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ORIGINAL RESEARCH

Designing of energy efficient stable clustering protocols based on BFOA for WSNs

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Abstract

Efficient clustering method can competently scale down the energy consumption of sensor nodes (SNs) in wireless sensor networks (WSNs). Selection of the best-suited SNs for the role of cluster heads (CHs) can lead to effective clustering process. In past few decades, a number of clustering protocols have been designed to handle these issues in distributed WSNs. However, most of these employed estimation/randomized algorithms for CH selection due to lack of globalized energy awareness problem in distributed WSNs. This paper resolves the problem by using proposed *Modified Intelligent CH election based on Bacterial foraging optimization algorithm (M-ICHB)*, which searches actual higher residual energy SNs for CH selection in distributed WSNs. M-ICHB algorithm does not require any estimation/randomized algorithms during CH selection process, which resolves the issue of energy unawareness problem in the WSN. Moreover in general, most of the existing clustering algorithms have been designed either for homogeneous or heterogeneous WSNs. However in contrary, proposed M-ICHB algorithm is designed for both homogeneous as well as heterogeneous WSNs in this paper. Furthermore, in many critical applications i.e., military surveillance, traffic management, natural disaster forecasting and structural health monitoring; reliability of data from each SN is the most crucial aspect. In this prospect, elongated stability region (from the network initiation till first node dies) of the network is the prime necessity. For this, we have applied proposed M-ICHB algorithm on conventional stability based clustering protocols i.e., LEACH, SEP and DEEC and proposed *M-ICHB based stable protocols* viz MILEACH, MIrLEACH, MISEP and MIDEEC protocols. Simulation results confirm that proposed MILEACH, MIrLEACH, MISEP and MIDEEC protocols are capable in searching actual higher residual energy nodes for CH selection without using any estimation/randomized algorithm, while maintaining distributive nature of WSNs. Moreover, these offer better stability region, stable CH selection in each round and higher number of packets reception at base station (BS) in comparison to LEACH, SEP and DEEC protocols. Further, MILEACH and MIrLEACH improve the stability region by 53 and 58% and number of packets received at BS by 91 and 97% respectively in comparison to LEACH. Furthermore, MISEP and MIDEEC improve 52 and 21% in stability region and 82 and 188% in number of packets received at BS in comparison to SEP and DEEC protocols.

Keywords Wireless sensor networks · Clustering · Network lifetime · Stability region · ICHB algorithm · Bacterial foraging optimization algorithm

1 Introduction

Past few years have witnessed great technological advancements in the field of very-large-scale-integrated (VLSI) circuits, micro-electro-mechanical systems (MEMS) and hardware of battery operated devices. This endowed the development of low-powered, tiny-size battery embodied sensor nodes (SNs) proficient in monitoring different phenomena like temperature, light, humidity, motion, vibration etc. (Akyildiz et al. 2002). These SNs typically comprise of three elementary principles: sensing data from physical

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environment, computational processing on local data and communication capabilities for data transmission wirelessly (Anastasi et al. 2009).

Hundreds or thousands of such SNs, when deployed in unstructured infrastructure for monitoring in a particular area, comprise a wireless sensor network (WSN). These SNs are expertised to conduct their tasks for prolonged period of time in hostile, challenging and extremely sensitive environments; where there is a limited access to human beings. WSNs are immensely demanding in critical applications such as military or battlefield surveillance, target tracking, traffic management and monitoring, natural disaster forecasting, environmental monitoring and structural health monitoring (Akyildiz et al. 2002; Singh et al. 2017).

With the fact that each SN is bestowed with limited power resource, the lifetime of WSN is limited. This gives birth to the prime necessity of designing energy efficient protocols that can prolong each individual SN's lifetime in the network. In this context, clustering procedures play a key role in designing such efficient protocols. In clustering approaches, organizing these SNs into small sub-groups to form clusters in the network have been widely practiced and appreciated by the research community in past two decades. Each cluster is governed by a cluster head (CH) that works as an intermediate node for communication and data transmission between SNs and base station (BS). Proper clustering procedure provides benefits in maintaining energy efficient consumption among SNs in the network. Instead of wasting energy in direct communication to the BS, SNs send their sensed data to their CHs that combine these data packets into a meaningful information by applying some mathematical operations such as aggregation, fusion etc. and further forward these packets to the BS through multi-hop or direct communication. This process saves a huge amount of energy dissipation of each SN, reduces excessive message forwarding towards the BS and retains network alive for longer timespan (Heinzelman et al. 2000; Mhatre and Rosenberg 2004; Afsar et al. 2014).

In past recent years, various energy efficient protocols have been designed for either homogeneous or heterogeneous networks. Conventionally, homogeneous networks comprise of SNs possessing same energy resources at the beginning of network whereas in heterogeneous networks, SNs are equipped with varying energy resources. A homogeneous model is a special kind of WSN possessing same energy resources by each SN at the beginning but later transforms into heterogeneous model once the network executes. Because each SN cannot dissipate same amount of energy resource due to radio communication characteristics, occurrence of random events or morphological characteristics of the network field. Notably, it shows a great challenge to design energy efficient protocols which can proficiently work for both homogeneous and heterogeneous networks (Smaragdakis et al. 2004; Qing et al. 2006; Sharma and Sharma 2016). In this paper, we have proposed algorithms considering for both homogeneous as well as heterogeneous network models.

All potential clustering protocols can be categorized into centralized or distributed WSN models. In centralized models, main events i.e., clustering procedure, network partitioning, searching CHs or finalizing optimal number of CHs are controlled by a powerful node like BS. However, this approach has some serious flaws i.e., knowledge requirement of whole network, nodes' energy awareness to the powerful node, failure of the powerful node can potentially shut down whole network drastically, scalability issues in large networks etc. Notably resolving these issues competently, distributed WSN models have gained much more popularity in network modelling (Qing et al. 2006; Afsar et al. 2014). However due to nodes' energy unawareness problem in distributed model, most of the protocols have to use some kind of estimation/randomized algorithms for electing CHs, which still indicates a major scope of refinement in this model.

In recent years, use of meta-heuristic optimization algorithms has significantly attracted many researchers because of their capabilities to find optimum solution and resolving complex uncertainties in any domain (Adnan et al. 2014). Even in WSN field, these algorithms are able to generate proficient solutions i.e., better routing path, proper coverage, fault-tolerant networks, formation of optimal number of clusters and designing energy efficient networks. Optimization techniques such as particle swarm optimization (PSO) (Kennedy and Eberhart 1995), bacterial foraging optimization algorithm (BFOA) (Passino 2002), ant colony optimization (ACO) (Dorigo and Di Caro 1999) and artificial bee colony (ABC) (Karaboga and Basturk 2007) etc. have handled such issues competently and produced better results in comparison to conventional algorithms. Numerous clustering protocols have been designed based on these optimization algorithms, where most of these follow centralized approach. Notably, clustering algorithms with centralized approach have scalability issues (Zungeru et al. 2012; Afsar et al. 2014). With this fact, designing a meta-heuristic based clustering algorithms with distributed approach showed greater confidence in providing better solution to the WSNs.

Reliability of data is a very crucial aspect in many applications i.e., military surveillance, traffic management, natural disaster forecasting and structural health monitoring. In this context, data must be propagated from each SN for prolonged period of network execution. Moreover, efficient clustering protocols must offer maximum stability region (from network initiation till first node dies) to satisfy such requirements. If network is efficiently designed, all SNs may last approximately for same span in the network, in others words all SNs may die at the same time (Qing et al.

2006). The well-known clustering protocols which work on the stability region are LEACH (Heinzelman et al. 2000), SEP (Smaragdakis et al. 2004) and DEEC (Qing et al. 2006) and referred as stability based clustering algorithms. Meanwhile, these also suffer from energy unawareness problem of distributed WSNs, due to which the CH selection process in these protocols is on the basis of estimation/randomized algorithms.

In this paper, *firstly*, we propose Modified ICHB (M-ICHB) algorithm, an extension of one of the recent bio-inspired technique i.e., Intelligent CH election based on BFOA (ICHB) algorithm (Gupta and Sharma 2017). Here, we employ M-ICHB algorithm with distributed approach on stability based clustering algorithms to provide solution to energy unawareness problem of distributed WSN models. Furthermore, by applying M-ICHB algorithm, we are able to identify the best SNs (in terms of energy) in the network, which may behave as CHs and generate an optimal set of CHs covering whole network field effectively. This improves the design of stability based clustering protocols, while maintaining the distributed nature of WSNs. *Secondly*, we have observed that the most of the existing clustering techniques have been designed for either homogeneous or heterogeneous networks. However, our M-ICHB based clustering approach is well-suited for both kind of networks. *Thirdly*, employing proposed M-ICHB algorithm on LEACH, SEP and DEEC protocols results in proposed *M-ICHB based stable protocols* i.e., M-ICHB based LEACH (MILEACH) protocol, M-ICHB based refined LEACH (MIrLEACH) protocol, M-ICHB based SEP (MISEP) protocol and M-ICHB based DEEC (MIDEEC) protocol. These protocols are featured with improved clustering procedures, capable in searching actual higher residual energy nodes for CH selection without using estimation/randomized algorithms, fully distributive in nature, provide elongated stability region, maintain stable CH selection in each round and allow higher number of packets reception at the BS in comparison to LEACH, SEP and DEEC protocols.

Rest of the paper is arranged as follows: Sect. 2 gives a brief about related work. Section 3 explains network model required for our work. Section 4 explains proposed work that includes M-ICHB algorithm and M-ICHB based stable protocols. In Sect. 5, we describe the simulation based results and discussions of proposed M-ICHB based stable protocols in comparison to conventional stability based clustering algorithms and at last, in Sect. 6 we conclude the paper.

2 Related work

In past two decades, number of clustering protocols have been proposed by various authors with efficient results in diverse WSN's domain. These protocols are categorized into two kinds of WSNs, i.e., homogeneous WSNs and heterogeneous WSNs (Qing et al. 2006).

Initially, clustering protocols have been designed for homogeneous networks such as LEACH (Heinzelman et al. 2000), LEACH-C (Heinzelman et al. 2002) and PEGASIS (Lindsey and Raghavendra 2002) etc. LEACH is one of the earliest and renowned distributed clustering protocols in WSNs. LEACH evolves distributed dynamic selection of CHs based on random probabilistic approach and permits uniformity for each SN to become CH in varying rounds. LEACH operates in two phases: (1) set-up phase and (2) steady-state phase. In the set-up phase, all SNs participate in the process of cluster formation, where each SN is allowed to choose a randomized value between 0 and 1. Based on elected value, each SN decides to become CH for the current round and executes cluster formation phase in the network. This decision is influenced by various factors like predetermined fraction of SNs, number of times a SN elected as CH and threshold value. Once the clusters are formed, steady-state phase starts, where each SN senses its environment and transmits data to the CH. On receiving these data packets, CHs aggregate them and send to the BS directly in single-hop. However, LEACH has some major drawbacks. First, due to probability based CH selection, non-eligible CH nodes are elected all through different rounds that put adverse effect on network lifetime. Second, considering no energy parameter, lower energy SNs are equally eligible for CH selection that makes network inefficient. Third, due to equal weightage CH election scheme, no CH is selected for many rounds especially in later half of network execution. In addition, no data is sent to the BS during these rounds which makes it highly vulnerable for time-critical applications, where continuous data reception from network is utmost essential.

