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MOEES-Multi Objective Energy Efficient Clustering Scheme for Wireless Sensor Networks

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Abstract: Recent advances in the field of the wireless sensor networks (WSNs) have led to their deployment in a wide range of agricultural, military, healthcare, and industrial applications. WSNs consists of small power-constrained sensors. Energy conservation is a challenging task in WSN. Optimal utilization of sensor energy is key issue in WSN. Various solutions have been proposed to solve the issues related to sensor energy. Energy-related concerns are best managed by clustering in WSNs. However, uneven energy consumption occurs because of a lack of balance in the clusters and the protocol behavior varies with the network size and node density. In this paper, a particle swarm optimization (PSO)-based multi-objective energy efficient scheme (MOEES) is proposed to create energy-efficient clusters in WSNs. MOEES elects energy-efficient cluster heads (CHs) by considering the intra-cluster distance, inter-cluster distance, and node degree. The main aim of MOEES is to form energy-efficient, balanced, and scalable clusters. The optimum values of these parameters are obtained using MOEES. Furthermore, exhaustive simulations and comparisons with PSO-C, BERA, PSO-ECHS and ECMOSSA have been performed through varying network sizes and node densities to evaluate the effectiveness of MOEES. The total energy consumption of MOEES for 100 nodes and 200 nodes is 8.52 J and 15.18 J respectively, it is lowest when compared with existing techniques.

Keywords: Wireless sensor networks, Energy, Base station, Cluster heads, Sensors, Multi-objective clustering.

1. Introduction

Wireless sensor networks (WSNs) [1] have grown at a very fast pace and has gained the attention of a huge number of applications in different domains in the recent past [2]. WSNs comprises the enormous number of battery-operated sensor nodes (SNs) dispersed over some geographic area as depicted in Fig. 1. In WSNs, SNs are deployed to monitor various environmental parameters such as humidity, temperature, and wind speed for desired information [3]. These SNs can be static or mobile and forward the collected information to the base station (BS). A SN [4] consists of (i) microcontroller (ii) memory (iii) battery (iv) radio transceiver and (v) sensor [5]. The microcontroller processes the sensed data and the radio transceiver is responsible for receiving and transmitting the data [6]. The SNs are equipped with limited power battery. When SNs are installed then it is not possible to recharge [7] and replace battery. The limited power source of SNs is a main constraint of the WSNs [8]. So, there is a need for proper techniques to handle the energy issues in SNs. The overall performance of WSN can only be managed with energy-efficient management schemes [9].

In the last two decades, researchers have proposed numerous protocols to manage the energy requirements in WSNs. The clustering algorithms introduced by Heinzelman are considered to be effective solutions regarding energy conservation [10]. In clustering, the WSN is partitioned into sub-areas known as Clusters [11] and are managed by Cluster heads (CHs) [12]. CH gathers data [13] from

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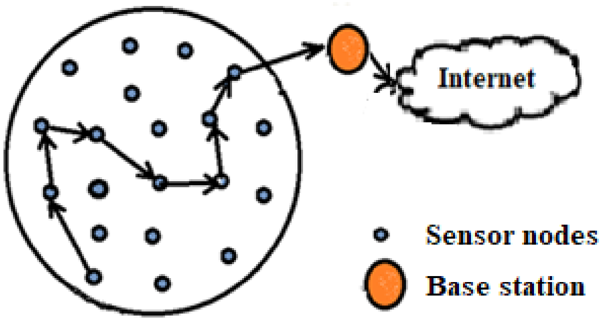

Figure. 1 WSN model

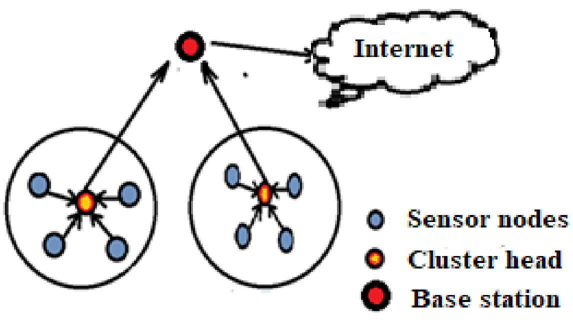

Figure. 2 Cluster based WSN model

SNs within their clusters, further, the collected data is aggregated into a packet [13].

The packet is forwarded using a single-hop or multi-hop communication channel to the base station (BS) depending upon CH and BS distance and reduces the long-distance communications [15]. Further, the BS forwards data to the user application to fulfil the real-time requirements [16]. Fig. 2 demonstrates a cluster-based WSN model, where orange, yellow and blue circles represent the BS, CHs and SNs respectively.

Before the clustering technique, SNs send data directly to BS. Direct transmission was not energy efficient because of long distance between SN and BS and data redundancy [2]. The clustering technique was introduced to avoid direct data transmission. In clustering, SNs elects CH that receives the data, remove redundancy, aggregates it, and transmit to the BS. So, the selection of CH plays an important role in energy consumption efficiently.

In past various conventional approaches such as LEACH (Low-Energy-Adaptive-Cluster-Hierarchy) [10], EEHC (Energy efficient hierarchical clustering) [24], HEED (Hybrid-Energy-Efficient-Distributed) [25], UCS (Unequal clustering size) [26] , EECS (Energy-efficient clustering scheme) [27] have been proposed for optimal CH selection. However, optimal CH selection has not been achieved with these techniques in WSNs.

The selection of an optimal set of CHs is a non-deterministic hard problem. Researchers have proposed numerous evolutionary techniques to solve CH selection problems such as particle swarm optimization (PSO) [17], Ant colony optimization (ACO) [18], and genetic algorithms (GA) [19]. These evolutionary techniques aim to solve energy-related constraints for the optimal solution in WSNs [20-22].

