Improved Particle Swarm Optimization Based Distributed Energy-Efficient Opportunistic Algorithm for Clustering and Routing in WSNs

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Abstract

Wireless Sensor Networks (WSNs) have been employed in various real-time applications and addressed fundamental issues, such as limited power resources and network life. Several sensor nodes in a WSN monitor the actual world and relay discovered data to base stations. The biggest issue with WSN is that the sensors have a limited lifetime and use much electricity to relay data to the base station. This paper proposes an improved PSO-based Enhanced Distributed Energy Efficient Clustering (EDEEC) algorithm to extend the network's life and reduce power consumption. Clustering is the process of forming groups of sensor nodes. The cluster aims to improve the network's scalability, energy efficiency, and other characteristics. The particle swarm optimization algorithm is modified to obtain energy-efficient WSNs. The assessment is based on the essential WSN characteristics, including network lifetime and energy efficiency (power consumption). Compared to LEACH, HEED, and DEEC, our proposed IPSO-EDEEC uses less energy.

Keywords: Sensor nodes (SN); Wireless sensor network (WSN); Network lifetime; Energy consumption; Clustering; Routing.

Introduction

A WSN comprises several SNs that are adaptable, compact, low-cost, and low-power for wireless communication across a short range (Akyildiz et al., 2002; Yick et al., 2008). WSN sensor nodes are often planted randomly in areas of interest and are frequently utilized for surveillance and monitoring (Bruckner et al., 2012; Yetgin et al., 2015; Han et al., 2015). WSNs can optimize themselves using a variety of performance measures, depending on the unique application case. Energy efficiency and network lifespan are critical challenges because SNs are frequently powered by batteries, which can be difficult to replace. Furthermore, network coverage, latency, and sensor node balancing are crucial to sustaining quality of service (Wang & Liu, 2010; Cheng et al., 2013). These signs usually contradict one another in practice. A thorough analysis of their trade-offs is essential to increase WSNs' overall performance in real-world applications.

Various research efforts have been made to optimize node power consumption by adopting unique clustering strategies to increase network performance, particularly longevity. Conserving energy generally leads to achieving the best balance between various energy-consuming tasks. Regardless of the lack of a centralized network and site portability, every node can aid in routing and relaying packets from nodes that cannot reach their destination (Ben Fradj et al., 2019). This research proposes a clustering method based on IPSO-EDEEC to offer an effective energy-saving scheme for WSNs. To avoid the detrimental effects of outliers, we apply the E-DEEC algorithm to get optimum clustering results. The proposed approach can effectively enhance energy efficiency and network life by balancing the network's burden.

Literature Review

Some fundamental principles relevant to the clustering in WSN are discussed, and alternative clustering procedures are compared. Looking back at the protocols provided in this article, it is evident that they all focus on extending the lifetime of a WSN and using the essential resources located in sensor nodes more efficiently without diminishing communication capabilities, but instead building clusters. Reduce the maximum number of nodes in the cluster and single-node (CH) clusters (Kavitha et al., 2014). A thorough examination of the available clustering techniques for WSNs is presented and ranked based on cluster formation

characteristics and cluster head (CH) selection criteria. We go over significant design hurdles and performance issues with clustering techniques. We compile and compare their results (Kumarawadu et al., 2008).

A balanced and energy-efficient cluster-based data aggregation method (EEBCDA) is suggested to address this problem in isomorphism and CH WSNs, where the CH sends data to the BS through single-hop communication. Divide the network into grids of varied sizes, with the grid furthest away from the BS having the most nodes and the largest size. On each grid, rotate CH. EEBCDA beats EECS in terms of network lifetime, power efficiency, and power dissipation balance, according to simulation data (Yue et al., 2012). W-LEACH was created to extend the LEACH method for WSN data stream aggregation. This proposed technique can handle unified and non-uniform networks without compromising network lifetime. Instead, it lengthens the sensor's average life. The results show that the suggested strategy increases network and sensor average lifespan in both homogeneous and non-uniform WSNs (Abdulsalam et al., 2010).