A number of refinements have been reported by various authors to resolve these shortcomings of LEACH. In Heinzelman et al. (2002), authors proposed LEACH-C based on centralized approach for CH selection by BS itself. In this approach, residual energy of each SN and its location was sent to the BS. Based on received information, BS excluded lower residual energy SNs for CH selection procedure. However due to centralized approach, LEACH-C protocol had scalability issues. In LEACH-M (Mhatre and Rosenberg 2004), a multi-hop scheme was proposed to investigate the performance of LEACH under single-hop versus multi-hop communication. In Lindsey and Raghavendra (2002), authors proposed PEGASIS, which is an extension of LEACH. Here, SNs were structured into a chain. Each SN can only communicate to its neighbor node in chain. Using chain, all SNs transmitted their data via neighboring nodes to one leader node, which further propagated data to the BS. The energy consumption of SNs in PEGASIS was lower as compared to LEACH, however data delay was much higher. With this fact, it is not suitable for large-sized networks.

In last decade, number of clustering protocols have been designed for heterogeneous WSNs. SEP (Smaragdakis et al. 2004) is one of the earliest heterogeneous clustering protocols based on LEACH which defines two level of nodes heterogeneity in terms of energy. Implementing two energy levels, SNs are classified in normal and advanced nodes. A fraction of m SNs consisting α times more energy than normal nodes is defined as advanced nodes. Consequently, advanced nodes are more desirable to become CHs in comparison to normal nodes due to their enhanced energy level. SEP provides better stability region in the network as compared to LEACH. However, SEP suffers from same problems of LEACH. First, considering no energy parameter, lower energy SNs are equally eligible for CH selection. Second, due to equal weightage CH election scheme, no CH is selected for many rounds especially in later half of network execution same as LEACH. Third, SEP is not applicable for multi-level heterogeneous model because it is specifically designed for two-level heterogeneous WSNs.

Influencing heterogeneity in LEACH, DEEC (Qing et al. 2006) is based on referential residual energy of each SN instead of providing pre-determined chance in rotating epoch for CH selection. DEEC uses the probability ratio of each SN's residual energy and estimated average energy of network for CH selection. DEEC provides better longevity to stability region in the network as compared to LEACH and SEP. Nevertheless, DEEC has some weaknesses. First, DEEC uses a particular algorithm to estimate the ideal network lifetime required to compute the estimated residual energy of each SN. Second, it requires estimation of average energy of network to compute the probability for CH selection. Although accurate estimation of network lifetime and average energy of network are not possible in actual deployment scenario due to radio communication characteristics, occurrence of random events or morphological characteristics of network field. These shortcomings of DEEC provide inefficient results in real deployment of WSNs.

Zhou et al. (2010) proposed EDFCM a stable selection and reliable transmission based protocol for two-level heterogeneous WSNs using residual energy and energy consumable rate metrics of all SNs. EDFCM used a first-order energy consumable forecast for energy consumption model during CH selection. For this, it required average energy consumption approximation of next round and whole network lifetime, which was hard to predict and may result in deviated outcomes. Liu et al. (2012) proposed DEECIC clustering protocol based on improved coverage, assignment of unique ID to each SN and periodically updated CH according to the nodes' residual energy and distribution information. SEARCH (Wang et al. 2015) offered a semi-centralized CH selection procedure by modifying threshold value of each SN and provided better stable region in the network. Tao et al. (2015) proposed EESSC protocol that worked on clustering process using special packet based on updates of each sensor node's residual energy during data transmission in the network. Lin et al. (2015) proposed an energy efficient clustering approach by partitioning a large scale WSN into fan-shaped clusters. Salim and Osamy (2015) proposed a chain based routing algorithm using compression and data aggregation techniques. By applying this procedure, authors tried to provide even energy consumption among SNs, minimized data traffic in the network and prolonged the lifetime of WSNs.

Numerous clustering and routing protocols have been designed by various authors using diverse meta-heuristic optimization algorithms that enhanced the performance of conventional protocols and provided the efficient results in the field of WSNs. Selvakennedy et al. (2007) discussed a meta-heuristics clustering protocol T-ANT based on ACO to determine optimal number of CHs and efficient clustering procedure in the WSN. Ziyadi et al. (2009) discussed an energy-aware clustering protocol ACO-C that used cost functions at BS to distribute and minimize the cost involving in long distance transmission and data aggregation among SNs. Karaboga et al. (2012) proposed an energy efficient clustering technique based on artificial bee colony algorithm to extend the lifetime of WSNs. Sahoo et al. (2016) proposed TRUST model with honey bee mating algorithm in prevention of malicious nodes to become CHs. This approach showed more secure and efficient clustering results in WSNs. Mohajerani and Gharavian (2016) discussed LTAWSN routing algorithm based on ACO. In this, a new parameter based on pheromone update was introduced, which helped to reduce the energy consumption of SNs in the network. Ni et al. (2017) proposed a multi-swarm PSO based on dynamic deployment strategy of SNs to enhance the network performance in terms of better coverage and lower energy consumption rate.

BFOA (Passino 2002) is one of the emerging meta-heuristics algorithms in the field of WSNs. It is inspired by social behavior of bacteria which is based on searching nutrient gradient in the network field. In Li et al. (2010), authors proposed a Low Energy Intelligent Clustering Protocol (LEICP), an improvement on LEACH based on positioning of CHs by means of BFOA. Gaba et al. (2011) discussed a technique for finding optimal coordinates for SN deployment in WSN by applying BFOA. Pitchaimanickam and Radhakrishnan (2013) discussed BFA-LEACH-C, a CH selection scheme based on BFOA and showed improved results in comparison to LEACH-C. However, firstly, the procedure used by BFA-LEACH-C in implementing BFOA involved more time and high complexities in its execution. Secondly, it was implemented with centralized approach which causes the scalability issues. Recently, Gupta and Sharma (2017) presented ICHB algorithm for searching better CH nodes (in terms of residual energy) in WSNs by simplifying BFOA to a great extent. ICHB algorithm proficiently reduced the complex functioning of BFOA for WSN and minimized the time complexity involved in it. Authors had implemented ICHB algorithm for Optimized HEED protocols and showed competent results in increasing the lifetime of WSNs. In this paper, we extend ICHB algorithm to propose M-ICHB algorithm for improving stability based clustering protocols i.e., LEACH, SEP and DEEC to overcome their shortcomings.

3 Network model

This section explains network modeling assumptions required by proposed M-ICHB based stable protocols for both homogeneous as well as heterogeneous networks.

3.1 Homogeneous network model

Here, we outline the assumption for homogeneous WSN model. For our work, N number of SNs are deployed uniformly in $M \times M$ square field. All SNs are stationary after the deployment. Each SN consists a unique identification number (IDN). Being unequipped with global positioning system (GPS) antenna, all SNs are location un-aware. Each SN is equipped with same energy level E_0 at the beginning of network. Each SN has similar sensing, processing and communication capabilities. Once deployed in network, SNs are left unattended and there is no provision to recharge their batteries. Maintaining general standards, BS is situated in the midst of the WSN field and have adequate resources in terms of energy and computations.

3.2 Heterogeneous network model

Here we describe the assumptions required for two-level and multi-level heterogeneous model used in WSN.

In two-level heterogeneity model, two types of SNs i.e., normal nodes and advanced nodes are deployed in the network field. SNs equipped with initial energy E_0 are said to be normal nodes, whereas SNs with initial energy of $E_0(1+\alpha)$ are labeled as advanced nodes. With fraction of m, advanced nodes own α times more energy than normal nodes. Therefore, WSN has mN number of advanced nodes and $(1-m)N$ number of normal nodes respectively. Considering the assignment of initial energy levels of different types of SNs, total initial energy of two-level heterogeneous network is given in Eq. (1). It shows that this specific network type consists αm times more energy level and virtually αm more SNs than homogeneous WSNs (Qing et al. 2006).

$$\begin{aligned} E_{tot_{twolevel}} &= (1-m)N \times E_0 + mN \times E_0(1+\alpha) \\ &= (1+\alpha \times m)N \times E_0 \end{aligned} \tag{1}$$

In multi-level heterogeneity model, each SN is equipped with varying initial energy level under the close-set of $[E_0, E_0(1+\alpha_{max})]$, where E_0 defines the lower boundary limit and parameter α_{max} (i.e., α_{max} is constant and $\alpha_{max} > 0$) helps in determining maximal value of energy. At the beginning of network, each SN k_i is assigned with initial energy of $E_0(1+\alpha_i)$. It shows that SN k_i has α_i times more energy with respect to lower boundary limit of E_0. Considering the assignment of initial energy levels for different types of SNs in multi-level heterogeneity, total initial energy of the network (Qing et al. 2006) is given by,

$$E_{tot_{mullevel}} = \sum_{i=1}^{N} E_0(1+\alpha_i) = E_0(N + \sum_{i=1}^{N} \alpha_i) \tag{2}$$

4 Proposed work

Designing a network architecture aimed to collect data from a target domain, N number of tiny sized SNs are dispersed in a square network field. At the beginning of network, BS broadcasts a *HELLO* beacon message expected by each SN $k_i, (1 \le i \le N)$ in the network. Furthermore, a $HELLO_{neighbor}$ beacon message is propagated by each SN in its communication range. By means of these beacon message exchange, each SN is able to diagnose its distance from BS and neighboring nodes in its proximity.

A set of cluster heads S_{CH} has been identified for each round during cluster formation phase covering whole network field using proposed *M-ICHB algorithm* in each of the designed *M-ICHB based stable protocols*, discussed in Sects. 4.1 and 4.2 respectively.

There is a restriction that each SN can become a part of maximum one cluster administered by a cluster head CH_j $(1 \le j \le S_{CH})$ nearest to it. After cluster formation phase for a particular round; data sensing, collection and forwarding phase is initiated in the network. Here, each SN is allowed to sense its surroundings (i.e., for humidity, temperature, vibration etc.), collects the data and forwards it to the respective CHs. After reception of data packets, CHs use automated method of combining or aggregating the raw data into a meaningful information and forward it to the BS directly in single-hop transmission. Eventually, whole network information is with the BS for data analysis and decision-making purpose.