In this paper, a PSO-based multi-objective energy-efficient scheme (MOEES) is proposed. MOEES selects the most optimal CHs to handle cluster activities. Parameters for CH selection considered in MOEES are intra-cluster distance, inter-cluster distance, and node degree. The novel fitness function has been developed using these parameters for CH selection. Nodes having minimum fitness values are selected as CHs [21], [23]. Further selected CHs gather data and transfer to BS. Specifically, in MOEES a novel fitness function is designed for the formation of balanced, scalable, and energy-efficient clusters. The major contributions of the paper are summarized as follows:

- The MOEES scheme uses the PSO technique to select the optimal CH for the clustering process.
- CHs are dispersed throughout the network by maximizing the average distance between CHs that enhances scalability.
- Minimized the difference in node degree and intra-cluster distance to form the balanced clusters. This is due to the inclusion of minimal deviation in node degree and intra-cluster distance objective in the fitness function.

The rest of the paper is arranged as follows: related protocols are discussed in Section 2, Energy consumption model in Section 3. Section 4 and Section 5 give the brief Outline of PSO and MOEES respectively. The proposed scheme and simulation results are described in Sections 6 and 7 respectively. Finally, Section 8 concludes the paper.

2. Related work

In recent times various researchers have proposed numerous techniques for energy-efficient clustering. Some of the recent and novel research works related to clustering schemes are reviewed and presented as below:

First Heinzelman [10] introduced the clustering protocol namely Low-Energy Adaptive Clustering Hierarchy (LEACH), to randomly distribute the CHs based on probability. LEACH uses Time Division Multiple Access (TDMA) schedule to get a time slot for data transmission. However, in LEACH Uniform distribution and load distribution cannot be ensured because CHs are elected based on probability.

Bandyopadhyay and Coyle [24] developed an Energy Efficient Hierarchical Clustering (EEHC) a distributed, randomized clustering algorithm that arranges the SNs into energy-efficient clusters. EEHC hierarchically organizes the CHs. In EEHC, CHs send the sensed data through single-hop and cannot be implemented for scalable applications. Younis [25] presented a distributed clustering scheme known as Hybrid Energy-Efficient Distributed clustering approach (HEED) that selects CH based on the residual energy of nodes and node degree. In HEED, chances to become CH of two nearby SNs are low. Soro and Heinzelman [26] proposed an Unequal Clustering Size (UCS) bi-layered model that leads to uniform energy consumption among the CHs. UCS does not work for large WSNs because of two hops inter-cluster communication. Ye in [27] developed an Energy-Efficient Clustering Scheme (EECS) that elects cluster heads having the highest residual energy. But global information for communication in EECS creates energy overheads due to single-hop communication. Bajaberand Awan [28] proposed an Adaptive Decentralized Re-Clustering Protocol (ADRP) for WSN's to achieve a longer lifetime. The CH's selection depends on the residual energy of SN and the average energy of clusters. But distance parameters are ignored in ADRP, as a result far SNs having high residual energy in single-hop communication got depleted. Wei [29] proposed a distributed Energy-efficient Clustering algorithm (EC), that conserves energy in multi-hop data delivery schemes. CH node density in EC is determined based on the hop to sink distance. The Firefly Synchronisation Multi-hop Geographical Energy Aware Routing (FSM-GEAR) method is introduced by Giva andriana mutiara [30] to enhance energy efficiency by reducing transmission distance. Furthermore, by performing firefly synchronisation among nodes, the waiting time was minimised. The LEACH and Improved Spider Monkey Optimization (ISMO) describe the optimal CH selection and routing respectively in [31]. The multiple parameters considered to optimize the ISMO are residual energy, distance, and routing traffic. In Energy-aware Clustering for WSNs using Particle Swarm Optimization Algorithm (PSO-C), parameters considered for CH selection are intra-cluster distance and residual energy [32]. PSO-C allocate the Cluster Head (CH) over the network area and enhanced the data delivery and network lifetime. Lalwani introduced Biogeography-based Energy-saving Routing Architecture (BERA) in [34]. BERA selects CH by considering the intra-cluster distance, residual energy, and CH-sink distance for the optimal cluster.

Moreover, for optimal routing three parameters residual energy, node degree, and intra-cluster distance are considered for the fitness function. Srinivasalu in [35] presented Energy Centric Multi Objective Salp Swarm Algorithm (ECMOSSA). The parameters considered for fitness function are residual energy, intra cluster distance, CH to BS distance, node degree and node centrality. Rao in [20], discussed particle swarm optimization-based Energy Efficient Cluster Head Selection (PSO-ECHS). To select CH, parameters considered in the protocol are residual energy, intra-cluster distance, and CH to BS distance.

The aforementioned protocols enhance the energy efficacy of WSNs. However, most of the protocols do not consider balance in clusters carefully, therefore, suffers from uneven energy consumption. Moreover, not all of these algorithms consider SN distribution and scalability so the performance of protocols varies with the network size and SN density. It is inferred from literature, that uneven energy consumption and scalability are given less importance. Therefore, to address the problems of energy efficiency, scalability, and balanced clustering, we have proposed a multi-objective energy-efficient clustering scheme using PSO. A comparison of different protocols is depicted in Table 1.

3. Energy consumption model

We use the first-order radio model as suggested in [33]. In this, both free space and multi-path fading propagation models are used. The energy consumption model used in MOEES is shown in Fig. 3. Based on the transmitter and receiver distance d, propagation model channels are selected. The free space fs model is used if the distance is less than a threshold d_0, and amp (multipath) is used otherwise. Thus, the energy consumption for transmitting a p bit message over distance d is as follows:

$$E_{TX}(p,d)=\begin{cases} pE_{elec} + p\epsilon_{fs}d^2, & d<d_0 \\ pE_{elec} + p\epsilon_{amp}d^4, & d\geq d_0 \end{cases} \tag{1}$$

to receive a p − bit message, the radio expends

$$E_{RX}(p)=pE_{elec} \tag{2}$$

Where ϵ_{fs} and ϵ_{amp} are energy consumption for free space and multi-hop. The energy consumption for transmission and receiving is as described in Eqs. (1) and (2).

