



Improved metaheuristic based energy-efficient clustering protocol for wireless sensor networks



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ABSTRACT

Energy-efficient clustering protocols are much sought specially for low-power, multi-functional Wireless Sensor Networks (WSNs). With the application of Computational Intelligence (CI) based approaches, various metaheuristics have been developed for energy-efficient clustering in WSNs. Artificial Bee Colony (ABC) is one such metaheuristic which arose much interest over other population-based metaheuristics for solving optimization problems in WSNs due to its ease of implementation and adaptive nature. However, its solution search equation, which is poor at exploitation process, contributes to its insufficiency. Thus, we present an improved Artificial Bee Colony (iABC) metaheuristic with an improved solution search equation to improve its exploitation capabilities. Additionally, in order to increase the global convergence of the proposed metaheuristic, an improved population sampling technique is introduced through *Student's-t* distribution. The proposed metaheuristic maintains a good balance between exploration and exploitation search abilities with least memory requirements, moreover the use of first of its kind compact *Student's-t* distribution makes it suitable for limited hardware requirements of WSNs. Further, an energy efficient clustering protocol *BeeCluster* based on iABC metaheuristic is introduced, which inherits the capabilities of the proposed metaheuristic to obtain optimal cluster heads (CHs) and improves energy-efficiency in WSNs. Simulation results show that the proposed clustering protocol outperforms other well known protocols on the basis of packet delivery, throughput, energy consumption, network lifetime and latency as performance metric.

1. Introduction

WSNs contain self-configured, distributed and autonomous Sensor Nodes (SNs) that monitor physical or environmental activities like humidity, temperature or sound in a specific area of deployment (Yick et al., 2008). SNs can have more than one sensor to capture data from the physical environment wherever deployed. A sensor with limited storage and computation capabilities receives the sensed data through analogue to digital Converter (ADC) and process it further for transmission to a main location, known as *Base Station* (BS), where the data can be analysed for decision making in variety of applications (Al-Karaki and Kamal, 2004). Every node also acts as a repeater for passing information of other sensor nodes to the sink. The most important part of the sensor node is its power supply, which caters to the energy requirements of sensors, processors and transceiver, however, its limited battery life can lead to premature exhaust of the network due to excessive usage (Akkaya and Younis, 2005). As manual recharging of batteries is not possible in complex deployments, efficient use of the energy becomes a tough challenge in applications where

prolonged life of the network is required (Gaura, 2010). A typical WSN scenario is shown in Fig. 1.

Researchers are heavily involved in designing of energy efficient solutions, however, on the other hand network life can also be extended by planning energy efficient approaches. It is well accepted that cluster based hierarchical approach is an efficient way to save energy for distributed WSNs (Abbasi and Younis, 2007; Tyagi and Kumar, 2012), which increase network life by effectively utilizing the node energy, and supports dynamic WSNs environment. In a cluster based WSN, SNs are divided into several groups known as clusters with a group leader known as *Cluster Head* (CH). All the SNs sense data and send it to their corresponding CH, which finally send it to the BS for further processing. Clustering has various significant advantages over classical schemes (Abbasi and Younis, 2007). First, data aggregation is applied on data, received from various SNs within a cluster, to reduce the amount of data to be transmitted to BS thus energy requirements decrease sharply. Secondly, rotation of CHs helps to ensure a balanced energy consumption within the network, which prevent getting specific nodes starved due to lack of energy (Chamam and Pierre, 2010).

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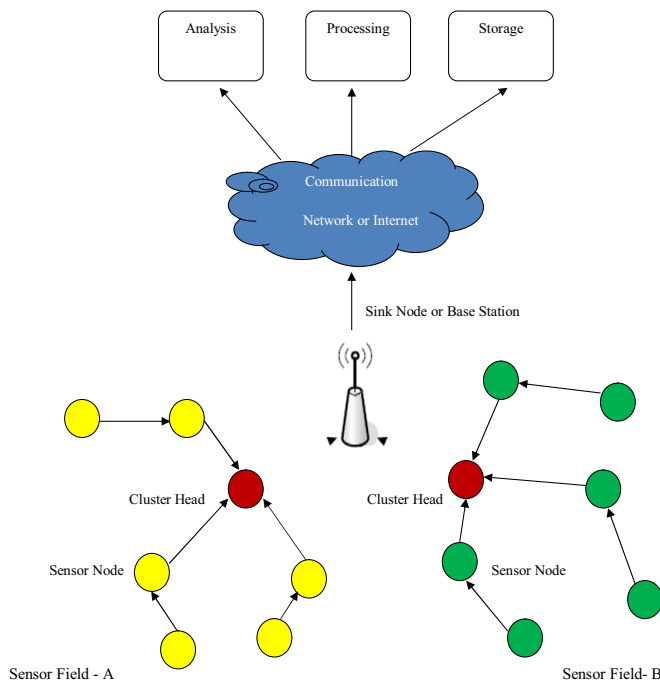


Fig. 1. A typical WSN scenario.

However, the selection of appropriate CH with optimal capabilities while balancing energy-efficiency ratio of the network is a well defined NP-hard optimization problem in WSNs (Khalil and Attea, 2011). Thus, Computational Intelligence (CI) (Kulkarni et al., 2011) based approaches such as Evolutionary algorithms (EAs), Reinforcement learning (RL), Artificial immune systems (AIS), and more recently, Artificial Bee Colony (ABC) have been used extensively as population based metaheuristic for energy-efficient clustering protocols in WSNs (Das et al., 2009). Results prove that the performance of the ABC metaheuristic is competitive to other population-based algorithms with the advantage of employing fewer control parameters, simplicity of use and ease of implementation (Sabat et al., 2010).

However, similar to other population-based algorithms, the standard ABC metaheuristic also faces some challenges, as it is considered to have poor exploitation phase than exploration, moreover convergence rate is typically slower, specially while handling multi-modal optimization problems (Karaboga and Akay, 2009). Therefore, we propose an improved Artificial Bee Colony (iABC) metaheuristic, with an improved solution search equation, which will be able to search an optimal solution to improve its exploitation capabilities and an improved technique for population sampling through the use of first of its kind compact *Student's-t* distribution to enhance the global convergence of the proposed metaheuristic. Further, to utilize the capabilities of the proposed metaheuristic, an improved Artificial Bee Colony based clustering protocol, *BeeCluster*, is introduced, which selects optimal cluster heads (CHs) with energy-efficient approach in WSNs.

2. Related work

We present the vital contributions of the researchers based on Classical as well as CI based metaheuristic approaches as follows: Low-energy adaptive clustering hierarchy (LEACH) (Heinzelman et al., 2002) is a classical clustering protocol which combines energy-efficient cluster-based routing to application oriented data aggregation and achieves better lifetime for a WSN. LEACH introduces algorithm for adapting clusters and rotating CHs positions to evenly distribute the energy load among all the SNs, thus enables self-organization in WSNs.