Notably, M-ICHB based stable protocols consist of two different categories of protocols i.e., for homogeneous WSNs and heterogeneous WSNs. For homogeneous networks, M-ICHB based stable protocols include MILEACH and MIrLEACH protocols whereas for heterogeneous networks, it includes MISEP and MIDEEC protocols. The complete flowchart of proposed protocols is described in Fig. 1

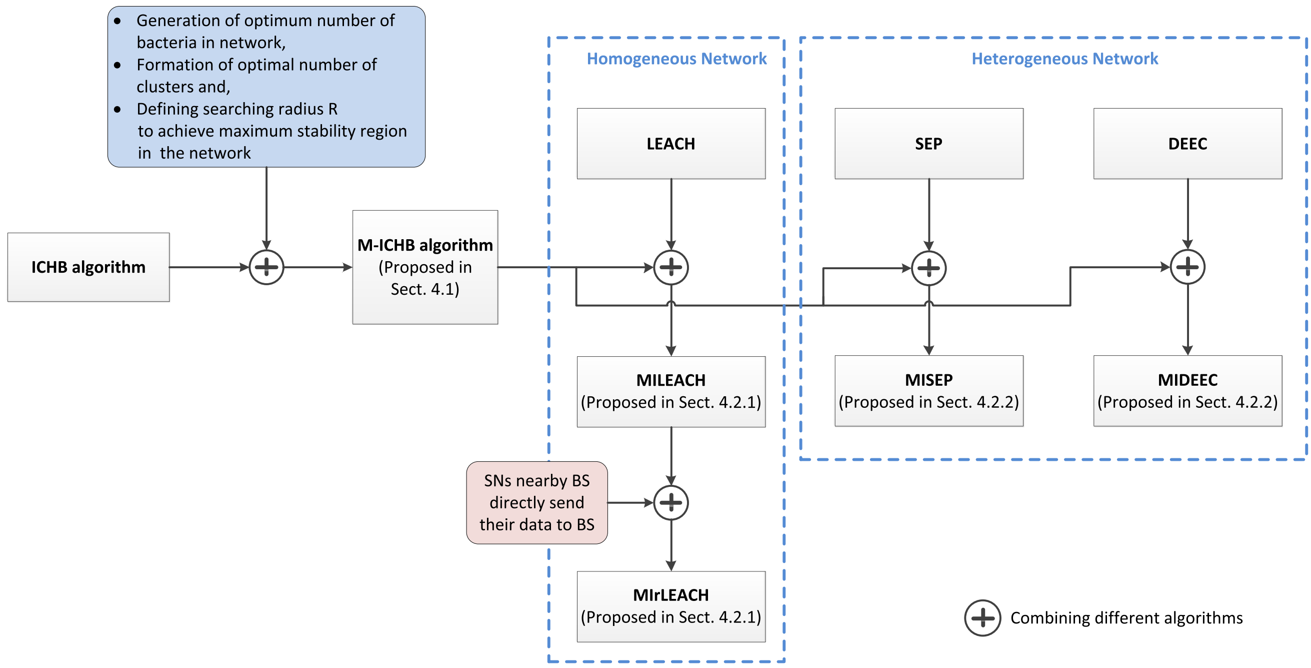

Fig. 1 Complete flowchart of proposed protocols

4.1 Modified ICHB (M-ICHB) algorithm

In M-ICHB algorithm, we extend the capabilities of ICHB algorithm (Gupta and Sharma 2017) in searching better CH nodes for generating better stability region in the WSNs. It is applicable on both homogeneous as well as heterogeneous networks while maintaining the distributed nature of WSNs. SNs with higher residual energy are searched by M-ICHB algorithm, which work as CH nodes in the network.

M-ICHB algorithm is based on Bacterial Foraging Optimization Algorithm (BFOA) (Passino 2002). It works on swarm intelligence of *Escherichia coli* (*E. coli*) bacteria. This technique relies on the computational modeling of real bacterium movement. Being capable in movement using tensile flagella, *E. coli* bacterium swims from lower to higher nutrient level in search of better nutrient concentration. With this fact, BFOA has excellent capabilities to discover global optimum value in any domain, which makes it reliable in place of conventional searching algorithms.

4.1.1 M-ICHB algorithm mode of operation

Using M-ICHB algorithm, our prime motive is to identify the better energy cost nodes $E(\Psi)$, where Ψ represents the IDN of each SN in the network. In evolution of this algorithm, we require *chemotaxis* mode of operation (Passino 2002), where artificial bacterium (i.e., a kind of control message) shifts from one SN to another in search of higher nutrient concentration (i.e., better energy cost node) in the network.

In primary phase, initialize the location of each bacterium $L(g) = \{\Gamma^b(g) | b = 1, 2, \ldots, P\}$ in population P at g-th chemotactic step. $E(b, g)$ indicates the energy cost function corresponding to the SN at which $\Gamma^b(g)$ bacterium is positioned. Notably, E is termed both as *nutrient function* (in biological prospect) as well as *energy cost function* (in optimization based theory).

Under *chemotaxis procedure*, M-ICHB algorithm requires only one mode *swim* that helps in shifting the population of artificial *E. coli* bacteria on different SNs one after another in a concerned specific region. It works for searching better energy cost nodes which may behave as CHs for current round in the network.

In the beginning of each round, SNs apply probability $BACT_{prob}$ for initiating a population of bacteria P randomly in the network field.

The position of each bacterium is characterized by Gupta and Sharma (2017),

$$\Gamma^b(g) = \Psi^b(IDN) \tag{3}$$

where, $\{b = 1, 2 \ldots, P\}$ indicates b-th bacterium at g-th chemotactic step and Ψ^b symbolizes the IDN of that SN at which b-th bacterium resides.

After initiation of bacteria in network, random vector $\mu(b)$ corresponding to each b-th bacterium is procreated containing the IDNs of SNs i.e., $\Psi_{rv}(IDN)$ that fall under the searching radius R_s of Ψ^b SN at which b-th bacterium is initialized and $\{rv = 1, 2, \dots, n\}$ symbolizes total number of SNs in random vector $\mu(b)$. The movement of each bacterium under g-th chemotactic step is shown as (Gupta and Sharma 2017),

$$\Gamma^b(g+1) = [\Psi^b_{rv+1}(IDN)]^{\mu(b)} \tag{4}$$

where, Ψ^b_{rv+1} signifies shifting of b-th bacterium on other SNs $\{rv+1, \dots, n\}$ in random vector $\mu(b)$.

In each random vector $\mu(b)$, bacterium b moves from one SN to another in search of better energy node, stores the energy cost $E(b, g)$ of last visited SN in variable E_{last} along with its IDN value under g-th chemotactic step. If bacterium identifies the better cost node, it updates the current value of E_{last} with $E(b, g+1)$ and stores its IDN value. Else, it moves on next SN in random vector $\mu(b)$ for further search.

4.1.2 M-ICHB algorithm parameters metric for WSNs

Let us outline the various parameters metric necessary for the implementation of M-ICHB algorithm. P denotes the population of bacteria in WSN field, C_s signifies required chemotactic steps, S_l symbolizes length of swim by each bacterium in a chemotactic step and R_s indicates defined searching radius for b-th bacterium in search of better residual energy nodes. To attain proficient outcomes, we have configured these parameters conferring to our network requisite. Their optimum initialization values for M-ICHB algorithm are listed in Table 1.

During searching process, each bacterium swims across every SN in its random vector $\mu(b)$ in a chemotactic step. Due to this, number of chemotactic steps i.e., $C_s = 1$ is sufficient to complete this process.

Furthermore, the population of bacteria P must be able to search better energy cost SNs with less complication. Moreover, maintaining optimal number of clusters c_{opt} in the network to provide elongated stability region, the confined value of P is considered $0.25 \times N$, where N represents total number of SNs in the network.

4.1.2.1 Optimal number of clusters Formation of optimal number of clusters c_{opt} in the network is an important aspect. However, if the clusters are not constructed in optimal way, total energy consumption increases exponentially, which negatively affects the network lifetime. Figure 2 shows an instance of cluster formation in a specific round for SEP and DEEC. Here, it can be seen that many clusters are having large cluster size (in terms of area). With this effect, many SNs have to send their data to distant located CHs (marked in red). Due to which energy dissipation by each individual SN becomes too high that puts a great negative impact on network stability region. Moreover, less number of CHs also cause large cluster size (in terms of density), which put additional workload of data processing on few of such CHs. This becomes a crucial aspect for fast energy dissipation by such CHs, which arises the condition of early death of these CHs, which leave network unstable. However, use of higher number of clusters in network can easily resolve these problems.

Let us assume an area of $M \times M$ square region with uniformly distributed N number of SNs and BS is placed at center of the field for simplicity. The optimal number of clusters c_{opt} can be obtained by (Amini et al. 2012; Kumar et al. 2014),

$$c_{opt} = \sqrt{\frac{90 \times N \times \epsilon_{fs}}{7 \times \pi \times M^2 \times \epsilon_{mp}}} \tag{5}$$

where, ϵ_{fs} and ϵ_{mp} are referred as amplifying indexes based on free space and multipath fading channel models. Here, the area of square field is defined as $100 \times 100m^2$; total number of SNs, N are considered as 100 and the value of $\sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}$ results 87.7. By employing these values in Eq. (5), c_{opt}

Table 1 Initialization parameters of M-ICHB algorithm for stable protocols

Parameter description	Value
Population of bacteria (P)	$BACT_{prob} = 0.25 \times N$
Required number of chemotactic steps (C_s)	1
Length of swim (S_l)	Number of SNs in random vector $\mu(b)$
Searching area of radius (R_s)	$17m$

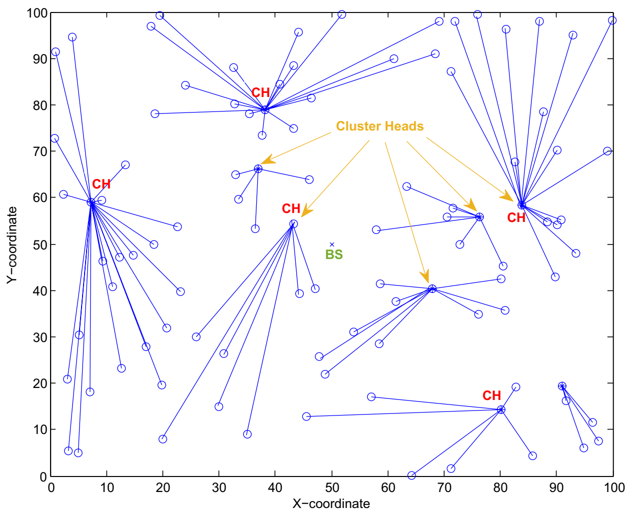

Fig. 2 Graphical representation depicting the problem causes due to improper number of clusters in the network

outcomes 17.74 ($\approx$ 18). Therefore, the optimal number of clusters c_{opt} required for our work is considered as 18.

Based on Eq. (5), the optimal probability of a SN to become a CH σ_{opt} is as follows,

$$\sigma_{opt} = \frac{c_{opt}}{N} \tag{6}$$

Proposed M-ICHB based stable protocols maintain higher number of clusters with optimal count c_{opt} to get the proficient stability region as the desired outcome. Figures 4 and 5 show the cluster formation in a specified round by proposed protocols for both homogeneous and heterogeneous network models. In these figures, cluster size remains small and no SN is associated to distant CH for data transmission, while maintaining higher number of clusters in the network. This approach helps in reduction of energy consumption by each individual SN and CH to a great extent which helps to prolong stability region in the network.