Table 1. Comparison of different protocols

Protocol	Selection parameter	Network/classification/Topology	Limitation
[10] LEACH	Probability-based CH selection	Homogeneous/Hierarchical	Non-uniform CH distribution, Unbalanced clustering
[24] EEHC	Find Optimal values p (probability) and k hops	Homogeneous Distributed Hierarchical	Non-scalable
[25] HEED	The residual energy of nodes and node degree	Independent of network size Distributed	Hot spot issue near the sink, Asymmetric energy consumption
[26] UCS	Bi-lateral model Unequal clustering scheme	Homogeneous Heterogeneous	Non-scalable Two hops inter-cluster communication
[27] EECS	Residual energy	Localized communication	Single hop
[28] ADRP	The residual energy of SN and Average energy of cluster	Distributed	CH failure, Asymmetric energy consumption
[29] EC	Hop to sink distance	Hierarchical	Inefficient energy consumption, unbalanced clusters
[30] Improved SMO	Residual energy, Distance	Hierarchical	Consider only energy and distance
[32] PSO-C	PSO (Algorithm) Intra-cluster distance Residual energy	Centralized	Direct CH-sink communication
[34] BERA	BBO (Algorithm) Intra-cluster distance, Residual energy, CH-Sink distance	Centralized	CH distributed non-uniform Non-scalable
[20] PSO-ECHS	PSO (algorithm) Intra-cluster distance, Residual energy, CH-Sink distance	Centralized	Non-scalable Unbalanced

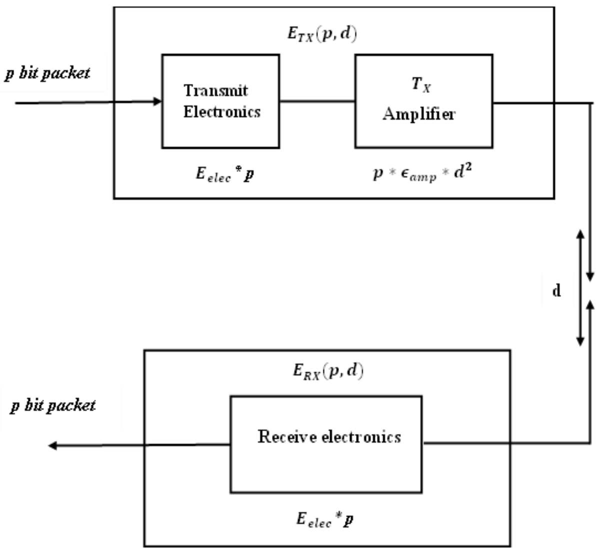

Figure. 3 Energy consumption model of WSN

where

- E_{TX} = transmission energy, E_{RX} = receiving energy for p data bits
- d= transmitter and receiver distance, d_0 = threshold distance
- Amplification coefficients are ϵ_{fs} and ϵ_{amp}
- E_{elec} = energy required for single bit transmission

4. Role of particle swarm optimization in proposed scheme

Kennedy and Eberhard have suggested nature-inspired optimization approach namely Particle swarm optimization. PSO mimics the behavior of bird swarms. The bird swarms reduce efforts by sharing group information to reach the destination [17]. In PSO, each particle represents a single solution for the

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problem. The group of particles altogether form a swarm that focus to search for an optimal solution. Every particle is represented by P_i. The particles in search space having different velocities find local optimal solution and to reach global best, particles change their positions and velocities. The main aim of PSO is to achieve the optimal solution for application using the fitness function. The Particle position and velocity are represented as X_{im} and V_{im} employed in M dimension search space. In each iteration particles generate local best and global best solution. In order to reach the final global best solution particles are continuously change their positions and velocities by using local and global best values. When a better fitness for position and velocity is found, particles at any time t are updated using the following equations:

$$V_{i,m}(t+1)= \omega \times V_{i,m}+c1 \times r1 \times \left(XP_{lbest_{i,m}}-X_{i,m}(t)\right)+c2 \times r2 \times (XP_{gbest_{i,m}}-X_{i,m}(t)) \quad (3)$$

$$X_{i,m}(t+1)=X_{i,m}(t)+V_{i,m} \quad (4)$$

where r1, r2 = the random values [0,1],
ω = inertia weight,
c1, c2 = acceleration coefficient.

These parameters ω, c1 and c2 converge the particle behavior towards global optimal.

4.1 Fitness function evaluation

The particles change their positions and velocities continuously to find global best solution. In order to check the optimality of new positions and velocity of particles fitness function is evaluated. Particle local best (P_{lbest}) and global best (P_{gbest}) are updated by evaluating the fitness function given as

$$P_{lbest_i}=\begin{cases} P_i, fitness\ (P_i)<fitness\ (P_{lbest_i}) \\ P_{lbest_i}, \quad Otherwise \end{cases} \quad (5)$$

$$P_{gbest_i}=\begin{cases} P_i, fitness\ (P_i)<fitness\ (P_{gbest_i}) \\ P_{gbest_i}, \quad Otherwise \end{cases} \quad (6)$$

Now the updated values of P_{lbest} *and* P_{gbest} are used to calculate the new positions and velocities of particles.

5. The proposed MOEES protocol

Energy related issues are efficiently managed by the clustering process in WSNs. The clustering techniques mainly focus to manage energy consumption efficiently and improve performance. The selection of an efficient CH can enhance the overall network performance and optimize energy consumption. The MOEES mainly concentrates on the efficient selection of CHs among SNs based on nature-inspired PSO algorithm. The optimal set of CHs is selected by considering the parameters like average intra-cluster distance, the distance between CHs and node degree.

Table 2. Notations used

Notation	**Meaning**
N	Total SNs
K	Number of CHs
$D_{s_p}^{ch_q}$	Distance between pth SN and qth CH
$D_{ch_p}^{ch_r}$	Distance between pth CH and rth CH
$\overline{CD}$	Average intra-cluster distance
ND_p	Node degree of pth CH
α_1, α_2 and α_3	Fitness function weight coefficients

5.1 CH selection parameters

Parameters play an important role for the selection of energy efficient CH. The parameters considered for the generation of fitness function focuses on improving the energy conservation of network. The fitness of each SNs depends on CH selection parameters. Notations used in MOEES are shown in Table 2.