LEACH remains a paradigm architect for designing clustering protocols for WSNs till date. HEED (Hybrid Energy-Efficient Distributed clustering) (Younis and Fahmy, 2004), is another classical clustering protocol that selects CHs based on hybridization of node residual energy and node proximity to its neighbours or node degree thus achieves uniform CH distribution across the network. HEED approach can be useful to design WSN protocols that require scalability, prolonged network lifetime, fault tolerance, and load balancing but it only provides algorithms for building a two-level hierarchy and no idea is presented for designing protocol to multilevel hierarchies. Power-efficient and adaptive clustering hierarchy (PEACH) (Yi et al., 2007) selects CHs without additional overhead of wireless communication and supports adaptive multi-level clustering for both location-unaware and location-aware WSNs but with high latency and low scalability thus making it suitable only for small networks. T-ANT (Selvakennedy et al., 2007), a swarm-inspired clustering protocol, exploits two swarm principles, namely separation and alignment, through pheromone control to obtain a stable and near uniform distribution for selection of CHs. Energy-Efficient Multi-level Clustering (EEMC) (Jin et al., 2008) achieves less energy consumption and minimum latency in WSNs by forming multi-level clustering with minimum algorithm overhead. However, it ignores the issue of channel collision which happens frequently in wireless networks. Energy efficient heterogeneous clustered scheme (EEHC) (Kumar et al., 2009) selects CHs based on weighted election probabilities of each node which is a function of the residual energy and further support node heterogeneity in WSNs. Multi-path Routing Protocol (MRP) (Yang et al., 2009) is based on dynamic clustering with Ant colony optimization (ACO) metaheuristic. A CH is selected based on residual energy of nodes and an improved ACO algorithm is applied to search multiple paths that exist between the CH and BS. MRP prolonged the network lifetime and reduces the average energy consumption effectively using proposed metaheuristic. Energy Efficient Cluster Formation protocol (EECF) (Chamam and Pierre, 2010) presents a distributed clustering algorithm where CHs are selected based on a three-way message exchange between each sensor and its neighbours while possessing maximum residual energy and degree. However the protocol does not support multi-level clustering and considers small transmission ranges. Mobility-based clustering (MBC) protocol (Deng et al., 2011) supports node mobility, hence CHs will be selected based on nodes residual energy and mobility, whereas a non-CH node maintains link stability with its CH during set-up phase. UCFIA (Mao and Zhao, 2011) is a novel energy efficient unequal clustering algorithm for large scale WSNs, which uses fuzzy logic to determine node's chance to become CH based on local information such as residual energy, distance to BS and local density of nodes. In addition, an adaptive max-min ACO metaheuristic is used to construct energy-aware inter-cluster routing between CHs and BS, thus balances the energy consumption of CHs. Distributed Energy-Efficient Clustering with Improved Coverage (DEECIC) (Liu et al., 2012) selects minimum number of CHs to cover the whole network based on nodes local information and periodically updates CHs according to nodes residual energy and distribution. By reducing overheads of time synchronization and geographic location information, it prolongs network lifetime and improves network coverage. Energy-Aware Evolutionary Routing Protocol (ERP) (Attea and Khalil, 2012) is based on Evolutionary algorithms (EAs) and ensures better trade-off between lifetime and node stability period of a network with efficient energy utilization in complex WSNs environment. Harmony search algorithm based clustering protocol (HSACP) (Hoang et al., 2014) is a centralized clustering protocols based on Harmony search algorithm (HSA), a music-inspired metaheuristic, which is designed and implemented in real time for WSNs. It is designed to minimize the intra-cluster distances between the cluster members and their CHs thus optimize the energy distribution for WSNs. BeeSensor (Saleem and Farooq, 2012) is an energy-aware, event driven, reactive and on-demand routing protocol for WSNs. Inspired from biological system of bees

Table 1
Relative comparison of protocols in WSNs.

Protocol	Classification	Energy-efficiency	Features	Limitations
LEACH (Heinzelman et al., 2002)	Classical	Average	Self-organization	High communication cost
HEED (Younis and Fahmy, 2004)	Classical	Average	Low communication cost	High latency
PEACH (Yi et al., 2007)	Classical	Average	Load balancing	High latency, low scalability
T-ANT (Selvakennedy et al., 2007)	Computational Intelligence	Good	Fast convergence, low overhead	Low coverage
EEMC (Jin et al., 2008)	Classical	Average	Minimum overhead, low latency	Only uniform node distribution
EEHC (Kumar et al., 2009)	Classical	Good	Support node heterogeneity	Low scalability
MRP (Yang et al., 2009)	Computational Intelligence	Good	Prolong network lifetime	Need parameters adjustment
EECF (Chamam and Pierre, 2010)	Classical	Average	Prolong network lifetime	Low transmission range
MBC (Deng et al., 2011)	Classical	Average	High node mobility, low packet loss	High communication cost
UCFLA (Mao and Zhao, 2011)	Computational Intelligence	Good	Prolong network lifetime	Need parameters adjustment
DEECIC (Liu et al., 2012)	Classical	Average	Better network coverage	Low scalability
ERP (Attea and Khalil, 2012)	Computational Intelligence	Average	Better network lifetime	Non-cluster based approach
HSACP (Hoang et al., 2014)	Computational Intelligence	Good	Fast convergence	No load balancing
BeeSensor (Saleem and Farooq, 2012)	Computational Intelligence	Good	Low processing cost	Non-cluster based approach
PSO (Kuila and Jana, 2014)	Computational Intelligence	Good	Better packet delivery	Network overhead

and based on a typical bee agent model, which works with four types of agents namely packers, scouts, foragers and swarms, BeeSensor demonstrates good performance over other CI based protocols with least communication and processing cost. One major drawback of the protocol is its flat nature or non-cluster based approach, which affects its performance on various fronts. Kuila and Jana (2014) present a Linear/Nonlinear Programming (LP/NLP) formulation of energy efficient clustering and routing problems in WSNs, followed by two algorithms for the same based on a Particle swarm optimization (PSO). Their proposed algorithms demonstrate their proficiency in terms of network life, energy consumption, and delivery of data packets to the BS. Further, some of the authors (Alfi and Khosravi, 2012, Jordehi, 2015a,b; Jordehi et al., 2015; Wu et al., 2015; Heidari et al., 2015) highlighted the need of CI based metaheuristic to diverse areas of application. In Table 1, we present a relative comparison of these protocols, highlighting their features and limitations for a better insight.

It is very much clear from the comparison that classical as well as CI based approaches have their own features as well as limitations. Classical approaches are better in self-organization, load balancing with minimum overhead but average in energy-efficiency whereas CI based metaheuristic are shown to be good in energy-efficiency with prolonged network life. Therefore, CI based metaheuristic approaches need to be further explored and improved for energy-efficient solutions in WSNs.

3. Artificial Bee Colony (ABC) metaheuristic

Original Artificial Bee Colony (ABC) metaheuristic is proposed by Karaboga and Akay (2009) for optimizing multi-variable and multi-modal continuous functions, which has aroused much interest in research community due to its less computational complexity with the use of few number of control parameters. Moreover, optimization performance of ABC is competitive to the well-known state-of-the-art meta-heuristics (Karaboga and Basturk, 2008). In ABC, there are three type of bees: employed bees, onlookers and scout bees (Zhang and Wu, 2011). The employed bee carries *exploitation* of a food source and shares information like direction and richness of food source with the onlooker bee, through a *waggle* dance, there after onlooker bee will select a food source based on a probability function related to the richness of that food source, whereas scout bee *explore* new food sources randomly around the hive. When a scout or an onlooker bee finds a new food source, they become employed again; on the other hand, when a food source has been fully exploited, all the employed bees will abandon the site and may become scouts again. In ABC metaheuristic, a food source corresponds to a possible solution to the optimization problem and the number of employed bees is equal to the

number of food sources.

Below we present the detailed procedure of ABC metaheuristic in different phases.

3.1. Initialization phase

ABC metaheuristic starts with initial population number (PN), randomly generated through D -dimensional real set of vectors. Let $x_{ij} = \{x_{i1}, x_{i2}, \dots, x_{iD}\}$ is the i -th food source, where $j = 1, 2, \dots, D$, which is obtained by:

$$x_{ij} = x_{minj} + rand(0, 1)(x_{maxj} - x_{minj}) \quad (1)$$

where x_{minj} and x_{maxj} denote for lower and upper limits respectively.