The development of a LEACH protocol based on fuzzy logic (LEACH-FL) considers distance, battery level, and node density (Ran et al., 2010). The proposed strategy was tested by selecting the best simulation using Matlab. The simulation results reveal that battery power is very significant in determining cluster heads, and our method makes better selections on cluster head selection. Although we compared LEACH-FL to LEACH and Gupta techniques, there are still numerous protocols to examine. A new WSN high-efficiency power pool technique reduces total network power usage while improving network longevity. The protocol is split into two sections. The first step is establishing the infrastructure for a specific WSN (Alia, 2018). A newly designed Harmony Search (HS)-based system mainly calculates the correct number of groups and allocates sensors to these groups.

LEACH- It distributes the high energy consumption of communicating with the base station overall SNs in the network by rotating the SNs into CHs. LEACH enables it to outperform other approaches. However, LEACH has significant drawbacks, such as it is not suited for broad area networks because it uses a single-hop inter-cluster routing mechanism. It is unsuitable for processing sensors with varying beginning energy nodes since the actual charge balance cannot be assured (Liu, 2012). These flaws prompted other researchers to enhance later cluster routing systems. Among the most popular are distributed hybrid energy efficiency clusters (Younis & Fahmy, 2004), distributed energy efficiency clusters (DEEC) (Qing et al., 2006), energy efficiency collection in sensor information systems (Lindsey et al., 2002), sensor networks threshold-sensitive energy efficiency protocols (Manjeshwar & Agrawal, 2001), stable choice protocols (Smaragdakis et al., 2004), and the neuro-fuzzy energy-aware clustering scheme (Thamaraimanalan & Sampath, 2019). While improved, some of the above methods neglect the issue of determining the optimal number of clusters for a given WSN.

Methodology

The proposed IPSO-EDEEC algorithm employs PSO to generate an optimized cluster of nodes. The improved rule frame and fitness function, when residual energy and other factors are taken into account, as well as the existence of advanced nodes, give IPSO-EDEEC a significant advantage over EDEEC. Second, the suggested IPSO-EDEEC method computes distinct CH selection criteria. The following is the substantial contribution to this research work:

• To introduce a better scaling factor parameter to minimize the energy of nodes within a cluster.

• To present a new updated Equation for more effectively computing threshold probability.

• The neighborhood information paradigm is used to extend network life.

This section examines the proposed working model. The concept of the proposed network model is explained in this article. The network is believed to be made up of sensors distributed randomly throughout the environment. All nodes have the same sensing and communication capabilities, as well as the same startup power.

System Model

The system architecture consists of many SNs and a BS. All SNs are classified into two types. One is the common node (CN), and the other is the CH node. The common nodes' job is to monitor environmental data and transmit detection data to the cluster's primary nodes. The CH node systematically selects and receives public nodes' data, processes it, and sends it to the BS. Figure 1 depicts the WSN cluster's architecture.

The energy model is based on the first-order radio model. During the communication phase, we only consider energy consumption. Total energy consumption includes data transmission, reception, and aggregation energy consumption. When a CN and a CH node exchange L-bit data in this model, the power usage can be determined using Equation (1).

$$E_{Tx}(L, d) = E_{elec} \times L + \varepsilon_{amp} \times L \tag{1}$$

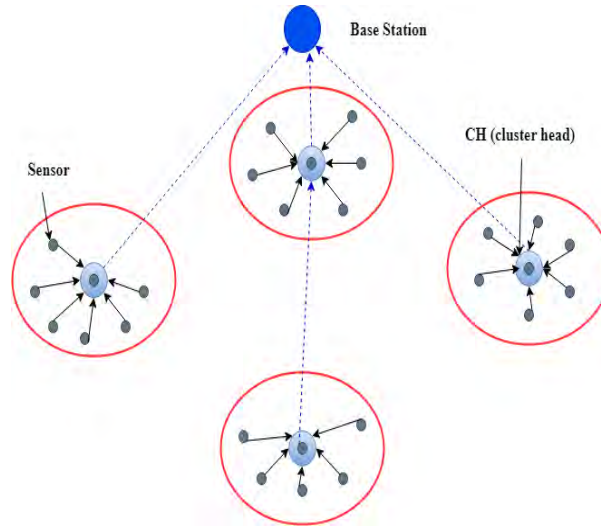$$E_{Rx}(L, d) = E_{elec} \times L \tag{2}$$