5.1.1. Intra-cluster distance

It is the distance from SN to their CH in a network. SNs transfer the sensed data to respective CHs. CH combines the collected data from cluster members into a single packet. So, if selected CH is nearer to SNs then energy consumption will be reduced. SNs having minimum intra-cluster distances have more chances to be CH.

In order to reduce the energy consumption in WSN, it needs to minimize average intra-cluster distance. This can be achieved by minimizing the function (f_1) formulated as below:

$$f_1=\sum_{q=1}^{K}\sum_{p=1}^{N} D_{s_p}^{ch_q} \quad (7)$$

Where K is total number of CH candidates, N total nodes and $D_{s_p}^{ch_q}$ is the distance between node and CH. f_1 function describes the total distance between SN to their respective CHs in network.

5.1.2. Inter-cluster distance

Distance between the respective CHs of clusters is inter-cluster distance. As the size of network increases, in order to keep communication stable CHs needs to be distributed uniformly. In this work a function f_2 has been defined to select CHs throughout the network. So, for uniform dispersion of CHs average inter-cluster distance is to be maximized. Required function (f_2) is formulated as below:

$$f_2 = \frac{K}{\sum_{p=1}^{K} \sum_{r=1}^{k} D_{ch_p}^{ch_r}} \tag{8}$$

where $D_{ch_p}^{ch_r}$ is the distance between CHs.

5.1.3. Balanced node degree and intra-cluster distance

Node degree is the number of neighbouring nodes found in the radio range of any sensor node. Energy expenditure is minimum for neighbour nodes joining adjoining CH. Generally, fitness function nominates CH having higher neighbour nodes to save communication energy.

In order to even consumption of energy, clusters should be of similar structures in terms of intra-cluster distances and CHs node degree. Standard deviation measures the variation from similarity. This can be achieved by reducing the variation of intra-cluster distances of all clusters and node degree of all CHs. Therefore, minimization objective function (f_3) is defined as below:

$$f_3 = \sqrt{\frac{\sum_{p=1}^{K} (CD_p - \overline{CD})^2}{K-1}} + \sqrt{\frac{\sum_{p=1}^{K} (ND_p - \overline{ND})^2}{K-1}} \tag{9}$$

Where CD_p denotes intra-cluster distance of pth CH and ND_p denotes node degree of pth CH.

6. CH selection fitness function

Fitness function generates a value for each SN based on parameters. SNs with minimum fitness value are selected as CH. Fitness function proposed in MOEES is given below:

$$F = \alpha_1 \times f_1 + \alpha_2 \times f_2 + \alpha_2 \times f_3$$

$$F = \alpha_1 \times \sum_{k=1}^{k} \sum_{i=1}^{N} D_{s_i}^{ch_k} + \alpha_2 \times \frac{K}{\sum_{i=1}^{k} \sum_{j=0}^{k} D_{ch_i}^{ch_j}} + \alpha_3 \times \sqrt{\frac{\sum_{i=0}^{k} (CD_I - \overline{CD})}{K-1}} + \sqrt{\frac{\sum_{i=0}^{k} (ND_i - \overline{ND})}{K-1}} \tag{10}$$

where α_1, α_2 and α_3 are fitness function weight coefficients.
and $\alpha_1 + \alpha_2 + \alpha_3 = 1$

The MOEES employs the PSO to nominate the optimal SNs as CH. PSO approach consider inter-cluster distance, intra-cluster distance and node degree as CH selection parameters for fitness function calculation for SNs. SNs in competition having minimum intra-cluster distance, minimum standard deviation and maximum inter-cluster distance i.e minimum fitness value are chosen as CH. After CH selection, nominated CHs conveys a massage to SNs in its range for cluster formation. SNs update their status on receiving the message. After clustering BS request for data. SNs transmit sensed data to respective CHs in allotted time slot. Then CHs transmit the aggregated single packet to BS.

Algorithm 1 presents pseudo code of the MOEES. In MOEES, each particle represents the possible solution of CH positions. A swarm population of s particles is represented as, P= $\{P_1, P_2, \dots \dots P_i, \dots \dots . P_s\}$. Each particle of swarm represents the k potential selected CH candidates. Then at any point in time, *i*th particle of swarm is represented as:

$$P_i = \left\{ (x_{i,1}, y_{i,1}), (x_{i,2}, y_{i,2}) .. (x_{i,j}, y_{i,j}) .. (x_{i,k}, y_{i,k}) \right\} \tag{11}$$

Co-ordinate form of *i*th particle is represented as $(x_{i,j}, y_{i,j})$ where $1 \le j \le k$ and $1 \le i \le s$

The particles change their positions and velocities to obtain its local best P_{lbest} and global best P_{gbest} described in Section 4. Position and velocity updations are represented as

$$V_{i,k}(t+1) = \omega \times V_{i,k} + c1 \times r1 * \left(XP_{lbest_{i,k}} - X_{i,k}(t) \right) + c2 \times r2 \times (XP_{gbest_{i,k}} - X_{i,k}(t)) \tag{12}$$

$$X_{i,k}(t+1) = X_{i,k}(t) + V_{i,k} \tag{13}$$

where r1, r2 = random values within [0,1] interval,
ω = inertia weight
c1 = cognitive component (acceleration coefficient)
c2 = social component (acceleration coefficient).

The particles change their positions and velocities to obtain its local best P_{lbest} and global best P_{gbest} described in Section 4.