4.1.2.2 Defining searching radius (R_s) To find the optimal value of searching radius R_s for each bacterium, the prime aspect is to define the cluster size of area $A_{cluster}$ with its radius $R_{cluster}$. Once these values are finalized, the searching radius R_s of each bacterium can be easily identified.

Considering the area of $M \times M$ square field with BS at center. Notably, a set of optimal number of clusters c_{opt} is required to cover N number of SNs deployed in the network field. For this, assume a hypothetical circle (inner circle) with radius R_{IC} keeping BS at center touching the periphery of square field as shown in Fig. 3. The area of hypothetical inner circle A_{IC} is given by,

$$\begin{aligned} A_{IC} &= \pi R_{IC}^2, \\ A_{IC} &= \pi \left(\frac{M}{2} \right)^2 \end{aligned} \tag{7}$$

However, the hypothetical circle A_{IC} leaves some area uncovered, as seen in Fig. 3 (with dashed area). Consider another hypothetical circle (outer circle) with radius R_{OC} touching the corners of the square field. The area of hypothetical outer circle A_{OC} is given by,

$$\begin{aligned} A_{OC} &= \pi R_{OC}^2, \\ A_{OC} &= \pi \left(\frac{M}{\sqrt{2}} \right)^2 \end{aligned} \tag{8}$$

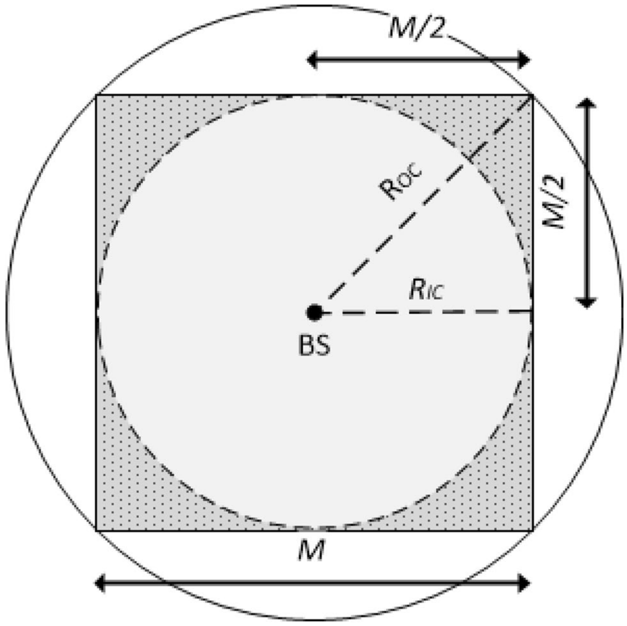

Fig. 3 Coverage representation of a square field using hypothetical circles

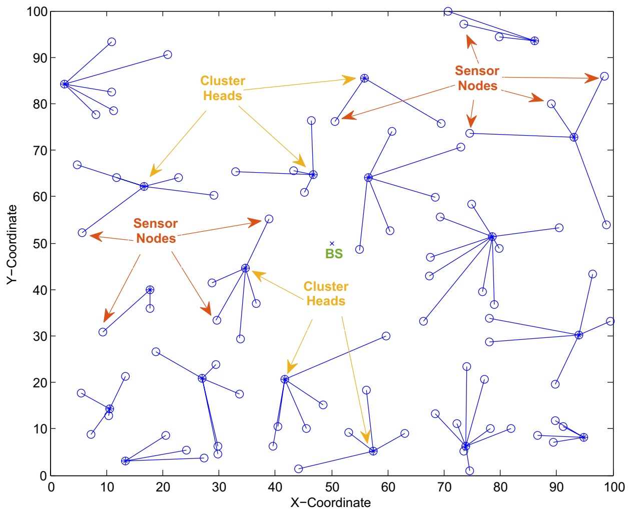

Fig. 4 Network clustering by MILEACH protocol in homogeneous WSN

Figure 3 shows that hypothetical outer circle covers the square sensing field competently for data sensing. With this reason, the total sensing area required to be covered by A_{OC} (Kumar et al. 2014).

The optimal number of clusters c_{opt} required to cover the desired area are calculated by using Eq. (5). Therefore, the area covered by each cluster $A_{cluster}$ is given by,

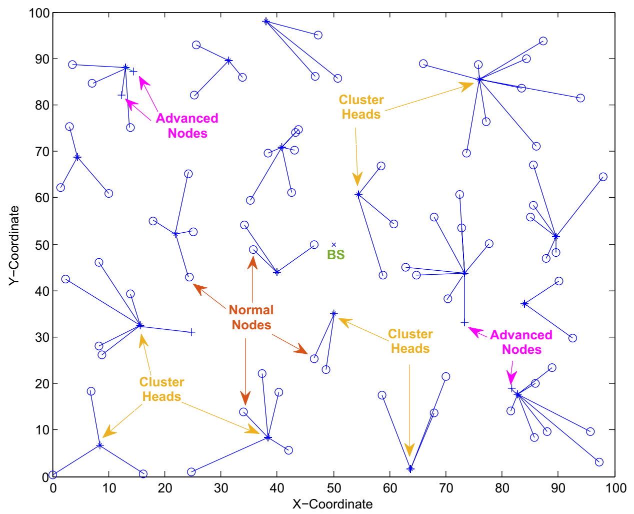

Fig. 5 Network clustering by MISEP in two-level heterogeneous WSN

$$A_{cluster} = \frac{A_{OC}}{c_{opt}},$$

$$\pi R_{cluster}^2 = \frac{\pi (M/\sqrt{2})^2}{\sqrt{\frac{90 \times N \times \epsilon_{fs}}{7 \times \pi \times M^2 \times \epsilon_{mp}}}} \tag{9}$$

Using Eq. (9), the effective cluster radius $R_{cluster}$ can be derived as,

$$R_{cluster} = \sqrt{\frac{(M/\sqrt{2})^2}{\sqrt{\frac{90 \times N \times \epsilon_{fs}}{7 \times \pi \times M^2 \times \epsilon_{mp}}}}} \tag{10}$$

Here, we assume that the square field is $100 \times 100m^2$ with BS at center. The quantity of SNs in the field is $N = 100$. The value of $\sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}$ results 87.7. Equating these values in Eq. (10), cluster radius $R_{cluster}$ comes nearby $17m$.

Based on calculated value of cluster radius $R_{cluster}$, each bacterium searches for better residual energy node in searching area with radius $R_s = R_{cluster}$.

The complete procedure of M-ICHB algorithm is conferred in Algorithm 1.

Algorithm 1 Modified ICHB (M-ICHB) algorithm for WSNs

(1) Let us initialize parameters P, C_s, S_l required for functioning of M-ICHB algorithm for WSN.
(2) To acquire optimal number of clusters c_{opt}, originate population of bacteria P with probability $BACT_{prob}$ in WSNs.
(3) Initialize positions of bacteria Γ^b, $\{b = 1, 2, ..., P\}$ on few SNs in sensor network randomly.
(4) Initialize variable $(g = 0)$ in favor of chemotaxis procedure for bacterial population algorithm. All updates in bacterial positions Γ^b are inevitably updated in variable L.
(5) Start chemotaxis loop: $g = g + 1$

- (i) A chemotactic step for each bacterium b is specified underneath, where $\{b = 1, 2, ..., P\}$ represents number of bacteria in population.
- (ii) Calculate energy function $E(b, g) = e(\Gamma^b(g))$ where e points to energy cost of that SN where bacterium b resides.
- (iii) Store the energy function value in $E_{last} = E(b, g)$, since better value can be figured out by bacterium b via run.
- (iv) Define the searching radius R_s for Ψ^b SN, at which bacterium b is initialized.
- (v) Initialize random vector $\mu(b)$ that can store IDNs of the SNs i.e., $\Psi_{rv}(IDN)$ lies in searching radius R_s.
- (vi) During *swim* function:
  - (a) Let $x = 1$ (counter required to analyze the number of shifts taken by a bacterium to other SNs in random vector $\mu(b)$).
  - (b) Shift, $\Gamma^b(g+1) = [\Psi_{rv+1}(IDN)]^{\mu(b)}$ consequences a shift taken by the bacterium b to next SN $\Psi_{rv+1}(IDN)$ stored in random vector $\mu(b)$.
  - (c) Determine $E(b, g+1) = e(\Gamma^b(g+1))$.
  - (d) While $x \leq S_l$ (loop continues till all SNs in random vector $\mu(b)$ are not considered in search of better energy cost function)
    - $x = x + 1$ (increment in counter)
    - If $E(b, g+1) > E_{last}$ (if finds better value) let, $E_{last} = E(b, g+1)$ and let, $\Gamma^b(g+1) = [\Psi_{rv+1}(IDN)]^{\mu(b)}$ updates the E_{last} with recently analyzed SN energy cost function value E, saves its IDN and shifts to another SN $\Psi_{rv+1}(IDN)$ in random vector $\mu(b)$.
    - Else, $\Gamma^b(g+1) = [\Psi_{rv+1}(IDN)]^{\mu(b)}$ shifts bacterium b to another SN in random vector $\mu(b)$.
- (vii) Again re-initialize this procedure for bacterium $(b+1)$ until $(b \neq P)$, go to step 5(ii).

(6) Continue above procedure till $g < C_s$, (i.e., go to step 5).

4.2 M-ICHB based stable protocols

This section describes the proposed M-ICHB based stable protocols viz MILEACH, MIrLEACH, MISEP and MIDEEC protocols. Here, MILEACH and MIrLEACH protocols are based on homogeneous WSNs, whereas MISEP and MIDEEC protocols work on heterogeneous WSNs.

4.2.1 For homogeneous WSNs

MILEACH and MIrLEACH protocols: Now we discuss the CH selection, cluster formation, data collection and transmission procedures for MILEACH and MIrLEACH protocols by employing M-ICHB algorithm on LEACH. Both proposed protocols follow same CH selection procedure, however these differ in cluster formation, data collection and transmission procedures.

Preliminary: In LEACH, λ_i is considered as number of rounds for which a SN k_i behaves as a CH and refers as a rotating epoch. LEACH works for homogeneous networks and uses rotating epoch λ_i to make each SN k_i a CH once every $1/\sigma_{opt}$ rounds to guarantee $\sigma_{opt}N$ average number of CHs every round. However *first*, during the network execution, there exists disparity of energy consumption between SNs, as each one dissipates different amount of energy due to radio communication characteristics, occurrence of random events or morphological characteristics of network field. *Second*, once network starts, homogeneous network also behaves as a kind of heterogeneous network. With this fact, it is clear that whatever requirements are necessary for heterogeneous networks are also essential for homogeneous networks. Due to these issues in LEACH and using same rotating epoch λ_i for each SN k_i to become CH creates imbalance in energy distribution of the network. Furthermore, lower energy nodes will die more quickly and shorten network stable region.

However, consideration of residual energy parameter during CH selection can resolve this situation. Still, searching for actual higher residual energy nodes for CH selection (without any randomized or estimation based algorithms) is a challenge in distributed WSNs. Resolving these issues, we employ our designed M-ICHB algorithm on LEACH and propose MILEACH and MIrLEACH protocols that overcome these shortcomings effectively. Notably, these protocols employ M-ICHB algorithm with distributed approach during CH selection procedure to overcome scalability issues of WSNs. In proposed protocols, for each SN k_i, we choose different rotating epoch λ_i based on their residual energies that will behave as CHs in each specific round r of the network.