Figure 1. WSN Clustering

Where d is the distance between the transmission and receiving nodes, $E_{Tx}(L, d)$ is the energy consumed during the transmitting phase of an L-bit packet, and $E_{Rx}(L, d)$ is the energy consumed during the receiving phase. The symbol denotes the energy consumption per bit in transmitter and receiver SNs E_{elec}. Equation (3) can be used to calculate the amplifier energy consumption during the transmission phase ε_{amp} .

$$\varepsilon_{amp}=\begin{cases} \varepsilon_{fs} \times d^2, & when\ d \le d_0 \\ \varepsilon_{amp} \times d^4, & when\ d > d_0 \end{cases} \qquad (3)$$

Where d_0 is a threshold value for the sensors' node. If the distance $d \le d_0$, the SN will use the free-space propagation model. On the contrary, the multipath fading channel model is used. ε_{fs} and ε_{amp} are communication energy parameters. Equation (4) calculates d_0.

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}. \qquad (4)$$

Distributed Energy Efficient Clustering (DEEC)

DEEC selects CH based on the nodes' starting and residual power levels. DEEC forecasts the optimal network lifespan value, which defines the baseline energy each node must spend in a round to avoid each node having to know global network information. DEEC is a well-known energy-saving protocol for heterogeneous WSN networks. A probability function determines whether a node is a cluster head (CH). This function is defined in terms of the network's residual and average energy. This function computes the ratio of each node's remaining power to the network's average power, calculated for each node in the cluster. This option always penalizes advanced nodes, especially when the remaining energy runs out and is within range of normal nodes. In this situation, advanced nodes perish faster than regular nodes.

Enhanced Energy Efficient Clustering (EDEEC)

EDEEC, or Enhanced Distributed Energy Efficiency Clustering, was created to allow general cluster leaders to select network nodes based on their remaining energy balance. As a result, advanced nodes are more likely to be picked as group heads during the initial distribution round. After their energy levels have dropped sufficiently, these nodes will have the same probability as regular nodes. Three DEEC protocol modifications are integrated into this study to increase its energy and packet lifetime performance. These enhancements are detailed further below.

Scaling Factor

A scale factor parameter is introduced to reduce the power of nodes inside a cluster. Because nodes are believed to connect directly with base stations over wider distances, communication inside the cluster must occur at a lower power level. For example, if the network field size is 100×100 and there are 10 clusters, each cluster is 10 x 10, limiting the maximum power for inter-cluster communication to a little larger than the 10x10 size. The amplification power ϵ_{fs} can be lowered by a factor of ten. Equation 5 can thus be used to define the scale factor.

$$Scaling\ factor= \{rand\ ()\ x\frac{Area\ of\ Network\ field}{area\ of\ the\ clusterXno.of\ nodes\ in\ a\ cluster} \tag{5}$$

Modified Threshold Probability

The probability threshold has a considerable impact on CH selection. Because CH after epoch n is determined using Equation 6, the node is manipulable. This formula calculates the number of nodes that survive after epoch n but does not consider the energy of nodes that stay after epoch n. As a result, a new correction equation is presented to assess the likelihood of a node becoming a CH, as stated below.

$$P_i = \frac{Energy\ of\ the\ ith\ node}{\sum_{i=1}^{n} Total\ energy\ of\ all\ nodes\ with\ in\ a\ cluster} \tag{6}$$

The threshold probability is used to determine whether a node can become a CH after calculating the likelihood of the ith node. To increase the efficiency of the proposed algorithm, the total energy of all nodes in the cluster is considered while computing the probability threshold, which may be determined using Equation (7).