7. Simulation and results

The performance of MOEES is investigated and compared with state-of-art existing protocols such as PSO-C [32], BERA [34], PSO-ECHS [20] and

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Algorithm 1 : Pseudo code for MOEES
1. Total number of SNs = N
2. Number of CHs = K
3. Swarm size (Particles)= s
4. Initialize particles
P= $\{P_1, P_2, \dots \dots P_{i,\dots\dots\dots} P_s\}$ where $1 \le i \le s$ // Swarm population of size s
$P_i = \{P_{i,1}, P_{i,2}, \dots . P_{i,j} \dots . P_{i,K}\}$ where $1 \le j \le K$ // ith particle
5. for i= 1 to s
6. Calculate F (P_i)=$\alpha_1 \times f_1 + \alpha_2 \times f_2 + \alpha_2 \times f_3$ / Fitness function
7. P_{lbest} = P_i
8. P_{gbest} = min (P_{lbest} $\forall\, i, j$ $1 \le i \le s$)
9. if $P_i < P_{lbest}$ // update the local best
10. $P_i = P_{lbest}$
11. endif
12. elseif $P_i < P_{gbest}$ // update the global best
13. $P_i = P_{gbest}$
14. endif
15. end for
16. for (t=1 to max iteration)
17. for i = 1 to s
18. Updation of particle velocity and position are according to Eqs. (3) and (4) respectively
19. Evaluate fitness of P_i
20. Update P_{lbest} and P_{gbest} using steps 10-14.
21. end for
22. end for

ECMOSSA [35]. The comparison is conducted on the basis of total energy consumption, average energy consumption, standard deviation of average energy and throughput in order to check the energy efficiency, stability and scalability in clusters. The simulations are performed using MATLAB R2016a simulator. Further, simulations are performed in different network scenarios with varying node densities and network sizes. Simulation parameters and variables are described in Table 3 and Table 4 respectively. In each WSN group, varying SNs 100 (S1) and 200 (S2) are taken for simulation. These SNs are deployed in an area of 100X100 (N1) and 200X200 (N2) randomly.

Table 3. Simulation parameters

Parameters	**Values**
E_{elec}	50 nJ/bit
ϵ_{fs}	10 pJ/bit/m2
ϵ_{amp}	0.0013 J/bit/m4
Eda	5 nJ/bit

CHs are chosen to be 10 % of SNs and the initial energy of SNs is chosen to be 2J.

7.1 Total energy consumption

It is the energy consumed by whole network (CHs and SNs) in each round. Fig. 4 and 5 describe the total energy dissipated by clustering protocols for varying network sizes N1 and N2 for 100 nodes in 1000 rounds.

As the sensor area increases for fixed number of SNs, distance between the SNs also increases but fluctuation in total energy consumption in MOEES is less in comparison to PSO-C, BERA, PSO-ECHS and ECMOSSA as shown in Fig. 4 and 5.

On the other hand, total energy consumption of MOEES for 200 nodes in N1 and N2 is shown in Fig. 6 and 7 respectively. Total energy consumption in MOEES also remains less with the increase in node density.

Table 4. Simulation variables

Variable	**Value**	
Sensor area size	100X100 m^2	N1
	200X200 m^2	N2
Number of SNs	100 (S1), 200 (S2)	
Initial energy	2 J	
CHs	10 % SNs	
Swarm size	20	

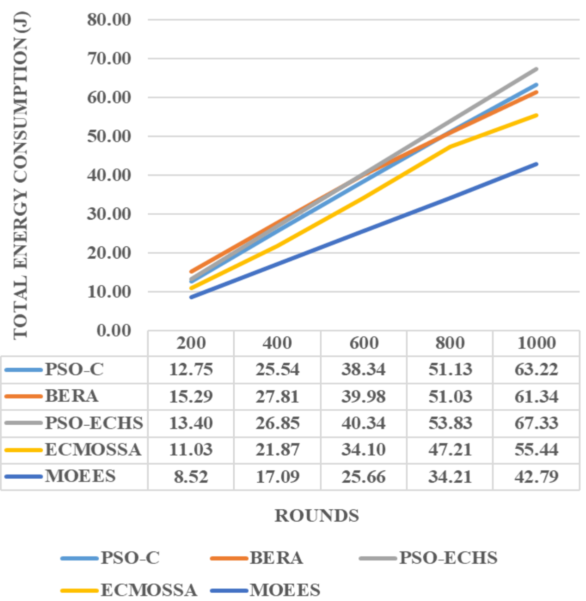

Figure. 4 Total energy consumption of 100 nodes (N1)

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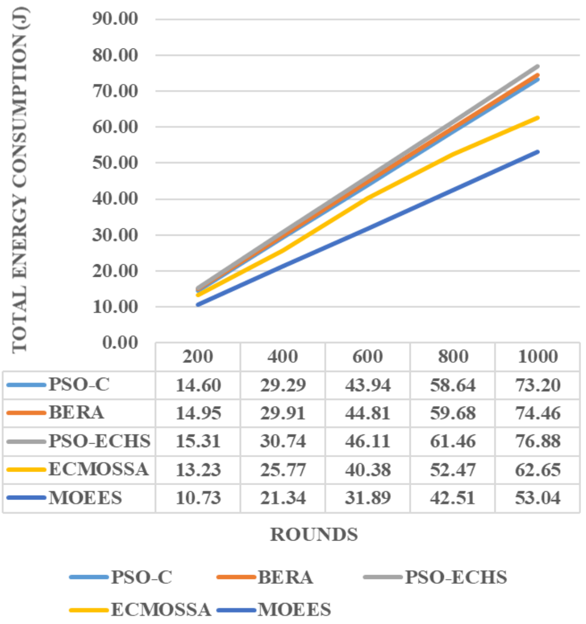
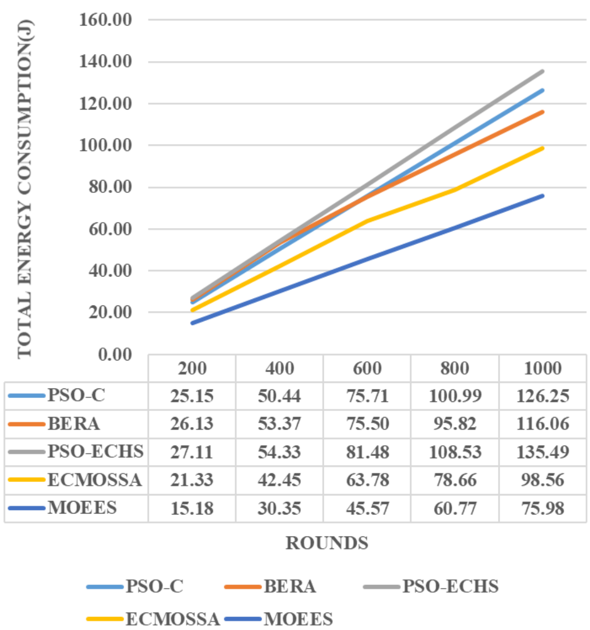