CH selection procedure

Let $\sigma_i = 1/\lambda_i$ considers as an average probability of a SN k_i to become CH in λ_i rounds. At the beginning of homogeneous network, when each SN k_i has same energy level, the average probability σ_i can be considered equivalent to σ_{opt}. However, once network evolves, it behaves like a heterogeneous network in which each SN varies its residual energy. With this fact, the probability of a SN to become CH should vary dynamically for each round accordingly. The value σ_i of higher residual node should be higher than σ_{opt}.

In the beginning of each round, MILEACH and MIrLEACH protocols apply M-ICHB algorithm, where a population of bacteria P has been initiated by few SNs with probability $BACT_{prob}$ (i.e., $0.25 \times N$) in the network. This maintains the distributive nature of WSN. The position of each bacterium is described in Eq. (3). Once the population of bacteria is initiated, a random vector $\mu(b)$ corresponding to each bacterium b is created. It holds the IDNs of SNs $\Psi_{rv}(IDN)$, which falls in the searching radius R_s of SN Ψ^b at which b-th bacterium is originated. Each bacterium b shifts from one SN to another in search of better residual energy node in its random vector $\mu(b)$. The movement process is described in Eq. (4). During shifting process in a random vector, bacterium b stores the residual energy of last visited SN in variable E_{last} along with its IDN value. Furthermore, shifts to next SN in the random vector and compares its residual energy value with E_{last}. If the residual energy of newly visited SN is greater than E_{last}, bacterium updates this value in E_{last} and stores the IDN of newly visited SN and shifts to next SN for further search. Otherwise, if the value of E_{last} is greater than the residual energy of newly visited SN, it shifts to next SN in the random vector for further search without any changes in E_{last}. Its complete working model is described in Algorithm 1.

During searching of better residual energy node in a random vector $\mu(b)$, the average probability of a SN to become CH is given as,

$$\begin{aligned}\sigma_i &= \sigma_{opt} \times \frac{e(\Gamma^b(g+1))(r)}{e(\Gamma^b(g))(r)} \\ &= \sigma_{opt} \times \frac{e([\Psi^b_{rv+1}(IDN)]^{\mu(b)})(r)}{e(\Psi^b(IDN))(r)}\end{aligned} \tag{11}$$

where, $e([\Psi^b_{rv+1}(IDN)]^{\mu(b)})(r)$ denotes the residual energy of each SN $\Psi^b_{rv+1}(IDN)$ in a random vector $\mu(b)$ analyzed during searching process at r-th round. $e(\Psi^b(IDN))(r)$ denotes the residual energy of SN $\Psi^b(IDN)$ at which b-th bacterium has been originated at r-th round. Based on Eq. (11), each SN k_i probability based threshold value to determine whether to become a CH in a round is given as,

$$T(k_i) = \begin{cases} \frac{\sigma_i}{1-\sigma_i \times \left(r \bmod \left(\frac{1}{\sigma_i}\right)\right)} & \text{if } k_i \in G \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

where, G represents a set of SNs $k_i\{i = 1, 2, \ldots, N\}$ that has not been CH for last λ_i rounds and eligible for the same. Moreover on the basis of Eq. (11), the rotating epoch λ_i can be expressed as

$$\lambda_i = \frac{1}{\sigma_i} = \frac{e(\Psi^b(IDN))(r)}{\sigma_{opt} \times e([\Psi^b_{rv+1}(IDN)]^{\mu(b)})(r)} = \lambda_{opt} \times \frac{e(\Psi^b(IDN))(r)}{e([\Psi^b_{rv+1}(IDN)]^{\mu(b)})(r)} \tag{13}$$

where, λ_{opt} signifies the reference rotating epoch for a SN k_i to become a CH, which is equivalent to $1/\sigma_{opt}$. Speciously, for each SN k_i the rotating epoch λ_i varies based on the fact that higher residual energy nodes have shorter rotating epoch i.e., higher residual nodes are eligible to work as CHs very frequently in comparison to lower energy nodes.

Cluster formation, data collection and transmission procedures

MILEACH protocol: For each round, once CHs are selected, cluster formation process starts. All non-CH nodes are required to join exactly one of the CHs as its cluster member. Each cluster head CH_i broadcasts an advertisement message ADV_{CH_i} intended for the non-CH nodes to join its cluster. On reception of this message from different CHs, a SN k_i calculates its distance from each CH using RSSI value of ADV_{CH_i} message and joins nearest CH node. If ties occur, any CH among them is selected. This completes the cluster formation phase.

Figure 4 shows an instance during clustering formation in a specific round by MILEACH. Here, BS is located at center of the field and denoted by cross-sign (×). Furthermore, each CH and its cluster members (i.e., SNs) are represented by circled star (⊛) and circle (∘) respectively. Moreover, the intra-cluster communication between them is shown by blue-lined connectivity for data transmission.

Once clusters are formed, each SN senses its environmental surroundings for data collection and transmits its data to respective CH. Each CH fuses the received data from their cluster members and sends aggregated data packet to the BS directly in single-hop.

MIrLEACH protocol: During cluster formation phase in MIrLEACH, SNs nearer to the BS do not join any CH and permissible to transmit their data to the BS directly in single hop. Rest of the cluster formation, data collection and transmission procedures are same as MILEACH.

4.2.2 For heterogeneous WSNs

Providing extension to M-ICHB based stable protocols for heterogeneous networks, we have applied M-ICHB algorithm to the conventional heterogeneity based stable protocols i.e., SEP and DEEC that results in MISEP and MIDEEC protocols. Their implementation procedures are discussed below.

4.2.2.1 MISEP protocol Here, we demonstrate the CH selection, cluster formation, data collection and transmission procedures for MISEP protocols by employing M-ICHB algorithm on SEP.

Preliminary: In two-level heterogeneity, SEP requires different weighted probabilities i.e., σ_{nrm} and σ_{adv} for normal and advanced nodes based on their initial energies during CH selection process, given in Eqs. (14) and (15),

$$\sigma_{nrm} = \frac{\sigma_{opt}}{(1 + \alpha \times m)} \tag{14}$$

$$\sigma_{adv} = \frac{\sigma_{opt}}{(1 + \alpha \times m)} \times (1 + \alpha) \tag{15}$$

where, σ_{opt} denotes preferred probability of CHs in the network. SNs with fraction of m consist α times more energy than normal nodes are defined as advanced nodes.

Proposed MISEP protocol eliminates the situation of different weighted probabilities by employing M-ICHB algorithm on SEP.

CH selection, cluster formation, data collection and transmission procedures

In the beginning of each round, MISEP applies M-ICHB algorithm, where a population of bacteria P searches for better residual nodes in their vicinity for CH selection. Notably, despite the knowledge of varying level of heterogeneous nodes in the network, M-ICHB algorithm searches better residual energy nodes using Eqs. (3) and (4). By employing this procedure, MISEP does not require different weighted probabilities for normal and advanced nodes. This provides a novel way of CH selection without the need of estimation/randomized based algorithms and eliminates the need of such weighted probabilities for different level of heterogeneous nodes.

Moreover, the probability σ_i of a node to become CH can be obtained from Eq. (11) and the threshold value $T(k_i)$ for each node can be observed from Eq. (12).

Once CHs are selected for each round, MISEP follows the same procedure for cluster formation, data collection and transmission as in MILEACH protocol.

Figure 5 shows an instance during clustering formation in a specific round for two-level heterogeneous network model by MISEP. Here, advanced nodes and normal nodes are represented by plus (+) and circle (∘) respectively, whereas CHs are denoted by star (∗) mark. Rest of the features are similar to Fig. 4.

Moreover, MISEP is easily extendable to the multi-level heterogeneous networks. Likewise two-level heterogeneity case, Eqs. (11) and (12) express the weighted probability and threshold value of each node k_i to become CH in multi-level heterogeneity case.

4.2.2.2 MIDEEC protocol Here, CH selection, cluster formation, data collection and transmission procedures for MIDEEC protocol employing M-ICHB algorithm on DEEC protocol are discussed.

Preliminary: In two-level heterogeneity model, the rotating probability for a SN to become CH in DEEC is given by,

$$\sigma_i = \begin{cases} \frac{\sigma_{opt} E_i(r)}{(1+\alpha\times m)E'(r)} & \text{if } k_i \text{ is the normal node} \\ \frac{\sigma_{opt}(1+\alpha)E_i(r)}{(1+\alpha\times m)E'(r)} & \text{if } k_i \text{ is the advanced node} \end{cases} \tag{16}$$

where, $E_i(r)$ represents residual energy of a SN, $E'(r)$ is estimated average energy of the network.

DEEC uses the varying weighted probabilities given in Eq. (16) for normal and advanced nodes in two-level heterogeneous networks which require initial, residual energy of each node, estimating average energy of network in each round and ideal network lifetime. However, these assumptions are not possible in actual deployment scenario due to radio communication characteristics, occurrence of random events or morphological characteristics of network field. Furthermore, these assumptions increase functional complexity of algorithm and create interruption in producing exact results in real deployment of WSNs.

To resolve these issues efficiently, proposed MIDEEC protocol uses M-ICHB algorithm during its CH selection process.

CH selection, cluster formation, data collection and transmission procedures

MIDEEC applies M-ICHB algorithm in each round, where a population of bacteria P is initiated by few SNs with probability $BACT_{prob}$ which searches for better residual energy nodes in its vicinity using Eqs. (3) and (4). The probability σ_i for a node to become CH is given in Eq. (11) and its threshold value $T(k_i)$ is described as Eq. (12). Notably, this scheme does not require to know initial energies of each node, estimation of average energy of network or ideal network lifetime. Additionally, it does not require different weighted probabilities of normal and advanced nodes. This simplifies the CH selection process remarkably and capable to enhance the stability region of WSNs.

Once CHs are selected for each round, MIDEEC follows the same procedure for cluster formation, data collection and transmission as in MIrLEACH.

Figure 5 represents the similar cluster formation for MIDEEC in two-level heterogeneous WSN. However, differentiation occurs in cluster formation phase, where SNs nearer to the BS do not join any CHs and send their data directly to BS.

Moreover, MIDEEC is easily extendable to the multi-level heterogeneous networks. Likewise two-level heterogeneity case, Eqs. (11) and (12) express the weighted probability and threshold value of each node k_i to become CH in multi-level heterogeneity case.

4.3 Energy consumption model

This section discusses the radio model used for functioning of trans-receiver circuitry for sensing, computation and transmission on data (Heinzelman et al. 2000; Smaragdakis et al. 2004; Qing et al. 2006).