$$T_{Si} = \begin{cases} \frac{P_i}{1-P_i(r\ mod\ \frac{P_i}{\sum_{i=1}^{n} pi_i}} & S_i\ \epsilon G \\ 0 & otherwise \end{cases} \tag{7}$$

Neighborhood Information

The concept of neighborhood information is used to identify the next possible CH. As a result, a distance-based measurement is applied to the current CH position to calculate the position of the next CH. Then, a threshold distance (do) is used to find the neighbors of the present CH. The node is chosen as the current CH's neighbor, and CH stores all of its neighbors. The goal of neighborhood information is to select a maximum energy CH in its neighborhood. As a result, nodes with more energy than their CH become neighbors of the current CH.

Improved Particle Swarm Optimization Algorithm (IPSO)

PSO is a population-based optimization method. The population initiates the network's random solution, and the optimal solution is sought in each generation. Each generation of potential solutions is referred to as a particle. Each particle in the PSO records all relevant coordinates to obtain the best solution by tracking the current best particle. Run the fitness function on each particle, then compute and save the fitness value (best solution). "pbest" is the fitness value of the current best particle. PSO optimizes the best population value of any neighboring particle obtained thus far, referred to as the best position. When it is assumed that all produced population numbers are topological neighbors of a particular particle, the best value in the produced population is chosen, and this specific best value is the best solution.

However, PSO performs poorly in local searches with premature convergence, especially for complex multimodal search problems. To address this case, we improve the traditional PSO algorithm by adjusting the inertia weights to avoid particles becoming trapped in local optima and then use the improved PSO algorithm to maximize the fitness function. As a result, more appropriate CHs and relay nodes are selected, resulting in a more energy-efficient protocol.

Cluster Head Selection using Hybrid IPSO-EDEEC

Cluster Formation

Based on centralized clusters, BSs or sinks form clusters. It sends information collection messages to all sensor nodes for the aggregated base station (receiver). After receiving this message, the sensor node begins transmitting node data such as position (distance from BS at positions X and Y), power loss, node ID, power loss rate (speed), and the transmitting base station's current power. The base station then begins the nesting process by performing the following steps.

Step 1: Transform the problem into PSO space, where PSO particles have two dimensions: position and velocity.

Step 2: Using the fitness function, calculate the fitness value.

Algorithm 1: EDEEC-IPSO
1. Initialize and evaluate each particle as a random set of centroids;
2. Update pbest for each particle;
3. Update the gbest;
4. while the convergence criterion is not met do
5. Update velocity and position
6. Evaluate each particle;
7. Update pbest for each particle;
8. Update the nbest;
9. End while

Fitness Function

The fitness functions of our proposed PSO-based clustering are the average energy and distance of the optimized member nodes and the current CH and number of CHs. Cluster formation using EDEEC-IPSO is depicted in Algorithm 1. This message is stored by each sensor node, which then initiates a roundabout method to perform CH selection.

CH Selection

Each SN keeps a "My Cluster List" after clustering. The current cluster-ID, speed, position, and power are all included. A series of procedures then follow the selection of the group leader. Figure 2 depicts the selection of cluster heads using the PSO algorithm.