	200	400	600	800	1000
PSO-C	14.60	29.29	43.94	58.64	73.20
BERA	14.95	29.91	44.81	59.68	74.46
PSO-ECHS	15.31	30.74	46.11	61.46	76.88
ECMOSSA	13.23	25.77	40.38	52.47	62.65
MOEES	10.73	21.34	31.89	42.51	53.04

Figure. 5 Total energy consumption of 100 nodes (N2)



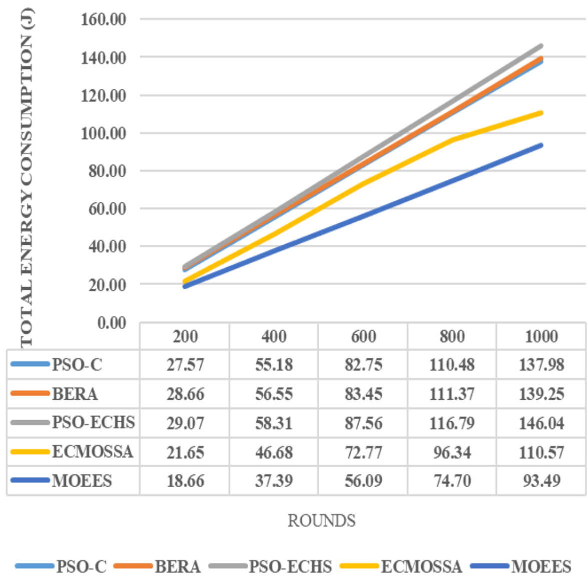
	200	400	600	800	1000
PSO-C	25.15	50.44	75.71	100.99	126.25
BERA	26.13	53.37	75.50	95.82	116.06
PSO-ECHS	27.11	54.33	81.48	108.53	135.49
ECMOSSA	21.33	42.45	63.78	78.66	98.56
MOEES	15.18	30.35	45.57	60.77	75.98

Figure. 6 Total energy consumption of 200 nodes (N1)

Hence, it is concluded that, the energy consumption by MOEES remains less with the increase in sensor area and node density. MOEES forms energy efficient clusters as the intra-cluster distance have minimized and CHs are dispersed throughout the network area.

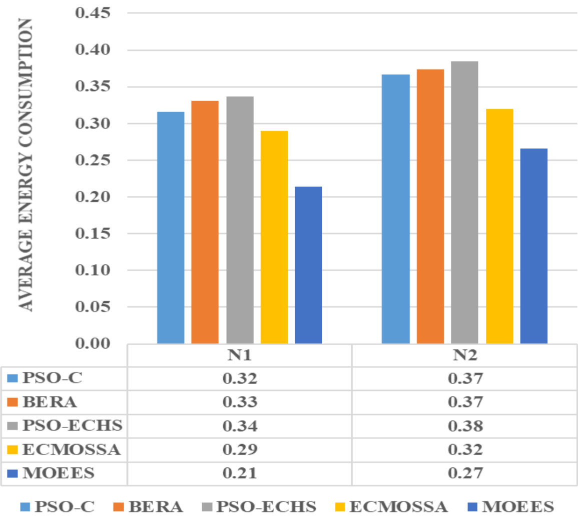
7.2 Average energy consumption

It is defined as the average energy consumed by a SN in one round. Fig. 8 and 9 depicts the performance of clustering protocols in terms average energy



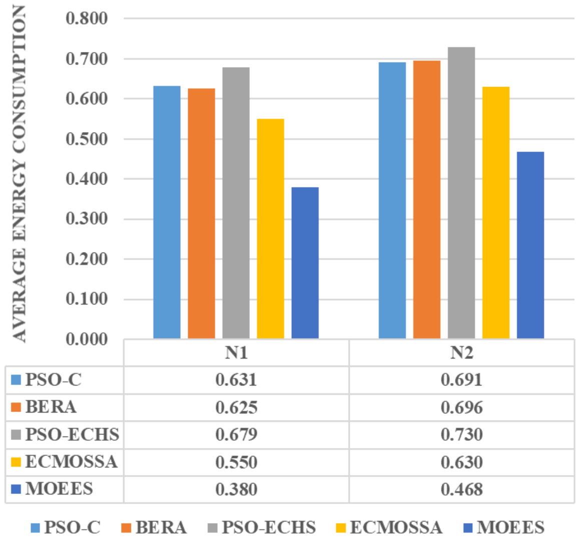
	200	400	600	800	1000
PSO-C	27.57	55.18	82.75	110.48	137.98
BERA	28.66	56.55	83.45	111.37	139.25
PSO-ECHS	29.07	58.31	87.56	116.79	146.04
ECMOSSA	21.65	46.68	72.77	96.34	110.57
MOEES	18.66	37.39	56.09	74.70	93.49

Figure. 7 Total energy consumption of 200 nodes (N2)



	N1	N2
PSO-C	0.32	0.37
BERA	0.33	0.37
PSO-ECHS	0.34	0.38
ECMOSSA	0.29	0.32
MOEES	0.21	0.27

Figure. 8 Average energy consumption (S1)



	N1	N2
PSO-C	0.631	0.691
BERA	0.625	0.696
PSO-ECHS	0.679	0.730
ECMOSSA	0.550	0.630
MOEES	0.380	0.468

Figure. 9 Average energy consumption (S2)

Table 5. Standard deviation of average energy consumption

Protocol	N1 S1	N1 S2	N2 S1	N2 S2
PSO-C	0.18373	0.36533	0.21193	0.39922
BERA	0.17484	0.32809	0.21540	0.40264
PSO-ECHS	0.19463	0.39184	0.22214	0.42228
ECMOSSA	0.16780	0.29610	0.17663	0.35662
MOEES	0.12372	0.21953	0.15312	0.26994

consumption by 100 (S1) and 200 (S2) SNs in sensor area N1 and N2.