3.2. Employed bee phase

In this phase, each employed bee obtains a new solution v_{ij} from x_{ij} using expression:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \quad (2)$$

where k is randomly obtained from $\{1, 2, \dots, SN\}$ and ϕ_{ij} is a uniform random number between $[-1, 1]$. The value of v_{ij} is obtained and compared to x_{ij} , further if the fitness of v_{ij} comes out better than x_{ij} , then the bee will forget the old solution and remember the new one. Otherwise, it will keep exploiting x_{ij} .

3.3. Onlooker bee phase

All employed bees share the nectar information of their food sources with the onlookers through a *waggle* dance performed at their hive, after which they select a food source depending on a probability p_i as:

$$p_i = \frac{f_i}{\sum_{n=1}^{SN} f_i}, \quad (3)$$

where f_i is the fitness of x_{ij} . Onlooker bee chooses a food source with higher fitness and search x_{ij} according to Eq. (2), now if the new solution has a better fitness, it will replace x_{ij} .

3.4. Scout bee phase

After a number of trials, called Maximum cycle number (MCN), if a solution cannot be improved further then food source is abandoned, and the corresponding employed bee becomes a scout again. The scout will then produce a new food source randomly by using Eq. (1) again.

4. Artificial Bee Colony variants

Various modifications have been proposed to inculcate efficiency in the existing original version of the ABC metaheuristic. One of the factors which affect the outcome of the metaheuristic is influenced by its solution search equations and thus requires many modifications. Advising an improved solution search equation tries to set a balance between the exploitation and exploration capabilities of the metaheuristic. Gao and Liu (2011) introduced search equations which are based on Differential evolution (DE) (Ferrante Neri, 2001) algorithms to solve numerous real-world optimization problems

$$v_{ij} = x_{bj} + \phi_{ij}(x_{ij} - x_{rj}) \quad (4)$$

$$v_{ij} = x_{r1j} + \phi_{ij}(x_{ij} - x_{r2j}) \quad (5)$$

where $\phi_{i,j}$ is a uniform random number and $x_{r,j}$ is the j th component of a random solution. In addition, Gao et al. (2012) introduced another variant later as

$$v_{ij} = x_{bj} + \phi_{ij}(x_{r1j} - x_{r1j}) \quad (6)$$

Other search equations are proposed by Abro and Mohamed-Saleh (2012) and Gao et al. (2013):

$$v_{ij} = x_{r1j} + \phi_{ij}(x_{r2j} - x_{r3j}) \quad (7)$$

$$v_{ij} = x_{bj} + \phi_{ij}(x_{r1j} - x_{r2j}) + \psi_{ij}(x_{r3j} - x_{r4j}) \quad (8)$$

$$v_{ij} = x_{bj} + \phi_{ij}(x_{r1j} - x_{r2j}) + \psi_{ij}(x_{sbj} - x_{ij}), \quad (9)$$

where x_{sbj} is the j th coefficient of the second best solution. However, the effectiveness of these DE based equations critically depends on the appropriate setting of population size and strategy parameters. Therefore, to obtain optimal solution, the parameters setting must be required.

These equations are further modified in Li et al. (2013) into Eq. (10), where w_{ij} is the relative weight and θ_1, θ_2 are parameters to control step size:

$$v_{ij} = w_{ij}x_{bj} + \phi_{ij}\theta_1(x_{ij} - x_{rj}) + \psi_{ij}\theta_2(x_{sbj} - x_{ij}) \quad (10)$$

Although the above-mentioned solution search equation may refine the exploitation process using two different control parameters sometimes leads to oscillation.

The search equations introduced above can be utilized in onlooker bee phase as well, however in that case neighbourhood search will be performed on most anticipating solutions with best fitness.

Scout bee phase also witnessed some improvements (Guo et al., 2011) in the following form of new solution search equations:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{bj} - x_{ij}) \quad (11)$$

$$v_{ij} = x_{ij} + \phi_{ij}(x_{sbj} - x_{ij}) \quad (12)$$

In addition, some improved versions of the ABC metaheuristic (Akay and Karaboga, 2012) include some parameters, like Modification Rate (MR) and Scale Factor (SF), MR controls the neighbourhood search whereas SF controls the length of the search.

However, most of the above-mentioned works do not control the adaptation of the population and do not specify any means to improve sampling space, which is a significant measure to improve the effectiveness of ABC metaheuristic.

5. Author's contribution

The main contributions of this paper are listed as follows:

1. *Improved Artificial Bee Colony (iABC) metaheuristic*: In an attempt to improve the convergence rate and attain a perfect balance between exploitation and exploration capabilities of existing ABC

metaheuristic, we propose an improved Artificial Bee Colony (iABC) metaheuristic with better sampling technique using *Student's-t* distribution; a compact probability density function (cPDF), which requires only one control parameter to be stored on memory. *Student's-t*-distribution is being introduced first time from the widely acclaimed family of Estimation of Distribution Algorithms (EDAs) framework. Further, an improved solution search equation named *ABC/rand-to-opt/1* is proposed, which is motivated by the existing Differential evolution (DE) family framework, and educes an optimal solution from the current best solutions thus improving convergence rate of the proposed metaheuristic.

2. *BeeCluster – an improved Artificial Bee Colony based clustering protocol*: Utilizing capabilities of the proposed metaheuristic, we introduce *BeeCluster*, an improved Artificial Bee Colony based clustering protocol for optimal cluster head (CH) selection, which is a well identified NP-hard optimization problem in WSNs.

6. Improved Artificial Bee Colony (iABC) metaheuristic

Like standard ABC metaheuristic, its variants too face some challenges, like the convergence rate is typically slow since they find difficulty in choosing the most promising search solution, while solving complex multi-modal optimization problems. To overcome these limitations we propose an improved Artificial Bee Colony (iABC) metaheuristic with an improved initialization phase for better sampling and improved solution search equation, named *ABC/rand-to-opt/1* with optimal search abilities. The details of the proposed metaheuristic are as follows.

6.1. Improved initialization phase

Population initialization is an important step in evolutionary algorithms as it can affect the convergence rate and quality of the final solution. Moreover, a large amount of the memory is needed either to store the trial solutions or control parameters of the problem. To reduce the memory requirements, the concept of virtual population has been introduced (Mininno et al., 2008) through family of Estimation of Distribution Algorithms (EDA) (Larranaga and Lozano, 2001) framework by considering compact probability density functions (cPDFs). Therefore, we propose *Student's-t* distribution (Walck, 2007); a cPDF which needs only one vector to be stored in the memory thus reduces storage and steps-up convergence rate. The proposed distribution can be described by Eq. (13) where $f(x_{ij})$ is the value of the cPDF corresponding to variable x_{ij} , the $(-\infty, \infty)$ domain of the proposed cPDF is truncated to $[-1, 1]$ and B represents a Beta function. By applying this cPDF, only vector κ needed to be stored on memory. This cPDF is being introduced first time in population-based metaheuristic due to its compact nature:

$$f(x_{ij}) = \frac{\left(1 + \frac{x_{ij}^2}{\kappa}\right)^{-(\kappa+1)/2}}{\sqrt{\kappa} B\left(\frac{1}{2}, \frac{\kappa}{2}\right)} \quad (13)$$

Further, we suggested a new alternative with Cumulative distribution function (CDF) of the proposed *Student's-t* distribution, where a pair of cPDFs that share the same parameters is derived through *Student's-t* CDF by taking integral from $-x$ to x with respect to dx for function $f(x)$ as mentioned below:

Table 2
Benchmark functions used in experiment.

