Computer Communications, 29,* 2230–2237. doi:10.1016/j.comcom.2006.02.017.
6. Kumar, D., Aseri, T. C., & Patel, R. B. (2009). EEHC: Energy efficient heterogeneous clustered scheme for wireless sensor networks. *Computer Communications, 32,* 662–667. doi:10.1016/j.comcom.2008.11.025.
7. Kumar, D. (2014). Performance analysis of energy efficient clustering protocols for maximising lifetime of wireless sensor networks. *IET Wireless Sensor Systems, 4*(1), 9–16. doi:10.1049/iet-wss.2012.0150.
8. Kang, S. H., & Nguyen, T. (2012). Distance based thresholds for cluster head selection in wireless sensor networks. *IEEE Communications Letters, 16*(9), 1396–1399. doi:10.1109/LCOMM.2012.073112.120450.

9. Tarhani, M., Kavian, Y. S., & Siavoshi, S. (2014). SEECH: Scalable energy efficient clustering hierarchy protocol in wireless sensor networks. *IEEE Sensors Journal, 14*(11), 3944–3954. doi:10.1109/JSEN.2014.2358567.
10. Tyagi, S., Gupta, S. K., Tanwar, S., & Kumar, N. (2013). EHE-LEACH: Enhanced heterogeneous LEACH protocol for lifetime enhancement of wireless SNs. In *Proceedings of international conference on advances in computing, communications and informatics* (ICACCI), August 22–25, 2013, Mysore, India (pp. 1485–1490). doi:10.1109/ICACCI.2013.6637399.
11. Aderohunmu, F. A., Deng, J. D., & Purvis, M. K. (2011). A deterministic energy-efficient clustering protocol for wireless sensor networks. In *Proceedings of 7th international conference on intelligent sensors, sensor networks and information processing* (ISSNIP '11), IEEE (pp. 341–346). doi: 10.1109/ISSNIP.2011.6146592.
12. Manjeshwar, A. & Agrawal, D. P. (2001). TEEN: A routing protocol for enhanced efficiency in wireless sensor networks. In *Proceedings international parallel and distributed processing symposium* (IPDPS'01) workshops, 2001 (pp. 2009–2015), San Francisco, CA, USA. doi: 10.1109/IPDPS.2001.925197.
13. Mittal, N., & Singh, U. (2015). Distance-based residual energy-efficient stable election protocol for WSNs. *Arabian Journal of Science and Engineering, 40*(6), 1637–1646. doi:10.1007/s13369-015-1641-x.
14. Mittal, N., Singh, U., & Sohi, B. S. (2016). A stable energy efficient clustering protocol for wireless sensor networks. *Wireless Networks*. doi:10.1007/s11276-016-1255-6.
15. Adnan, Md A, Razzaque, M. A., Ahmed, I., & Isnin, I. F. (2014). Bio-Mimic optimization strategies in wireless sensor networks: A survey. *Sensors, 14,* 299–345. doi:10.3390/s140100299.
16. Jin, S., Zhou, M., & Wu, A. S. (2003). Sensor network optimization using a genetic algorithm. In *7th World multi-conference on systemics, cybernetics and informatics*, Orlando, FL, USA (pp. 1–6).
17. Hussain, S. & Matin, A. W. (2006). Hierarchical cluster-based routing in wireless sensor networks. In *IEEE/ACM international conference on information processing in sensor networks*, IPSN.
18. Khalil, E. A., & Attea, B. A. (2011). Energy-aware evolutionary routing protocol for dynamic clustering of wireless sensor networks. *Swarm and Evolutionary Computation*. doi:10.1016/j.swevo.2011.06.004.
19. Attea, B. A., & Khalil, E. A. (2012). A new evolutionary based routing protocol for clustered heterogeneous wireless sensor networks. *Applied Soft Computing, 12,* 1950–1957. doi:10.1016/j.asoc.2011.04.007.
20. Rao, P. C., & Banka, H. (2015). Energy efficient clustering algorithms for wireless sensor networks: Novel chemical reaction optimization approach. *Wireless Networks*. doi:10.1007/s11276-015-1156-0.
21. Rao, P. C., & Banka, H. (2016). Novel chemical reaction optimization based unequal clustering and routing algorithms for wireless sensor networks. *Wireless Networks*. doi:10.1007/s11276-015-1148-0.
22. Rao, P. C., Jana, P. K., & Banka, H. (2016). A particle swarm optimization based energy efficient cluster head selection algorithm for wireless sensor networks. *Wireless Networks*. doi:10.1007/s11276-016-1270-7.
23. Shokouhifar, M., & Jalali, A. (2015). A new evolutionary based application specific routing protocol for clustered wireless sensor networks. *International Journal of Electronics and Communications, 69,* 432–441.
24. Bansal, J. C., Sharma, H., Jadon, S. S., & Clerc, M. (2014). Spider monkey optimization algorithm for numerical Optimization. *Memetic Computing, 6,* 31–47.
25. Singh, U., & Salgotra, R. (2016). Optimal synthesis of linear antenna arrays using modified spider monkey optimization. *Arabian Journal for Science and Engineering*. doi:10.1007/s13369-016-2053-2.
26. Singh, U., Salgotra, R., & Rattan, M. (2016). A novel binary spider monkey optimization algorithm for thinning of concentric circular antenna arrays. *IETE Journal of Research*. doi:10.1080/03772063.2015.1135086.
27. Al-Azza, A. A., Al-Jodah, A. A., & Harackiewicz, F. J. (2015). Spider monkey optimization: A novel technique for antenna optimization. *IEEE Antennas and Wireless Propagation Letters*. doi:10.1109/LAWP.2015.2490103.
28. Karl, H., & Willig, A. (2005). *Protocols and architectures for wireless sensor networks*. New York: Wiley.

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