The energy spent by transmitter circuitry to send L-bit data for short distance d, i.e., $d \leq d_0$ using free space model is given by,

$$E_{Tx_S}(L,d) = E_{elec} \times L + \epsilon_{fs} \times L \times d^2 \tag{17}$$

The energy spent by transmitter circuitry to send L-bit data for long distance d, i.e., $d > d_0$ using multipath model is given by,

$$E_{Tx_L}(L,d) = E_{elec} \times L + \epsilon_{mp} \times L \times d^4 \tag{18}$$

The energy spent by receiver circuitry in sensing or reception of L-bit data is given by,

$$E_{Rx}(L) = E_{elec} \times L \tag{19}$$

where, E_{elec} symbolizes the energy consumption by trans-receiver circuitry during radio dissipation process. Amplifying index ϵ_{fs} and ϵ_{mp} based on free space and multipath fading channel models are undertaken for consideration depending on the respective distance between transmitter and receiver nodes. Threshold distance d_0 indicates as a reference measurement in calculation of distance d.

The energy consumed by each SN (i.e., non-CH node) in a round is given as,

$$E_{SN} = E_{elec} \times L + \epsilon_{fs} \times L \times d^2_{toCH} \tag{20}$$

The energy consumed by each CH node in a round is given as,

$$\begin{aligned} E_{CH} =& \left(\frac{N}{c} - 1\right) \times E_{elec} \times L + \left(\frac{N}{c} - 1\right) \times E_{DA} \times L \\ &+ E_{elec} \times L + \epsilon_{mp} \times L \times d^4_{toBS} \end{aligned} \tag{21}$$

Total energy dissipated in a round by the network is given by,

$$\begin{aligned} E_{tot_r} =& N \times L \times \Big(2 \times E_{elec} + E_{DA} \\ &+ \frac{c}{N} \times \epsilon_{mp} \times d^4_{toBS} + \epsilon_{fs} \times d^2_{toCH}\Big) \end{aligned} \tag{22}$$

Table 2 Simulation parameters

Parameter description	Value
Network field ($M \times M$)	$100 \times 100m^2$
Number of sensors (N)	100
Base station location	(50, 50)
Initial energy of each node (E_0)	$0.5J$
Energy consumption to run transmitter or receiver circuitry (E_{elec})	$50nJ\,/\,bit$
Energy consumption by amplifier to transmit signal at shorter distance (ϵ_{fs})	$10pJ/bit/m^2$
Energy consumption by amplifier to transmit signal at longer distance (ϵ_{mp})	$0.0013pJ/bit/m^4$
Data aggregation cost (E_{DA})	$5nJ\,/\,bit\,/\,message$
Message size (L)	$4000\ bits$
Threshold distance (d_0)	$70m$

Table 3 Comparative analysis for LEACH, MILEACH and MIrLEACH protocols in terms of FND, TND, HND and stability region

Protocol	FND	TND	HND	Stability region	
				(in rounds)	(improvement in %)
LEACH	790	996	1201	790	0.0
MILEACH	1208	1229	1238	1208	52.91
MIrLEACH	1247	1268	1278	1247	57.85

where, N depicts the number of SNs uniformly distributed in an area of $M \times M$ square region, c denotes number of clusters in network, E_{DA} shows data aggregation cost spent at CH, d_{toBS} is the average distance between CH and BS, d_{toCH} indicates the average distance between CH and its cluster members and their values can be obtained as (Qing et al. 2006),

$$d_{toCH} = \frac{M}{\sqrt{2\pi c}}, \qquad d_{toBS} = 0.765 * \frac{M}{2} \tag{23}$$

5 Simulation results and discussions

This section discusses the simulated results and performance of proposed M-ICHB based stable protocols (i.e., MILEACH, MIrLEACH, MISEP and MIDEEC) in comparison to LEACH, SEP and DEEC by using MATLAB. The proposed protocols are well-suited for those applications, where maximum stability region is the prime necessity of WSN. For simplicity, we use ideal MAC layer and ignore signal collision and interference effect in wireless communication links. The parameters required for simulation are shown in Table 2 (Heinzelman et al. 2000; Qing et al. 2006). Each simulation is carried on ten different random strategies and statistics is averaged over these ten runs.

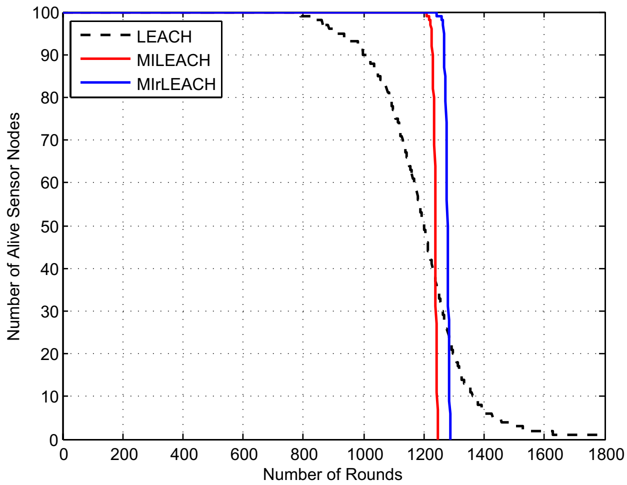

Fig. 6 Number of alive nodes per round for homogeneity based M-ICHB stable protocols

5.1 For homogeneous WSNs

In this section, comparative analysis of results for homogeneity based M-ICHB stable protocols i.e., MILEACH and MIrLEACH with LEACH is described. Various parameters i.e., number of alive nodes per round, number of packets received by BS, number of clusters formed per round and total energy consumption per round have been employed to analyze the performance of proposed protocols.

Figure 6 depicts the number of alive nodes remaining at the end of each round and Table 3 represents the first node dead (FND), tenth node dead (TND), half node dead (HND) and stability region for LEACH, proposed MILEACH and MIrLEACH protocols. Results confirm that using M-ICHB algorithm for CH selection on LEACH, the stability region is increased by 53% in MILEACH. The reasons are as follows: Firstly, M-ICHB algorithm allows only high residual energy nodes to become CHs in the network, which in turn delays the death rate of each SN and helps in increasing the stability region of the WSN. Secondly, maintaining

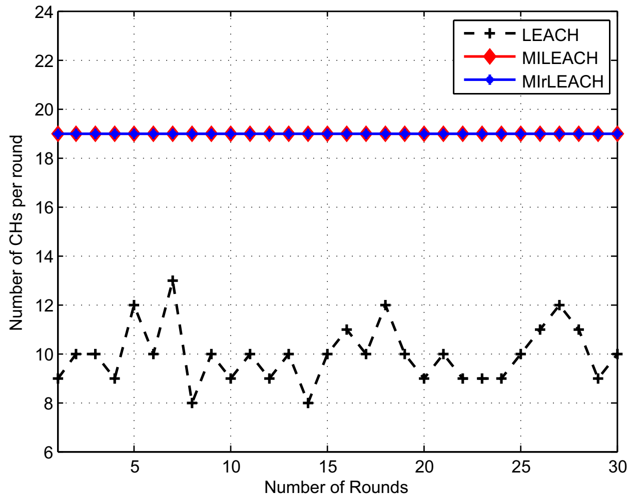

Fig. 7 Number of clusters formed per round for homogeneity based M-ICHB stable protocols

optimal number of CHs c_{opt} in the network helps to prolong each node's life in the network. In addition to MILEACH, if any SN is nearby to the BS, it communicates directly to the BS instead of being any cluster member. This results in MIrLEACH protocol, which improves the performance by 58% in comparison to LEACH.

Figure 7 shows the number of clusters formed in each round for LEACH, MILEACH and MIrLEACH. In case of proposed protocols; first, number of CHs formed are almost constant for consecutive rounds in comparison to LEACH because of using constant population of bacteria in M-ICHB algorithm for CH selection. Second, number of CHs per round is kept high to provide optimal CHs count c_{opt} satisfiable, which is essential for better stability region in the network. With these facts, cluster size (in terms of area) remains small in proposed protocols (as shown in Fig. 4), and no far distant cluster member i.e., SN exists (problem depicted in Fig. 2) which may cause higher energy dissipation and shorten stability region as in LEACH. Due to constant and higher number of CHs per round, our protocols are capable to produce better stability region in comparison to LEACH.

Figure 8 indicates the number of packets received by the BS per round till the network is alive. In MILEACH and MIrLEACH protocols, BS receives number of packets at higher rate because of more CHs formation per round in comparison to LEACH. As higher number of CHs in the network produces higher number of packets per round, intended for the BS. This results in reception of 91 and 97% more number of packets at the BS respectively in comparison to LEACH. Moreover, MIrLEACH produces maximum number of packets, because it remain alive for more number of rounds.

Figure 9 shows the energy consumption in consecutive rounds for LEACH, MILEACH and MIrLEACH protocols. Results show higher energy consumption in LEACH, because less number of CHs are formed in network. Due to this, the issue of optimal number of clusters c_{opt} arises in LEACH protocol, whereas by maintaining c_{opt} value in MILEACH and MIrLEACH protocols, energy consumption per round is minimized. Furthermore in LEACH, there exists high variation in energy consumption for consecutive rounds because of variation in number of CHs, whereas electing constant number of CHs per round in MILEACH and MIrLEACH, this variation is almost negligible. This shows that maintaining constant CHs count helps in providing constant energy consumption per round. Moreover,

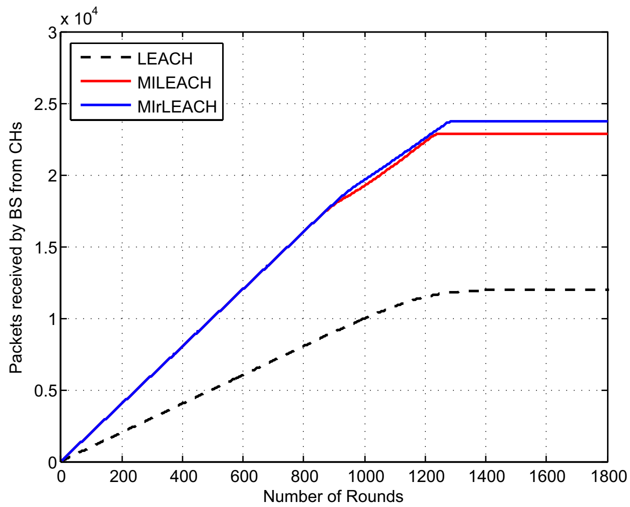

Fig. 8 Number of packets received by the BS per round for homogeneity based M-ICHB stable protocols

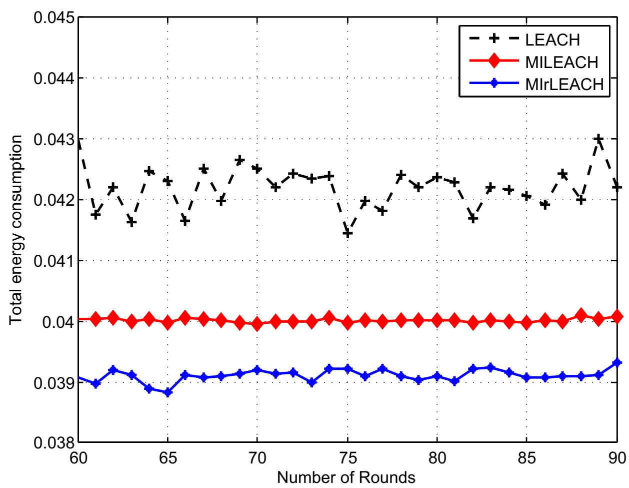

Fig. 9 Energy consumption per rounds for homogeneity based M-ICHB stable protocols