Function	Search range
$f_1(x) = \sum_{i=1}^n x_i^2$	$[-100, 100]^n$
$f_2(x) = \sum_{i=1}^n ix_i^2$	$[-10, 10]^n$
$f_3(x) = \sum_{i=1}^n x_i ^{i+1}$	$[-10, 10]^n$
$f_4(x) = \sum_{i=1}^n x_i + \prod_{i=1}^n x_i $	$[-10, 10]^n$
$f_5(x) = [x_i^2 - 10 \cos(2\pi x_i) + 10]$	$[-6.45, 6.45]^n$
$f_6(x) = [y_i^2 - 10 \cos(2\pi y_i) + 10]$	$[-6.45, 6.45]^n$
where	$[-6.45, 6.45]^n$
$y_i = \begin{cases} x_i & \text{if } x_i < \frac{1}{2} \\ \frac{\text{round}(2x_i)}{2} & \text{if } x_i \geq \frac{1}{2} \end{cases}$	
$f_7(x) = \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	$[-500, 500]^n$
$f_8(x) = -\sum_{i=1}^n \sin(x_i) \sin^{20}\left(\frac{i \times x_i^2}{\pi}\right)$	$[0, \pi]^n$

$$\begin{aligned}
\int_{-x}^x f(x) dx &= \frac{1}{\sqrt{\kappa} B\left(\frac{1}{2}, \frac{\kappa}{2}\right)} \int_{-x}^x \left(1 + \frac{x^2}{\kappa}\right)^{-(\kappa+1)/2} dx \\
&= \frac{2}{\sqrt{\kappa} B\left(\frac{1}{2}, \frac{\kappa}{2}\right)} \int_0^x \left(1 + \frac{x^2}{\kappa}\right)^{-(\kappa+1)/2} dx \\
&= \frac{-2}{\sqrt{\kappa} B\left(\frac{1}{2}, \frac{\kappa}{2}\right)} \int_1^{\kappa/\kappa+x^2} \frac{x^{\kappa+1/2} \kappa \sqrt{x}}{2x^2 \sqrt{\kappa} \sqrt{(1-x)}} dx \\
&= \frac{1}{B\left(\frac{1}{2}, \frac{\kappa}{2}\right)} \int_{\kappa/\kappa+x^2}^1 (1-x)^{-1/2} x^{\kappa/2-1} dx = \frac{1}{B\left(\frac{1}{2}, \frac{\kappa}{2}\right)} \left(B\left(\frac{\kappa}{2}, \frac{1}{2}\right) - B_{\frac{\kappa}{\kappa+x^2}}\left(\frac{\kappa}{2}, \frac{1}{2}\right) \right) \\
&= 1 - I_{\frac{\kappa}{\kappa+x^2}}\left(\frac{\kappa}{2}, \frac{1}{2}\right) = I_{\frac{x^2}{\kappa+x^2}}\left(\frac{1}{2}, \frac{\kappa}{2}\right)
\end{aligned} \quad (14)$$

where I corresponds to incomplete Beta function. Therefore, the search space corresponding to variable x_{ij} is now divided into $[-1,0]$ and $[0,1]$ and instead of applying one cPDF, a pair of cPDFs $P_j(x)$ (15) and $Q_j(x)$ (16) are employed for better sampling based on a parameter ξ that controls the probability of sampling:

$$P_j(x) = \frac{1}{2} - \frac{1}{2} I_{\frac{x_{ij}^2}{\kappa+x_{ij}^2}}\left(\frac{1}{2}, \frac{\kappa}{2}\right) \quad \text{for } -1 < x < 0 \quad (15)$$

$$Q_j(x) = \frac{1}{2} + \frac{1}{2} I_{\frac{x_{ij}^2}{\kappa+x_{ij}^2}}\left(\frac{1}{2}, \frac{\kappa}{2}\right) \quad \text{for } 0 \leq x < 1 \quad (16)$$

These equations are employed to refine the sampling process which ultimately enhance the convergence rate of the proposed metaheuristic globally.

6.2. Improved solution search equation

Differential evolution (DE) (Storn and Price, 2010) employs most powerful stochastic real-parameter algorithms to solve multi-modal optimization problems with the optimal combination of population size and their associated control parameters. In other words, a well-contrive parameter adaptation approach can effectively solve various optimization problems and convergence rate can improve further if the control

parameters are adjusted to appropriate values with improved solution search equations at different evolution stages of a specific problem. There are various DE variants which are different in their mutation strategies but *DE/rand-to-best/1* (Das and Suganthan, 2011; Gonuguntla et al., 2015) is one of its kind which explore *best* solutions to direct the movement of the current population and can effectively maintain population diversity as well:

$$DE/rand-to-best/1: \quad v_i = x_i + SF_1(x_{bes} - x_i) + SF_2(x_r - x_s) \quad (17)$$

where SF_1 and SF_2 are scaling factors for neighborhood search. Inspired by this DE variant (17) and inculcating properties of the ABC metaheuristic, we propose a new solution search equations *ABC/rand-to-opt/1* as follows:

$$ABC/rand-to-opt/1: \quad v_{ij} = x_{ij} + \phi_{ij}(x_{opt,j} - x_{ij}) + \psi_{ij}(x_{r1j} - x_{r2j}) \quad (18)$$

where r_1 and r_2 are random variables from $1, 2, \dots, SN$, x_{opt} is the optimal individual solution with optimal fitness in the current population with ϕ_{ij} and ψ_{ij} being scaling factors.

The proposed solution search equation *ABC/rand-to-opt/1*, which utilizes the information of only optimal solutions in the current population, can improve the convergence rate of the proposed metaheuristic.

To increase the multifariousness of the population further, a crossover operation is performed as:

$$u_{ij} = \begin{cases} v_{ij} & \text{if } r[0, 1] \leq CR, \\ x_{opt,j} & \text{otherwise} \end{cases} \quad (19)$$

Then a selection operation will be performed as:

$$x_{i,j} = \begin{cases} u_{ij} & \text{if } f(u_{ij}) \leq f(x_{ij}), \\ x_{opt,j} & \text{otherwise} \end{cases} \quad (20)$$

where $f(x_{ij})$ is the fitness function, if the new solution seems to have high fitness value, then it replaces the corresponding old solution; otherwise the old solution is retained in the memory. Therefore, with the proposed improved solution search equation, optimal solution is obtained with optimal exploration and exploitation ability thus contributing to a better convergence rate.

We have evaluated the convergence rate of our proposed *iABC* metaheuristic with the standard ABC metaheuristic using set of eight scalable benchmark functions f_1 to f_8 , where functions f_1 to f_4 are uni-modal and functions f_5 to f_8 are multi-modal functions as shown in Table 2.

Graphs (Figs. 2 and 3) show that the proposed *iABC* metaheuristic convergence fast with optimal or closer-to-optimal solutions on the uni-modal as well as complex multi-modal functions over to its standard ABC variant. Therefore, the proposed metaheuristic can improve searching abilities, increase convergence rate and possess

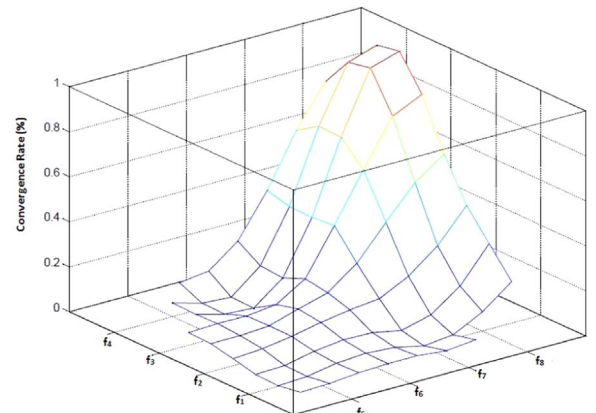


Fig. 2. Convergence rate of iABC.