Fig. 8 presents the results for networks N1 and N2 using the S1 nodes and Fig. 9 for networks N1 and N2 using S2 nodes. It is evident from Fig. 8 and 9 that, the average energy consumption by MOEES is minimum in all network sizes, moreover it has also seen that energy consumption for sparse and dense networks is less as compare to other protocols. MOEES utilize the energy of SNs in an efficient manner which has reduced the average energy consumption per SN. Minimum value of average energy consumption for MOEES depicts energy efficient data gathering.

7.3 Standard deviation (SD) of average energy consumption

Basically, SD measures, how much the members of group are differing from the mean value. Moreover, SD evaluates the stability behaviour by investigating the variation in average energy consumption. Table 5 depicts SD of average energy for varying node densities and sensor areas.

In Table 5, SD for scenarios (N1, S1), (N1, S2), (N2, S1) and (N2, S2) has been calculated and compared with other protocols. It is observed from Table 5**.** that SD for MOEES is comparatively less for different network scenarios. Minimum value of SD for MOEES proves that the fluctuations in average energy consumption is minimum, therefore MOEES shows its ability of balanced cluster formation. Moreover, MOEES is stable for varying node densities and sensor areas. The superiority of MOEES is due to the inclusion of minimal deviation in node degree and intra-cluster distance in the proposed fitness function.

7.4 Throughput

Throughput is the total number of raw packets transferred to BS in its lifetime. Table 6 presents the throughput comparison for different node densities.

Table 6. Throughput comparison

PROTOCOL	Throughput (S1, N1)	Throughput (S1, N2)
PSO-C	9.32×10^4	10.73×10^4
BERA	8.89×10^4	9.52×10^4
PSO-ECHS	8.12×10^4	9.10×10^4
ECMOSSA	10.39×10^4	11.88×10^4
MOEES	11.91×10^4	13.52×10^4

It is observed from table 6 that MOEES transfer maximum packets in comparison to PSO-C, BERA, PSO-ECHS and ECMOSSA. Moreover, MOEES shows consistent performance with the increase in node density.

MOEES enhances the energy efficiency, scalability and balanced clustering by efficiently utilizing the energy resources in WSNs. Fitness function designed in MOEES reduces the communication cost by minimizing the intra-cluster distance. To support scalability, CHs are dispersed throughout the network by maximizing the average distance between CHs. Balanced clusters are formed by minimizing the standard deviation of intra-cluster distance and node degree in all the clusters. Further, the supremacy of MOEES is shown in terms of total energy consumption, average energy consumption and throughput.

8. Conclusion

The proper energy consumption is considered the most important factor in WSNs performance. The clustering approaches mainly focus on utilization of node energy efficiently and reduction of energy consumption. In this paper, an algorithm namely MOEES is proposed which improves the energy efficiency, increase scalability and form balanced clusters in WSNs. MOEES exploits a PSO based novel fitness function that considers parameters intra-cluster distance, inter-cluster distance and node degree for optimal CH selection. In order to prove the superiority of MOEES exhaustive simulation has been performed by varying network size and node density. The Performance analysis shows that the proposed strategy consumed 8.52 J, average energy consumption is 0.21 J, standard deviation of average energy consumption is 0.1237, and throughput attained is 11.91×10^4. The obtained results prove that MOEES clearly excel in comparison to PSO-C, BERA, PSO-ECHS and ECMOSSA. At last, it is inferred that MOEES is capable to be deployed in heterogeneous environment in terms of varying network size or node density without any degradation in the performance.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Data collection, concept, analysis, methodology, original draft preparation and writing have been carried out by 1st author. The supervision, analysis, editing, and investigation have been done by 2nd author. The supervision, concept validation, review, investigation and finalization have been accomplished by 3rd author.

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References

[1] A. Yahya, *Emerging Technologies in Agriculture, Livestock, and Climate,* Vol. 1, 2020.

[2] I. Dietrich and F. Dressler, "On the lifetime of wireless sensor networks", *ACM Transactions on Sensor Networks (TOSN)*, Vol. 5, No.1, pp. 1-39, 2009.

[3] A. Karaki, N. Jamal, and A. E. Kamal, "Routing techniques in wireless sensor networks: a survey", *IEEE Wireless Communications*, Vol. 11, No. 6, pp. 6-28, 2004.

[4] M. Farsi, M. A. Elhosseini, M. Badawy, and H. A. Ali, "Deployment techniques in wireless sensor networks, coverage and connectivity: A survey", *IEEE Access*, Vol. 7, pp. 28940-28954, 2019.

[5] K. Sohraby, D. Minoli, and T. Znati, "Basic wireless sensor technology", *Wiley Telecom*, pp. 75-92, 2007.

[6] J. Yick, B. Mukherjee, and D. Ghosal, "Wireless sensor network survey", *Computer Networks*, Vol. 52, No. 12, pp. 2292-2330, 2008.

[7] B. M. Sahoo, T. Amgoth, and H. M. Pandey, "Particle swarm optimization based energy efficient clustering and sink mobility in heterogeneous wireless sensor network", *Ad Hoc Networks*, Vol. 106, p. 102237, 2020.

[8] A. J. G. Sanchez, F. G. Sanchez, and J. G. Haro, "Wireless sensor network deployment for integrating video-surveillance and data-monitoring in precision agriculture over distributed crops", *Computers and Electronics in Agriculture*, Vol. 75, No. 2, pp. 288-303, 2011.

[9] J. Roselin, P. Latha, and S. Benitta, "Maximizing the wireless sensor networks lifetime through energy efficient connected coverage", *Ad Hoc Networks*, Vol. 62, pp. 1-10, 2017.

[10] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-efficient communication protocol for wireless microsensor networks", In: *Proc. of the 33rd Annual Hawaii International Conference on System Sciences*, p. 10, 2000.