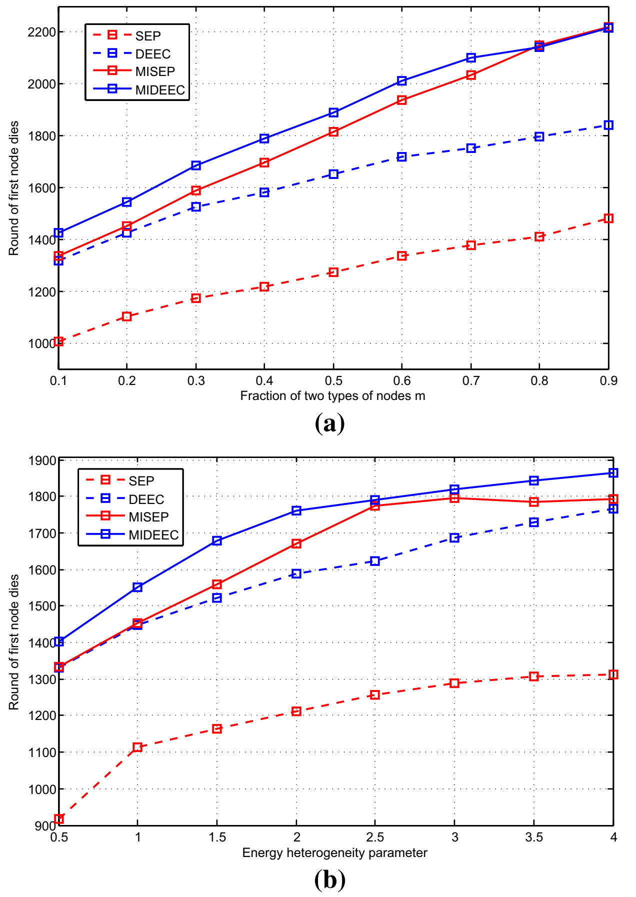

Fig. 10 Number of rounds at which first SN dies for heterogeneity based M-ICHB stable protocols in two-level heterogeneous WSNs when m and α are varying

MIrLEACH produces minimum energy consumption, because nearby SNs (i.e., to BS) directly send their data to BS. This further reduces the computational energy cost of CHs in the network.

5.2 For two-level heterogeneous WSNs

Figure 10 expresses the stability region for MISEP and MIDEEC protocols on varying the values of m and α under two-level heterogeneous WSNs. In Fig. 10a, the value of α is set to 1 and m varies from 0.1 to 0.9, whereas in Fig. 10b, the value of m is set to 0.2 and α varies from 0.5 to 4. Tables 4 and 5 represent FND, TND, HND and stability region for MISEP and MIDEEC protocols in comparison to SEP and DEEC respectively for different two-level heterogeneity cases i.e., $m = 0.2$ and $\alpha = 3$; $m = 0.3$ and $\alpha = 3.5$; and $m = 0.4$ and $\alpha = 4$. Notably, the advantage of applying M-ICHB algorithm on conventional protocols can be seen clearly. Especially in Fig. 10a, the performance of MISEP and MIDEEC is improved 52 and 21% approximately in comparison to SEP and DEEC respectively. Additionally in Fig. 10b, MISEP and MIDEEC perform better 46 and 11% approximately in comparison to SEP and DEEC respectively. Further, Fig. 11 depicts number of alive nodes per round for MISEP and MIDEEC in two-level heterogeneous WSNs when $m = 0.2$ and $\alpha = 3$, which outperform 30.51 and 7.14% better in stability region than SEP and DEEC respectively. The reasons are as follows: Firstly, due to searching of actual high residual energy nodes for CH selection by applying M-ICHB algorithm. Secondly, maintaining optimal number of CHs c_{opt} helps to prolong each node's life in the network. Moreover, the performance of MIDEEC is better than MISEP, because SNs nearby BS can directly communicate to the BS, which further reduce the energy consumption required for data processing by the CHs. This improves the performance of MIDEEC from others in terms of stability region.

Figure 12 indicates the number of clusters formed in each round of SEP, DEEC, MISEP and MIDEEC protocols under two-level heterogeneity case (at $m = 0.2$ and $\alpha = 3$). Similar to homogeneous case, our MISEP and MIDEEC protocols form almost constant number of CHs for consecutive rounds in comparison to SEP and DEEC, because of using constant population of bacteria in M-ICHB algorithm for CH selection. Furthermore, keeping higher number of CHs per

Table 4 Comparative analysis of SEP and MISEP protocols under two-level heterogeneity in terms of FND, TND, HND and stability region

Value for heterogeneity	Protocol	FND	TND	HND	Stability region	
					(in rounds)	(improvement in %)
m=0.2, α =3	SEP	1301	1385	1550	1301	0.0
	MISEP	1698	1893	1923	1698	30.51
m=0.3, α=3.5	SEP	1368	1503	1669	1368	0.0
	MISEP	1822	2174	2408	1822	33.19
m=0.4, α=4	SEP	1573	1677	1859	1573	0.0
	MISEP	1951	2223	2426	1951	24.03

Table 5 Comparative analysis of DEEC and MIDEEC protocols under two-level heterogeneity in terms of FND, TND, HND and stability region

Value for heterogeneity	Protocol	FND	TND	HND	Stability region (in rounds)	(improvement in %)
m=0.2, α=3	DEEC	1596	1761	1985	1596	0.0
	MIDEEC	1710	2027	2144	1710	7.14
m=0.3, α=3.5	DEEC	1763	2027	2206	1763	0.0%
	MIDEEC	1868	2214	2471	1868	5.95
m=0.4, α=4	DEEC	1871	2123	2290	1871	0.0
	MIDEEC	2031	2260	2481	2031	8.55

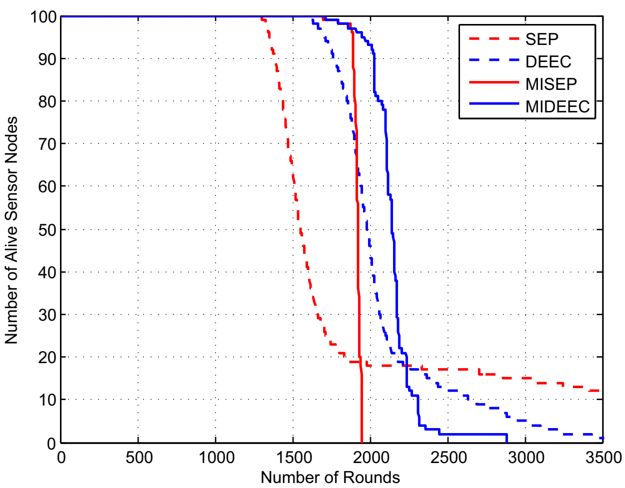

Fig. 11 Number of alive nodes per round for heterogeneity based M-ICHB stable protocols in two-level heterogeneous WSNs when $m = 0.2$ and $\alpha = 3$

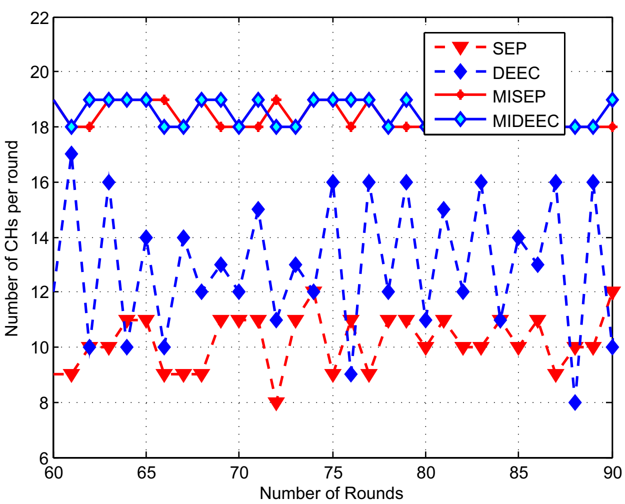

Fig. 12 Number of clusters formed per round for heterogeneity based M-ICHB stable protocols in two-level heterogeneous WSNs when $m = 0.2$ and $\alpha = 3$

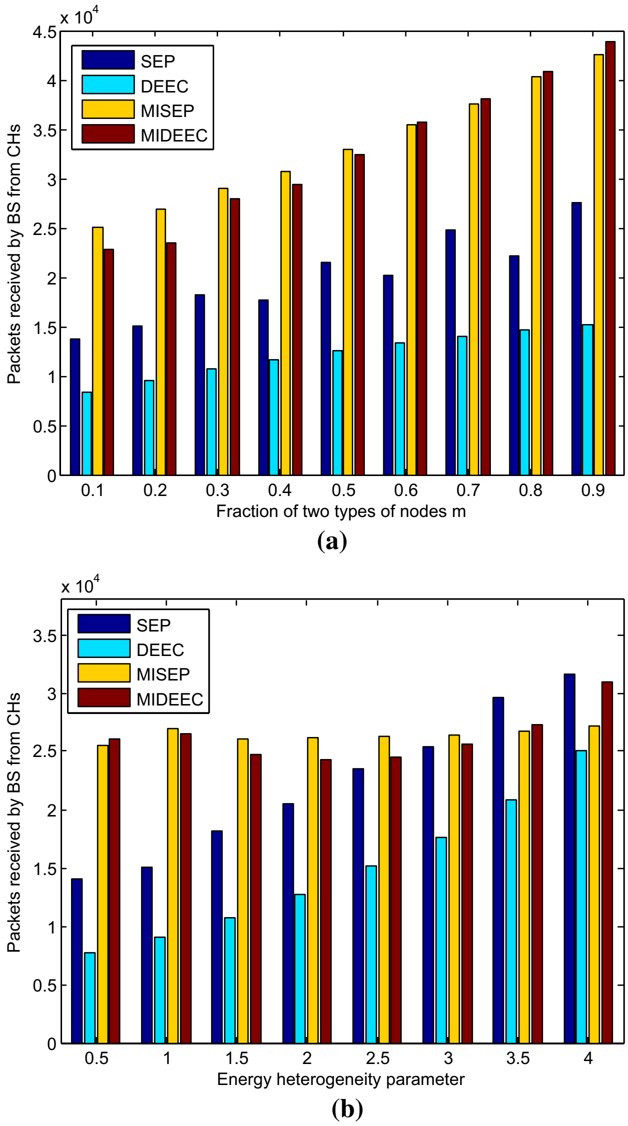

Fig. 13 Number of packets received by the BS for heterogeneity based M-ICHB stable protocols in two-level heterogeneous WSNs when m and α are varying