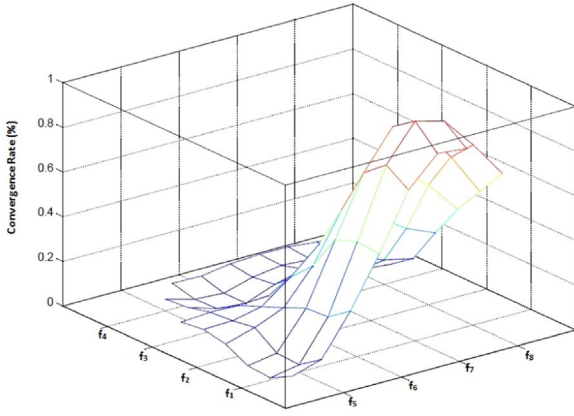


Fig. 3. Convergence rate of ABC.

more computational efficiency.

7. BeeCluster – proposed clustering protocol

We inherit the capabilities of our proposed metaheuristic to solve well known NP-hard optimization problem of energy-efficient clustering in WSNs by proposing *BeeCluster*, an improved Artificial Bee Colony based clustering protocol with an optimal CH selection ability. Additionally, we also determine the optimal location of the BS through analytical evaluation of energy equations, which reduce the energy consumption of the network and help to enhance the network life of existing WSN.

7.1. Network model

The network model is based on following notations in our proposed work:

1. S is the set of sensor nodes $S = \{s_1, s_2, \dots, s_n\}$, which are randomly distributed over a geographical area of defined dimensions $m \times m$, whereas s_{n+1} denotes the BS. Each sensor node has a communication radius r .
2. L is the set of bidirectional wireless links between two sensor nodes, where $l_{ij} \in L$ represents wireless link between node s_i and s_j .
3. Set of Cluster Heads (CH's) are denoted by $S_{ch} = \{ch_1, ch_2, \dots, ch_k\}$ where $S_{ch} \in S$.
4. $D_{s_i}^{s_j}(\max)$ denotes the maximum distance between a sensor node s_i and s_j which is calculated by squared Euclidean distance between them as

$$D_{s_i}^{s_j}(\max) = \text{Max} \{ \text{dis}(s_i, s_j) \} \quad | \quad \forall s_i, s_j \in S = \|s_i - s_j\|^2 = \sum (s_i - s_j)^2 \quad | \quad \forall s_i, s_j \in S \quad (21)$$

5. $D_{s_i}^{s_{n+1}}(\max)$ denotes the maximum distance between a sensor node s_i and BS which is calculated by squared Euclidean distance between them as

$$D_{s_i}^{s_{n+1}}(\max) = \text{Max} \{ \text{dis}(s_i, s_{n+1}) \} \quad | \quad \forall s_i \in S = \|s_i - s_{n+1}\|^2 = \sum (s_i - s_{n+1})^2 \quad | \quad \forall s_i \in S \quad (22)$$

6. $D_{s_i}^{ch_j}(\max)$ denotes the maximum distance between a sensor node s_i and cluster head ch_j which is calculated by squared Euclidean distance between them as

$$D_{s_i}^{ch_j}(\max) = \text{Max} \{ \text{dis}(s_i, ch_j) \} \quad | \quad \forall s_i, ch_j \in S = \|s_i - ch_j\|^2 = \sum (s_i - ch_j)^2 \quad | \quad \forall s_i, ch_j \in S \quad (23)$$

7. $D_{ch_j}^{s_{n+1}}(\max)$ represents the maximum distance between a cluster

head ch_j and BS, is calculated by squared Euclidean distance between them as

$$D_{ch_j}^{s_{n+1}}(\max) = \text{Max} \{ \text{dis}(ch_j, s_{n+1}) \} \quad | \quad \forall j \in S_{ch} = \|ch_j - s_{n+1}\|^2 = \sum (ch_j - s_{n+1})^2 \quad | \quad \forall j \in S_{ch} \quad (24)$$

8. Transmission power of a sensor node s_i is calculated as:

$$P_{tran_i} = \frac{1}{k} \left(\frac{\gamma \cdot T_{delay}}{dc} \right)^\alpha \quad (25)$$

where T_{delay} is the sum of three delay components:

$$T_{delay} = T_{que} + T_{tran} + T_{ack} \quad (26)$$

The first component, T_{que} , is the queuing delay; the second component, T_{tran} , is the transmission delay; and the third one, T_{ack} , is the delay due to acknowledgement packet. γ , α , and dc are signal to noise ratio, path loss exponent, and delay constraint respectively whereas k is a power constant.

7.2. Energy model

The energy model is assumed to be same which has been used in earlier work (Heinzelman et al., 2002) in which CHs receive data packets from SNs for aggregation but include an additional acknowledgment packet (ACK) in return to the source node after receiving a correct packet. This is first time we incorporate the significance of energy consumption by the exchange of a ACK in WSNs. The radio hardware which include a transmitter dissipates energy to run transmitter radio electronics and power amplifier whereas the receiver dissipates energy to run the receive radio electronics as shown in Fig. 4.

Therefore, the energy consumption for transmission of l bits of data is composed of three parts: the energy consumed by the transmitter E_{trans} , by the receiver E_{rec} and by the ACK packet exchange E_{ack} :

$$E_{total}(l, d) = E_{trans}(l, d) + E_{rec}(l, d) + E_{ack} \quad (27)$$

now, energy consumed for transmitting l bits of data is given by:

$$E_{trans}(l, d) = l \cdot E_{elec} + E_{amp}(l, d) \quad (28)$$

further, if the distance between transmitter, and receiver is d , then

$$E_{trans}(l, d) = \begin{cases} lE_{elec} + l\epsilon_{fs}d^2 & \text{if } d < d_0, \\ lE_{elec} + l\epsilon_{mp}d^4 & \text{if } d \geq d_0, \end{cases} \quad (29)$$

where d_0 is the threshold distance and to receive l bit message, the radio spends $E_{rec}(l, d)$ as follows:

$$E_{rec}(l, d) = l \cdot E_{elec} \quad (30)$$

Energy consumed for ACK packet exchange is given by

$$E_{ack} = \tau_{ack}(E_{trans} + E_{rec}) \quad (31)$$

where $\tau_{ack} = \frac{l_{ack}}{l}$ is the ratio between length of acknowledgement packet to data packet.

Therefore, the residual energy of each sensor node is calculated as:

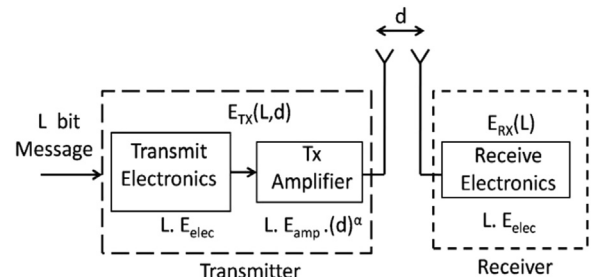


Fig. 4. Radio Model for energy analysis.

$$E_{res} = E_{total} - (E_{trans} + E_{rec} + E_{ack}) \quad (32)$$

If there will be n nodes uniformly distributed in an $m \times m$ field with k clusters, then there will be $\frac{n}{k}$ nodes per cluster. Out of these, there will be one CH node and remaining $\frac{n}{k} - 1$ non-CH nodes.