Energy efficient Opportunistic Routing (EEOR) between Cluster-Heads

The group header employs signal processing to compress the data after receiving a datagram from each group member. The combined signal is routed to the receiver utilizing energy-efficient opportunistic routing through other cluster heads. An energy-saving opportunity routing protocol for WSN is a novel inequality algorithm dubbed EEOR (Energy Saving Opportunity Routing). Routing algorithms must be examined to evaluate the effectiveness and dependability of the policies employed.
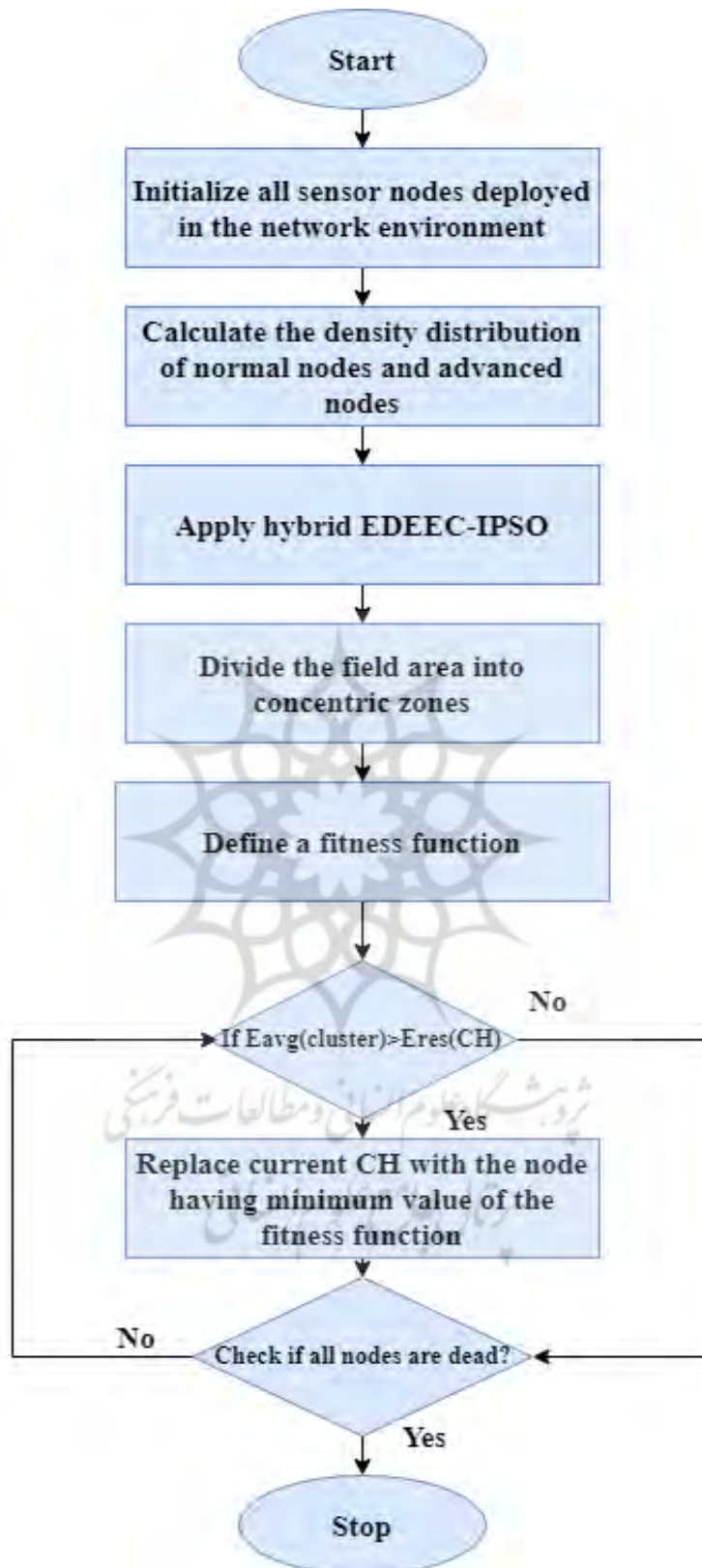
Figure 2. Flowchart of the proposed IPSO-EDEEC algorithm

The routing phases are as follows:

• Each node frequently provides data about the quality of the links.

• Based on this data, a node selects the default route and a list of transfer nodes that can be transmitted.

• It then sends out a data packet containing this data.

• The transfer list nodes save the packet and provide a transfer timer.

• The packet is broadcasted first by the node with the most petite timer closest to the destination.

• To prevent transmission rate, the other nodes will remove the appropriate packet from their queues.