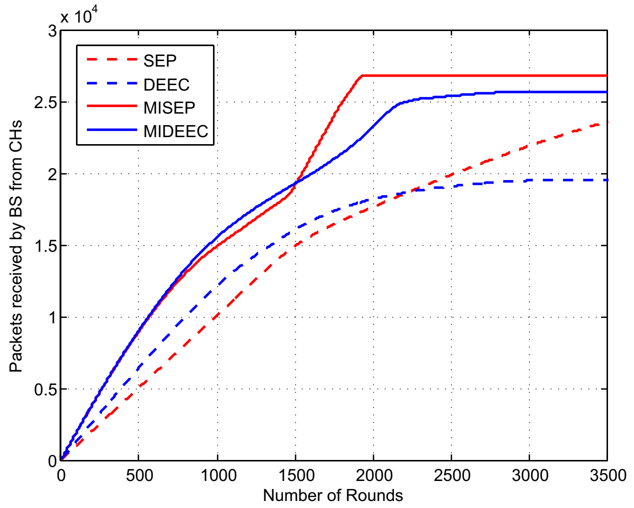

Fig. 14 Number of packets received by the BS per round for heterogeneity based M-ICHB stable protocols in two-level heterogeneous WSNs when $m = 0.2$ and $\alpha = 3$

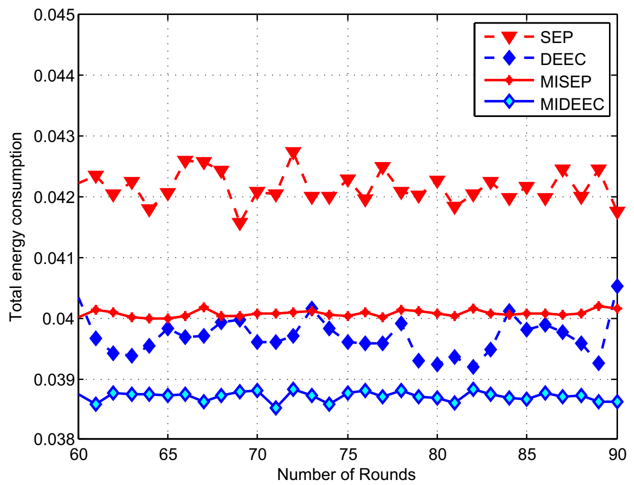

Fig. 15 Energy consumption per round for heterogeneity based M-ICHB stable protocols in two-level heterogeneous WSNs when $m = 0.2$ and $\alpha = 3$

round resolves the issue of optimal CH count c_{opt} in network same as MILEACH and MIrLEACH. With these reasons, our M-ICHB based stable protocols have higher number of CHs per round and capable to produce better stability region in comparison to SEP and DEEC.

Figure 13 displays the number of packets received by the BS with varying m and α, and Fig. 14 shows the number of packets received by the BS per round in heterogeneity based M-ICHB stable protocols under two-level heterogeneous WSNs (when $m = 0.2$ and $\alpha = 3$). Maintaining higher number of CHs per round, results in generation of higher number of packet rate per round for the BS. With this reason

Table 6 Comparative analysis of SEP and MISEP protocols under multi-level heterogeneity in terms of FND, TND, HND and stability region

Protocol	FND	TND	HND	Stability region	
				(in rounds)	(improvement in %)
SEP	1533	1931	2925	1533	0.0
MISEP	2202	2924	3078	2202	43.64

Table 7 Comparative analysis of DEEC and MIDEEC protocols under multi-level heterogeneity in terms of FND, TND, HND and stability region

Protocol	FND	TND	HND	Stability region	
				(in rounds)	(improvement in %)
DEEC	2091	2616	3435	2091	0.0
MIDEEC	2252	2990	3291	2252	7.7

in MISEP and MIDEEC protocols, the BS receives 82 and 188% approximately more number of packets in comparison to SEP and DEEC.

Figure 15 shows the energy consumption in consecutive rounds of proposed heterogeneity based M-ICHB stable protocols in two-level heterogeneous WSNs. Result shows maximum energy consumption per round in SEP, because very less number of CHs are formed in network. Due to this, the problem of optimal number of clusters c_{opt} arises in SEP. Furthermore, SEP does not allow the formation of

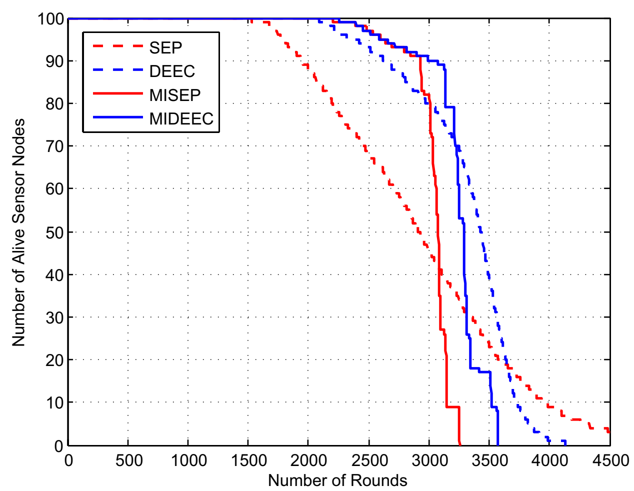

Fig. 16 Number of alive nodes per round for heterogeneity based M-ICHB stable protocols in multi-level heterogeneous WSNs

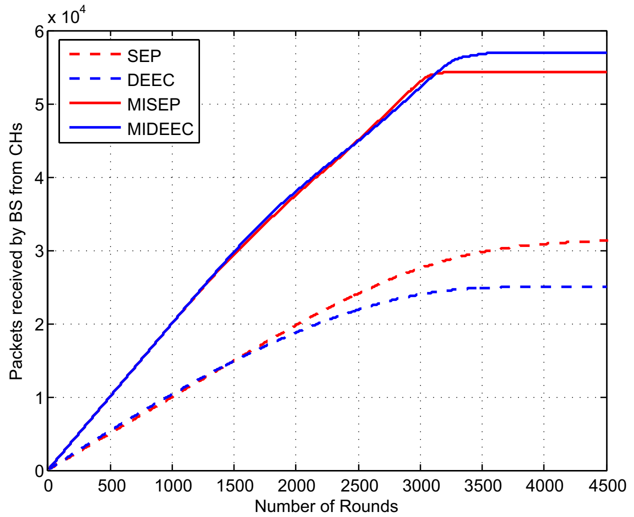

Fig. 17 Number of packets received by the BS per round for heterogeneity based M-ICHB stable protocols in multi-level heterogeneous WSNs

constant number of CHs, which in turn generates variation in energy consumption in consecutive rounds. However, using M-ICHB algorithm in SEP, MISEP resolves these issues and capable to consume less as well as constant energy in consecutive rounds.

Similar to SEP, DEEC also suffers from varying number of CHs in consecutive rounds. On the other hand, increasing number of CHs per round in DEEC, it minimizes the energy consumption as compared to SEP. Still, the scope of refinement persists. To improve these issues in MIDEEC, we applied M-ICHB algorithm on DEEC that generates constant as well as higher number of CHs per round. Due to this, it becomes possible to achieve almost constant energy consumption with reduced rate for consecutive rounds efficiently. Notably, the energy consumption is minimum in MIDEEC as compared to MISEP because of load reduction, caused by SNs nearby to BS that directly send their data to the BS in spite of any CH, lessens the extra burden of CHs' data processing.

5.3 For multi-level heterogeneous WSNs

Figure 16 expresses the number of alive nodes per round and Tables 6 and 7 represent FND, TND, HND and stability region for MISEP and MIDEEC protocols in comparison with SEP and DEEC protocols respectively under multi-level heterogeneous WSNs. Similar to two-level heterogeneity case, MISEP and MIDEEC protocols produce 44 and 8% more stable region in comparison to SEP and DEEC because of applying M-ICHB algorithm. Figure 17 shows the number of packets received at the BS for M-ICHB based

Table 8 Comparative analysis of M-ICHB based stable protocols under different level of heterogeneity in terms of FND, TND, HND and stability region

Level for heterogeneity	Total amount of energy (J)	Protocol	FND	TND	HND	Stability region (in rounds)
Homogeneous case	50	LEACH (Heinzelman et al. 2000)	790	996	1201	790
		ALEACH (Ali et al. 2008)	885	1004	1108	885
		ICOH2TC (Gupta and Sharma 2017)	529	843	1182	529
		HEED2TC (Gupta and Sharma 2017)	907	1036	1141	907
		MILEACH	1208	1229	1238	**1208**
		MIrLEACH	1247	1268	1278	**1247**
Two-level heterogeneous case (m = 0.2, a = 3)	80	SEP (Smaragdakis et al. 2004)	1301	1385	1550	1301
		DEEC (Qing et al. 2006)	1596	1761	1985	1596
		TDEEC (Saini and Sharma 2010)	1602	1769	1988	1602
		SEARCH (Wang et al. 2015)	1611	1780	1992	1611
		MISEP	1698	1893	1923	**1698**
		MIDEEC	1710	2027	2144	**1710**
Multi-level heterogeneous case	125	SEP (Smaragdakis et al. 2004)	1533	1931	2925	1533
		DEEC (Qing et al. 2006)	2091	2616	3435	2091
		TDEEC (Saini and Sharma 2010)	1632	2068	3998	1632
		SEARCH (Wang et al. 2015)	1766	2235	3272	1766
		MISEP	2202	2924	3078	**2202**
		MIDEEC	2252	2990	3291	**2252**

Bold values represent the better values in comparison to others stable protocols under multi-level heterogeneity case. Likewise, here also BS receives 72 and 128% higher number of packets in MISEP and MIDEEC protocols in comparison to SEP and DEEC respectively, due to higher CHs counts per round. Furthermore, remaining alive for higher number of rounds, MIDEEC receives more packets at the BS in comparison to MISEP.

Furthermore, we have compared our M-ICHB based stable protocols with some of the similar kind of protocols under different level of heterogeneity showing FND, TND, HND and stability region in Table 8. This describes the comparative analysis between them and concludes that our proposed protocols provide better results in terms of stability region.

6 Conclusion and future work

In this paper, M-ICHB algorithm and a set of M-ICHB based stable protocols applicable for both homogeneous as well as heterogeneous WSNs have been proposed for providing elongated stability region in the network execution. In homogeneous WSNs, MILEACH and MIrLEACH protocols are designed, whereas heterogeneous WSNs consist MISEP and MIDEEC protocols. These protocols employ proposed M-ICHB algorithm based on bacterial foraging optimization technique for CH selection procedure in WSNs. M-ICHB algorithm shows efficient results in searching of actual higher residual energy SNs for CH selection in the network without depending on any kind of estimation/randomized algorithms, generally required in distributed architecture of WSNs. Simulation results show that MILEACH and MIrLEACH are able to improve the stability region 53 and 58% and number of packets received at BS by 91 and 97% respectively in comparison to LEACH. Moreover, MISEP and MIDEEC improve 52 and 21% in stability region and 82 and 188% in number of packets received at BS in comparison to SEP and DEEC protocols. This confirms the effectiveness of M-ICHB algorithm implementation in stability based clustering protocols for both homogeneous as well as heterogeneous WSNs with distributive nature.

In future, the proposed work can be extended by including secure data transmission features, fault detection and tolerant capabilities and mobility features.

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