Now energy consumed by a non-CH node is given by:

$$E_{non-ch}(l, d) = E_{trans}(l, d) \quad (33)$$

$$E_{non-ch}(l, d) = l \cdot E_{elec} + E_{amp}(l, d) \quad (34)$$

and energy consumed by a CH node is given by:

$$E_{ch}(l, d) = E_{trans}(l, d) + \left(\frac{n}{k} - 1\right) \cdot l \cdot E_{elec} + \frac{n}{k} \cdot l \cdot E_{da} + \left(\frac{n}{k} - 1\right) E_{ack} \quad (35)$$

where E_{da} is the energy consumed by CH for data aggregation at its end.

Now, the total energy consumed in a cluster is given by:

$$E_{cluster} = E_{ch}(l, d) + \left(\frac{n}{k} - 1\right) E_{non-ch} \quad (36)$$

Therefore, energy consumed in whole network per round is given as:

$$E_{round} = \sum_{j=1}^k E_{cluster}(j) \quad (37)$$

7.3. Optimal CH selection phase

CH selection is one of the crucial task for cluster formation in WSNs as it affects the overall performance of the network. CH will be responsible for the collection of data coming from various SNs and transmission of aggregated data to the BS. Selection of appropriate node as a CH will remain a challenging multi-modal optimization problem. Therefore, we propose an optimal CH selection algorithm based on our proposed *iABC* metaheuristic for an improved energy-efficient clustering protocol. The working of proposed algorithm is as follows.

7.3.1. Initialization phase

The population number (PN) and corresponding food sources (SN) are initialized along with control parameters Maximum cycle number (MCN), control parameter ξ and Crossover rate (CR).

We employ the proposed improved sampling technique of *iABC* metaheuristic to generate the i -th food source x_{ij} , for which we generate $r \in [0, 1]$ according to uniform distribution and obtain x_{ij} as:

$$x_{ij} = \begin{cases} \frac{1}{2} - \frac{1}{2} I \frac{x_{ij}^2}{\kappa + x_{ij}^2} \left(\frac{1}{2}, \frac{\kappa}{2} \right) & \text{if } r \leq \xi, \\ \frac{1}{2} + \frac{1}{2} I \frac{x_{ij}^2}{\kappa + x_{ij}^2} \left(\frac{1}{2}, \frac{\kappa}{2} \right) & \text{if } r > \xi, \end{cases} \quad (38)$$

7.3.2. Fitness function derivation

Now, we construct a fitness function to evaluate the fitness of individual food source of the population. There are three objectives in our proposed CH selection algorithm, firstly the node elected as CH will have maximum residual energy, i.e.

$$f_i \propto \text{Max}(E_{res}) \quad (39)$$

Secondly, we ensure to minimize the maximum distance between elected node as CH and BS with minimum transmission power to transmit aggregated data from CH to BS:

$$f_i \propto \frac{1}{\text{Min}(D_{chj}^{s_{n+1}}(\text{max}) + P_{tran_i})} \quad (40)$$

Aggregating Eqs. (39) and (40) as

$$f_i \propto \frac{\text{Max}(E_{res})}{\text{Min}(D_{chj}^{s_{n+1}}(\text{max}) + P_{tran_i})} \quad (41)$$

$$f_i = K \frac{\text{Max}(E_{res})}{\text{Min}(D_{chj}^{s_{n+1}}(\text{max}) + P_{tran_i})} \quad (42)$$

where K is the constant of proportionality, assuming $K=1$,

$$f_i = \frac{\text{Max}(E_{res})}{\text{Min}(D_{chj}^{s_{n+1}}(\text{max}) + P_{tran_i})} \quad (43)$$

Therefore, Eq. (43) will determine the fitness value of each solution of population.

7.3.3. Employed bee phase

Now each employed bee selects a new solution v_{ij} using proposed improved search equation (19) of proposed *iABC* metaheuristic as:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{opt,j} - x_{ij}) + \psi_{ij}(x_{r1j} - x_{r2j}) \quad (44)$$

The obtained value of v_{ij} is compared to x_{ij} and if the fitness of v_{ij} comes out better than x_{ij} , the bee will forget the previous old solution and retain the new optimal solution $x_{opt,j}$ found so far, otherwise, it will keep working on x_{ij} .

7.3.4. Onlooker bee phase

Now, employee bee will share the information of their food source with the onlooker bee, through a *waggle* dance performed at their hive, each of whom will then generate a food source u_{ij} according to distribution as:

$$u_{ij} = \begin{cases} v_{ij} & \text{if } r[0, 1] \leq CR, \\ x_{opt,j} & \text{otherwise} \end{cases} \quad (45)$$

where CR is the crossover rate, further fitness of generated food source $f(u_{ij})$ is calculated and compared with the previous food source as:

$$x_{i,j} = \begin{cases} u_{ij} & \text{if } f(u_{ij}) \leq f(x_{ij}), \\ x_{opt,j} & \text{otherwise} \end{cases} \quad (46)$$

where $f(x_{ij})$ is the fitness value of x_{ij} . Onlooker bee will then choose a food source with higher fitness and conduct a local search on x_{ij} , if the new solution has a better fitness, then it will replace x_{ij} with optimal solution $x_{opt,j}$ and assigned as a CH, otherwise the old solution will be retained.

7.3.5. Scout bee phase

Now, if the fitness cannot improve further, after a number of trials then the corresponding employed bee becomes a scout to produce a new food source randomly by using Eq. (38) again.

The detail Cluster Head (CH) Selection Algorithm is discussed as below.

Optimal Cluster Head (CH) Selection Algorithm

Input:

$PN \leftarrow$ Population number,
 $MCN \leftarrow$ Maximum cycle number,
 $D \leftarrow$ Dimension of vector to be optimized,
 $SN \leftarrow$ Food sources,
 $x_{min} \leftarrow$ Lower bound of each element,
 $x_{max} \leftarrow$ Upper bound of each element,
 $\xi \leftarrow$ Control parameter,
 $CR \leftarrow$ Crossover rate.

Output:

$Ch_j \leftarrow x_{opt,j}$

```

begin
round  $\leftarrow$  0
for  $i = 1 \rightarrow SN$  do
    Generate  $r \in [0, 1]$  according to uniform distribution.
    ▷ population initialization
    if  $r \leq \xi$  then
        Generate  $x_{ij} \in [-1, 0]$  according to PDF  $P_j(x)$ .
    else
        Generate  $x_{ij} \in [0, 1]$  according to PDF  $Q_j(x)$ .
        Evaluate fitness  $f_i(x_{ij})$ 
        trial(s)  $\leftarrow$  0
        round++
    end if
end for
repeat
until
for  $i = 1 \rightarrow SN$  do
    Generate  $v_{ij}$  according to Eq. (44)    ▷Employed Bee Phase
    Evaluate fitness  $f_i(v_{ij})$ 
    round++
    if  $f_i(x_{ij}) < f_i(v_{ij})$  then
         $x_{ij} \leftarrow v_{ij}$ 
         $f_i(x_{ij}) \leftarrow f_i(v_{ij})$ 
        trial(s)  $\leftarrow$  0
    else
        trial(s)  $\leftarrow$  trial(s) + 1
    end if
end for
if round == MCN then
    Memorize the optimal solution,  $x_{opt,j}$  achieved so far and exit repeat.
     $Ch_j \leftarrow x_{opt,j}$ 
end if
repeat
until
for  $i = 1 \rightarrow SN$  do    ▷OnlookerBeePhase
     $r \leftarrow \text{rand}[0, 1]$ 
    if  $r \leq CR$  then
         $u_{ij} \leftarrow v_{ij}$ 
    else
         $u_{ij} \leftarrow x_{opt,j}$ 
    end if
    Evaluate fitness  $f_i(u_{ij})$  and  $f_i(x_{opt,j})$ 
    if  $f_i(u_{ij}) \leq f_i(x_{opt,j})$  then
         $x_{i,j} \leftarrow u_{ij}$ 
        if  $f_i(u_{ij}) > f_i(x_{opt,j})$  then
             $x_{opt,j} \leftarrow u_{ij}$ 
             $f_i(x_{opt,j}) \leftarrow f_i(u_{ij})$ 
            trial(s)  $\leftarrow$  trial(s) + 1
        end if
    end if
end for
if solution need to be abandoned
    replace with a new solution, produced using Eq. (38)
    ▷ScoutBeePhase
    round++
end for
If round == MCN then
    Memorize the optimal solution,  $x_{opt,j}$  achieved.
     $Ch_j \leftarrow x_{opt,j}$ 
end if
end