[11] X. Feng, F. Yan, and X. Liu, "Study of wireless communication technologies on Internet of Things for precision agriculture", *Wireless Personal Communications*, Vol. 108, No. 3, pp. 1785-1802, 2019.

[12] S. P. Singh and S. C. Sharma, "A survey on cluster-based routing protocols in wireless sensor networks", *Procedia Computer Science*, Vol. 45, pp. 687-695, 2015.

[13] M. Liu, J. Cao, and G. Chen, "An energy-aware routing protocol in wireless sensor networks", *Sensors*, Vol. 9, No. 1, pp. 445-462, 2009.

[14] S. Kaur and R. Mahajan, "Energy efficient clustering protocol for wireless sensor networks", *Modern Physics Letters B*, Vol. 32, No. 32, p. 1850400, 2018.

[15] A. S. Rostami, M. Badkoobe, and F. Mohanna, "Survey on clustering in heterogeneous and homogeneous wireless sensor networks", *The Journal of Supercomputing*, Vol. 74, No. 1, pp. 277-323, 2018.

[16] P. Kuila and P. K. Jana, "Energy efficient clustering and routing algorithms for wireless sensor networks: Particle swarm optimization approach", *Engineering Applications of Artificial Intelligence*, Vol. 33, pp. 127-140, 2014.

[17] T. Hayashida, I. Nishizaki, and S. Sekizaki, "Improvement of Particle Swarm Optimization Focusing on Diversity of the Particle Swarm", *2020 IEEE International Conference on Systems, Man, and Cybernetics*, pp. 191-197, 2020.

[18] M. Dorigo, M. Birattari, and T. Stutzle, "Ant colony optimization", *IEEE Computational Intelligence Magazine*, Vol. 1, No. 4, pp. 28-39, 2006.

[19] J. H. Holland, "Genetic algorithms", *Scientific American*, Vol. 267, No. 1, pp. 66-73, 1992.

[20] P. C. S. Rao, P. K. Jana, and H. Banka, "A particle swarm optimization-based energy efficient cluster head selection algorithm for wireless sensor networks", *Wireless Networks*, Vol. 23, No. 7, pp. 2005-2020, 2017.

[21] S. P. Singh and S. C. Sharma, "A PSO based improved localization algorithm for wireless sensor network", *Wireless Personal Communications*, Vol. 98, No. 1, pp. 487-503, 2018.

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[22] S. K. Singh, M. P. Singh, and D. K. Singh, "Routing protocols in wireless sensor networks– A survey", *International Journal of Computer Science & Engineering Survey*, Vol. 1, No. 2, pp. 63-83, 2010.

[23] A. Shahraki, A. Taherkordi, Ø. Haugen, and F. Eliassen, "Clustering objectives in wireless sensor networks: A survey and research direction analysis", *Computer Networks*, Vol. 180, p. 107376, 2020.

[24] S. Bandyopadhyay and E. J. Coyle, "An energy efficient hierarchical clustering algorithm for wireless sensor networks", *IEEE INFOCOM 2003. Twenty-second Annual Joint Conference of the IEEE Computer and Communications Societies (IEEE Cat. No. 03CH37428)*, Vol. 3, pp. 1713-1723, 2003.

[25] O. Younis and S. Fahmy, "HEED: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks", *IEEE Transactions on Mobile Computing*, Vol. 3, No. 4, pp. 366-379, 2004.

[26] S. Soro and W. B. Heinzelman, "Prolonging the lifetime of wireless sensor networks via unequal clustering", *19th IEEE International Parallel and Distributed Processing Symposium*, p. 8, 2005.

[27] M. Ye, C. Li, G. Chen, and J. Wu, "EECS: an energy efficient clustering scheme in wireless sensor networks", *PCCC 2005. 24th IEEE International Performance, Computing, and Communications Conference*, pp. 535-540, 2005.

[28] F. Bajaber and I. Awan, "Adaptive decentralized re-clustering protocol for wireless sensor networks", *Journal of Computer and System Sciences*, Vol. 77, No. 2, pp. 282-292, 2011.

[29] D. Wei, Y. Jin, S. Vural, and K. Moessner, "An energy-efficient clustering solution for wireless sensor networks", *IEEE Transactions on Wireless Communications*, Vol. 10, No. 11, pp. 3973-3983, 2011.

[30] G. A. Mutiara, O. Mohd, N. Suryana, and A. N. Pee, "Weights-Based Energy-Efficient Wireless Sensor Network Protocol with Firefly Synchronization for Illegal Logging", *International Journal of Intelligent Engineering and Systems*, Vol. 14, No. 3, pp. 374-387, 2021, doi: 10.22266/ijies2021.0630.31.

[31] R. K. Sanapala and S. R. Duggirala, "An Optimized Energy Efficient Routing for Wireless Sensor Network using Improved Spider Monkey Optimization Algorithm", *International Journal of Intelligent Engineering and Systems*, Vol. 15, No. 1, pp. 188-197, 2022, doi: 10.22266/ijies2022.0228.18.

[32] N. M. A. Latiff, C. C. Tsimenidis, and B. S. Sharif, "Energy-aware clustering for wireless sensor networks using particle swarm optimization", In: *Proc. of 2007 IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications*, pp. 1-5, 2007.

[33] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks", *IEEE Transactions on Wireless Communications*, Vo1. 4, pp. 660-670, 2002.

[34] P. Lalwani, H. Banka, and C. Kumar, "BERA: a biogeography-based energy saving routing architecture for wireless sensor networks", *Soft Computing*, Vol. 22, No. 5, pp. 1651-1667, 2018.

[35] Srinivasalu, Gundeboyina, and H. Umadevi, "Cluster Based Routing Protocol Using Energy Centric Multi Objective Salp Swarm Algorithm for WSNs.", *International Journal of Intelligent Engineering and Systems*, Vol. 14, No. 5, pp. 35-45, 2021, doi: 10.22266/ijies2021.1031.04.