Results and Discussion

The suggested technique's performance is compared to the conventional clustering and routing protocols DEEC, LEACH, and HEED. Compared to other current approaches, performance parameters such as power consumption, network lifetime, end-to-end latency (E2ED), Packet delivery ratio (PDR), and so on are calculated using 500 nodes. In these simulations, 1000 x 1000 square meter region is filled with 100 homogenous sensor nodes and nine unlimited battery-powered cluster head nodes. MATLAB software will be used to accomplish the proposed method and the simulation parameters are listed in Table 1.

Table 1. Simulation parameters

Parameter	Value
Area	1000 x 1000 m
Number of nodes	500
Initial energy	0.6mJ
Bandwidth	7Mbps
Packet size	512 bytes
Node distribution	Random
Speed of mobile sink	1m/s
Transmission range	30m
Number of mobile sinks	1

Table 2. Packet delivery ratio (%)

Number of nodes	DEEC	LEACH	HEED	Proposed
100	80	87	90	95
200	78	85	89	93
300	75	80	88	90
400	73	77	85	88
500	70	75	80	85

PDR is defined as the ratio of packets received by the receiver to packets sent by the sender as given in Table 2. Figure 3 shows the PDR of current and new systems. According to the graph, the proposed approach is more advanced than other methods. The suggested technique obtains a high PDR (95%) compared to existing methods. The PDR will be driven by the increase in the number of SN.
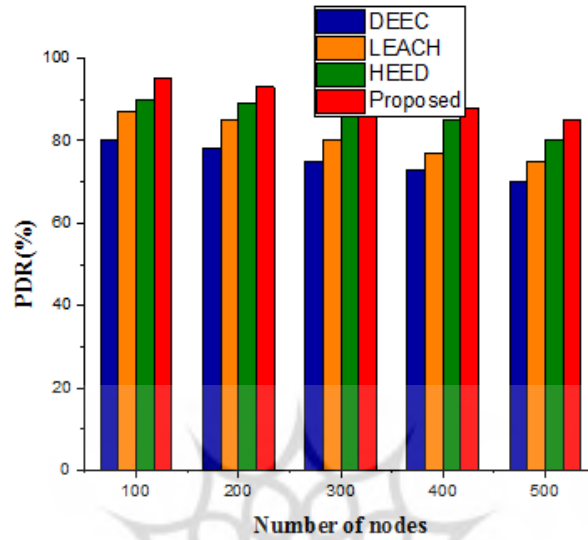

Figure 3. Packet Delivery Ratio (%)

Table 3. Energy consumption (nJ)

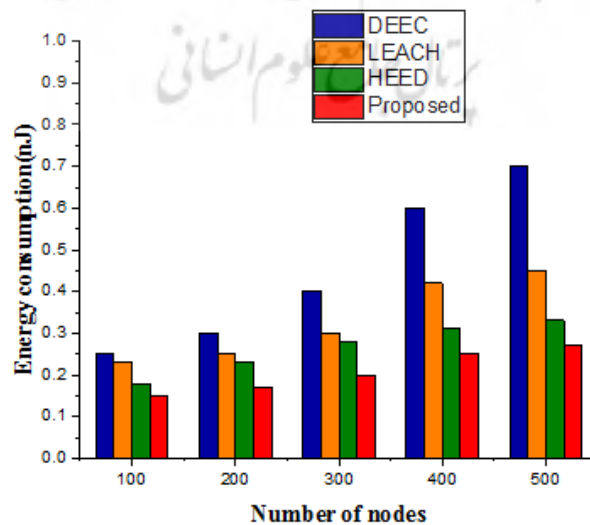| Number of nodes	DEEC	LEACH	HEED	Proposed
100	0.25	0.23	0.18	0.15
200	0.3	0.25	0.23	0.17
300	0.4	0.3	0.28	0.2
400	0.6	0.42	0.31	0.25
500	0.7	0.45	0.33	0.27

Figure 4. Energy consumption(nJ)

The sum of received power, transmit power, and the number of nodes is defined as energy consumption. Figure 4 compares the proposed scheme's energy consumption to other existing technologies. In 500 nodes, the developed technology uses less energy (0.27nJ) than other existing methods. Table 3 provides the comparison of energy consumption for several nodes.