```

7.4. Cluster formation phase

After selection of CHs, each CH will advertise a Join-Request (J-REQ) message to all its neighbour nodes for cluster formation. Then each non-CH node will join the nearest CH node based on squared Euclidean distance between them (Eq. (24)) through a Join-Acknowledgment (J-ACK) short message which will be transmitted using a CSMA/CD MAC protocol, to become member of the cluster. During this communication, all CH nodes must keep their receivers on and listen to the channel. If a particular node receives multiple J-REQ message from same CH then it discards the message to eliminate duplicate frames. After receiving J-ACK messages from all the surrounding nodes each CH must maintain a cluster member table and create a TDMA schedule for each member node of the cluster for data transmission. During cluster formation it is ensured that each non-CH node must join a cluster under a CH to avoid node isolation.

7.5. Data transmission phase

After cluster formation, when TDMA schedule is communicated to each member node for data transmission, SNs collect data and transmit it to their CH during their allocated TDMA schedule. The *non-CH* nodes can turn their radio transmitter off during other members transmission turn to save energy consumption. After receiving all the data, CH nodes aggregate it at its end using data aggregation algorithms and route the aggregated data packets to the BS.

8. Simulation results and discussion

Now we evaluate the performance of proposed BeeCluster protocol with the existing HSACP, PSO and LEACH protocols using ns-2 simulator. The protocols are simulated over two different BS position scenarios to assess their behaviour towards packet delivery ratio, throughput, energy consumption, network lifetime and average latency. The simulation will be performed over standard MAC protocol with Free space radio propagation and CBR traffic type, considering other parameters as shown in Table 3.

In the first scenario WSN # 1, a network of sensor nodes ranging from 100 to 700 is deployed randomly over an area of size 150*150 m² with a BS, located at (75 m, 100 m) within the network field, whereas in the second scenario WSN # 2, a BS will be placed at position (100 m, 275 m) outside the network field. First, we execute the protocols to compare Packet delivery ratio (PDR) in the network for both the scenarios.

In scenario WSN # 1, Fig. 5 shows that the proposed protocol delivers highest number of packets among its all peers, even at highest density of nodes. *BeeCluster* delivers approximately 100% packets at 100 nodes in WSN # 1 scenario. Even in WSN # 2 scenario, Fig. 6 shows that *BeeCluster* has highest PDR among its peers. It is important to mention that even when the BS is placed outside the network field, it

Table 3
Simulation Parameters.

Parameter	Value
Terrain size	150 * 150 m ²
MAC protocol	802.11
Radio propagation	Free space
Traffic type	CBR
ϵ_{fs}	8 pJ/bit/m
ϵ_{mp}	0.0015 pJ/bit/m ⁴
Propagation limit	-111 dBm
Receiver sensitivity	-89
Data rate	3 Mbps
Packet size	5000 bits
Message size	300 bits

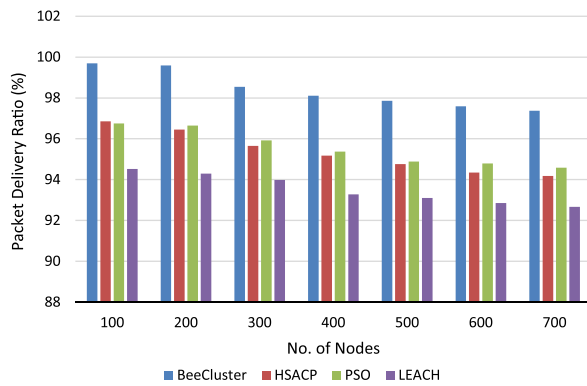


Fig. 5. Packet delivery ratio in WSN # 1.

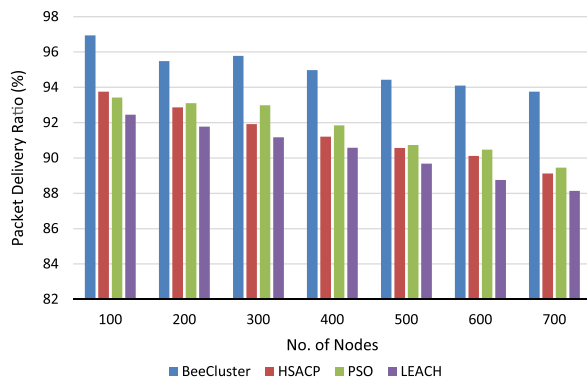


Fig. 6. Packet delivery ratio in WSN # 2.

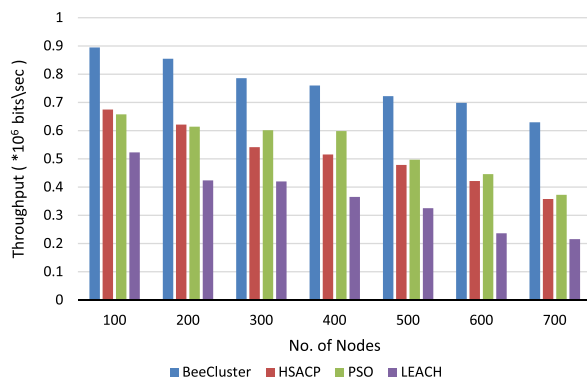


Fig. 7. Throughput in WSN # 1.

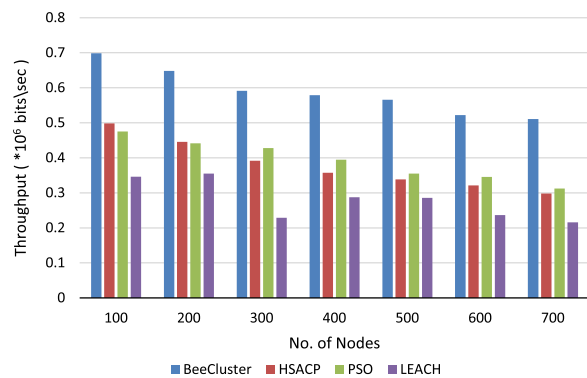


Fig. 8. Throughput in WSN # 2.

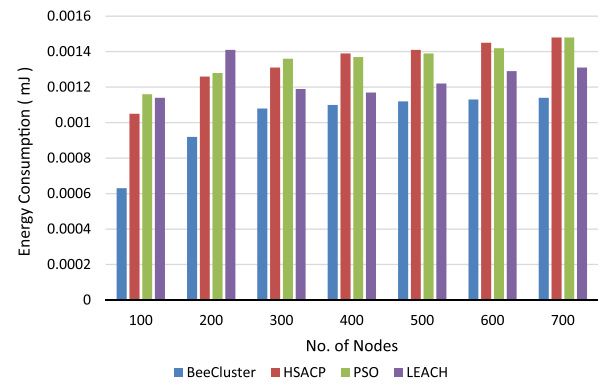


Fig. 9. Energy consumption in WSN # 1.

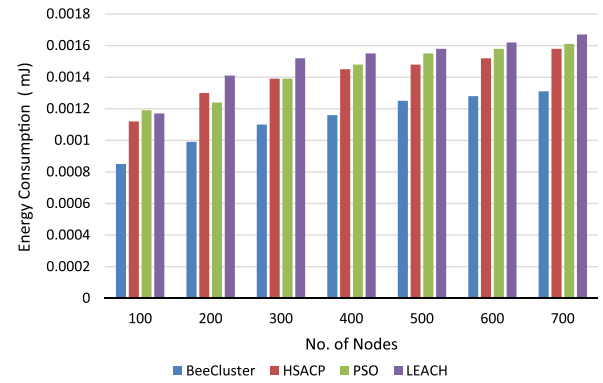


Fig. 10. Energy consumption in WSN # 2.

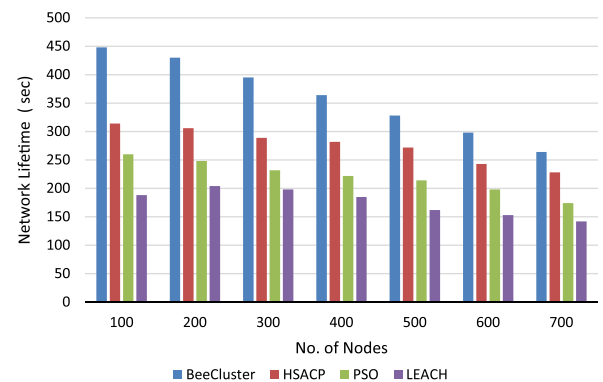


Fig. 11. Network lifetime in WSN # 1.

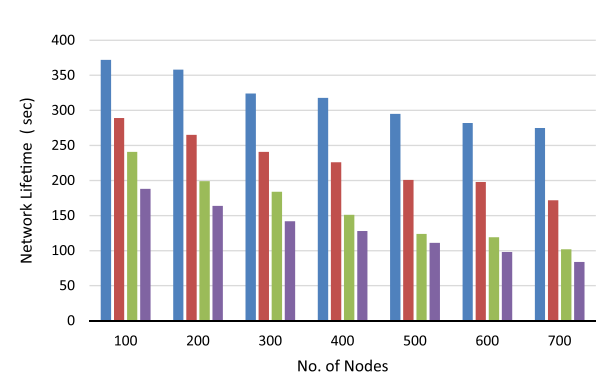


Fig. 12. Network lifetime in WSN # 2.

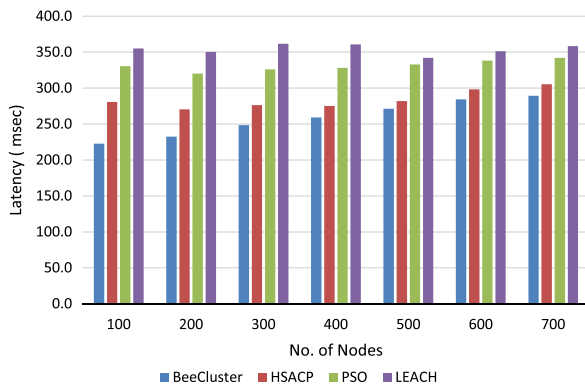


Fig. 13. Average latency in WSN # 1.

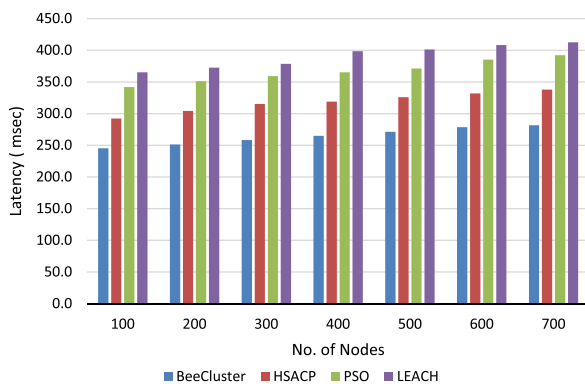


Fig. 14. Average latency in WSN # 2.

does not affect the performance of the proposed protocol, which deliver the highest number of packets at BS.

Figs. 7 and 8 show that *BeeCluster* is delivering highest number of packets per second even at highest number of nodes deployed in the both the scenarios. LEACH is delivering the lowest number of packets as it is a classical protocol and does not employ any optimization algorithm. The throughput rate of HSACP and PSO is almost same in both the scenarios but far behind *BeeCluster* which employs *iABC* metaheuristic.

Fig. 9 shows that in scenario WSN # 1, energy consumption of the proposed protocol is approximately 34%, 48%, and 69% less than HSACP, PSO and LEACH protocols respectively, which is attributed to the use of compact Student's-*t* distribution and improved solution search equation to select optimal CHs, thus minimize energy consumption in the network. Even in scenario WSN # 2 (Fig. 10), *BeeCluster* consumes 32% less energy as compared to its contender HSACP, which clearly shows the effectiveness of the proposed metaheuristic *iABC*. In *BeeCluster*, optimal CHs are selected not only based on their proximity to BS but also with the condition of minimum power consumption in data transmission, moreover the SNs are assigned to their nearest CH, thus consume less energy and as a result the overall energy consumption of the network becomes lesser than other protocols. In LEACH, all CHs are inevitably used as a relay node to forward the data packets to the BS, therefore consume more energy.

Figs. 11 and 12 show that *BeeCluster* extends the average network lifetime by approximately 47% and 56% compared to HSACP and PSO in WSN # 1 and WSN # 2 respectively, which is the effect of nodes surplus energy availability due to less computation and an optimal selection of CHs with proposed metaheuristic. LEACH has smallest network lifetime among its peers due to absence of a clear data aggregation and communication framework, specially for WSN # 2 like scenarios.

The energy thus saved will prolong the network lifetime and the nodes will be able to transmit data for a longer duration. In PSO, due to

unsymmetric data forwarding effects on the CHs, those near to the BS will die quickly thus reduce network lifetime.

Figs. 13 and 14 compare the average latency in both scenarios after number of pre-defined rounds. It is clearly visible that *BeeCluster* delivers data packets with minimum latency in both the scenarios among other protocols which ultimately increase reliability of the network. In WSN #1, average latency decreases sharply with increase in number of rounds in *BeeCluster*, which is due to the fact that the proposed protocol delivers data packets to the BS with minimum relay after calculating the optimal possible distance for the next hop. Also in WSN #2, when the BS is located at a far distance from sensor nodes, the proposed protocol will be able to deliver the data packets with minimum delay successfully. In other protocols, data will be transmitted to BS using maximum number of hop-count ultimately exhaust the network with unnecessary end-to-end delay.

9. Conclusion

This paper presents *BeeCluster*, a clustering protocol for WSNs, based on an *iABC* metaheuristic which uses first of its kind Student's-*t* cPDF and DE inspired improved solution search equation *ABC/rand-to-opt/1* to improve exploitation capabilities as well as convergence rate of existing ABC metaheuristic. The proposed protocol uses an energy-efficient approach, which selects optimal CHs based on an improved search equation and an efficient fitness function. We evaluated the performance of the proposed protocol with other well known cluster based protocols to prove its validity over various performance metrics. Simulation results show that *BeeCluster* consumes less energy as compared to other protocols and prolong network life while delivering highest number of packets with minimum end-to-end delay in diverse WSNs scenarios. In future, we want to implement the network scenarios on real test bed of sensors with a specific application domain.

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