Table 4. End to End delay (ms)

Number of nodes	DEEC	LEACH	HEED	Proposed
100	5	4.5	4	3.5
200	6.8	5.6	5.2	4
300	8.2	7.4	6	4.8
400	10	8	7	6
500	12.5	11	9	7.8

It is the percentage of the time required to deliver a packet to the recipient to the number of packets received. Figure 5 depicts the end-to-end delay analysis of suggested and conventional approaches. The proposed method achieved a lower E2ED (7.8 ms) than other systems. From the simulated results mentioned in Table 4, it is clear that the number of nodes will increase E2ED.
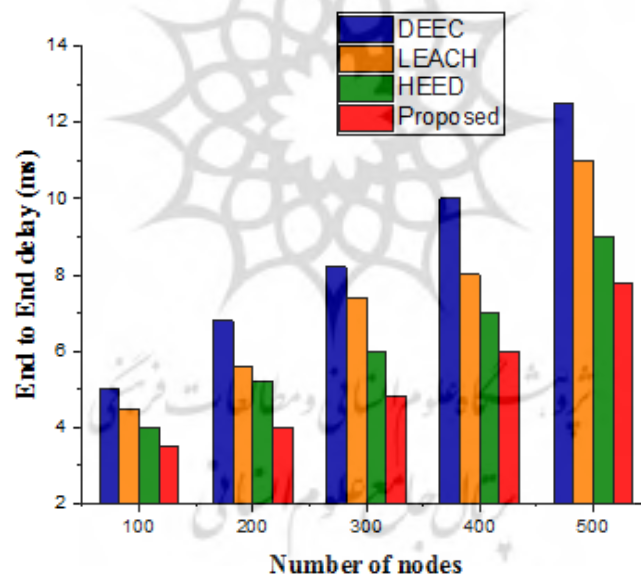

Figure 5. End to End delay(ms)

The system's lifespan is how long it can operate and perform the assigned duty. Figure 6 compares the proposed method's effectiveness to that of the conventional method over the lifetime of a network. The suggested method has a greater network lifetime than traditional systems. The lifespan of the system decreases as the number of nodes increases as listed in Table 5.

Table 5. Network lifetime (rounds)

Number of nodes	DEEC	LEACH	HEED	Proposed
100	4100	4600	4800	5000
200	4000	4400	4500	4800
300	3700	3800	4000	4400
400	3100	3500	3800	4000
500	2500	2800	3000	3500
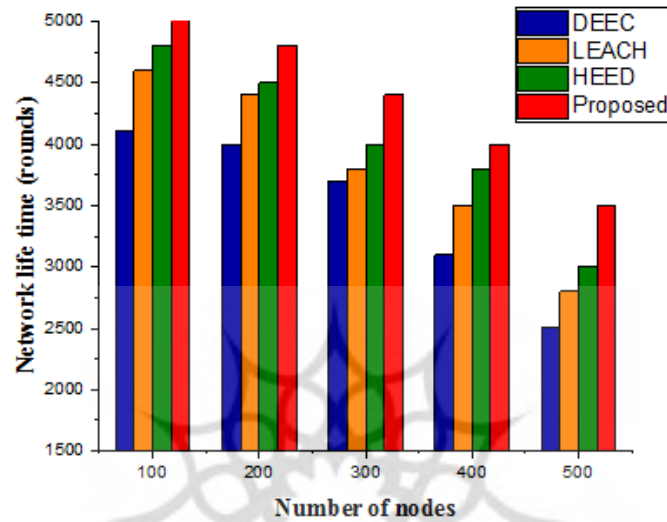
Figure 6. Network lifetime (rounds)

Table 6. Throughput (Mbps)

Number of nodes	DEEC	LEACH	HEED	Proposed
100	0.75	0.80	0.92	1.4
200	0.72	0.77	0.83	0.92
300	0.7	0.74	0.77	0.90
400	0.6	0.63	0.7	0.86
500	0.52	0.55	0.65	0.75

Figure 7 depicts the throughput performance. The proposed method has a throughput of 1.4 (Mbps), the existing algorithm DEEC has a throughput of 0.785 (Mbps), LEACH has a throughput of 0.80 (Mbps), and HEED has a throughput of 0.92 (Mbps). From the comparison given in Table 6, the existing algorithms have poor performance. However, the proposed method achieves a high-performance ratio compared to the state-of-the-art. As a result, our proposed method outperforms others.
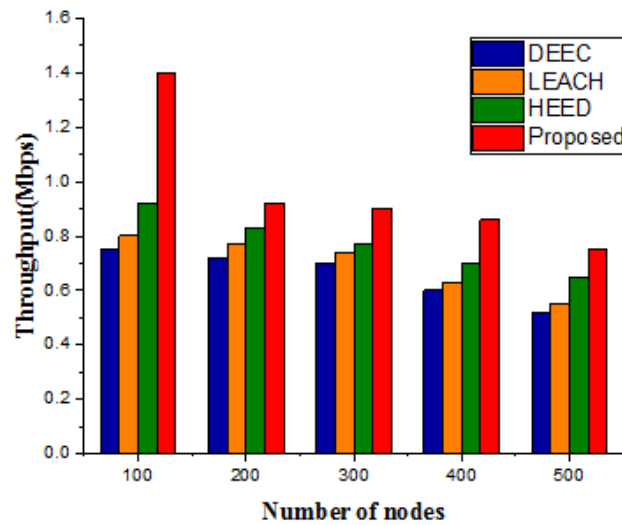
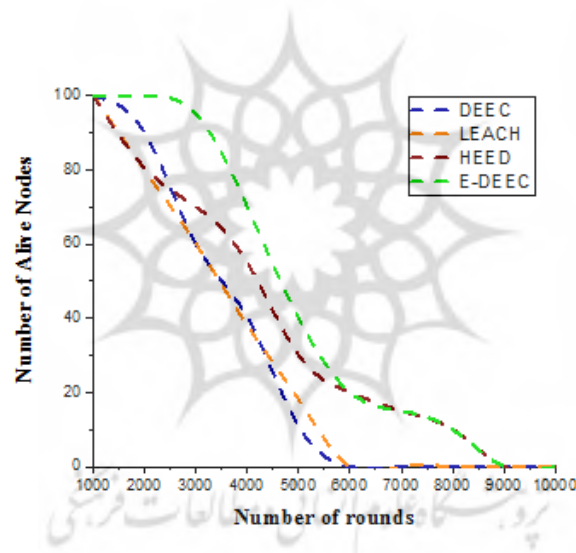**Figure 7. Throughput (Mbps)**

Figure 8. Number of the Alive nodes per round

Furthermore, as shown in Figure 8, the death rates in E-DEEC are lower than those in previous approaches. It demonstrates that the proposed method effectively reduced the number of dead nodes, resulting in a more extended network lifetime.

Conclusion

The IPSO-EDEEC protocol stands for Enhanced Distributed Energy-Efficient Clustering for heterogeneous wireless sensors. An energy-aware adaptive clustering protocol using an adaptive approach that uses the network's average energy as the reference energy. Suppose SN selects itself as the group leader based on its initial and residual energy and has no global awareness of power in each round of the election. EDEEC implements a balanced and dynamic method of distributing energy consumption evenly among nodes to improve the

performance of the DEEC protocol even further. These changes improve the benefits of our EDEEC protocol over others. The network lifetime can thus be extended. It has been demonstrated that the network can improve energy efficiency by minimizing total power consumption and balancing power consumption among nodes over the network's life under various node densities, network area sizes, and BS locations. The simulation results show that this protocol outperforms other clustering protocols in comparison.

Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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References

Abdulsalam, H.M.; Kamel, L.K. W-LEACH: Weighted Low Energy Adaptive Clustering Hierarchy aggregation algorithm for data streams in wireless sensor networks. In Proceedings of IEEE International Conference on Data Mining Workshops (ICDMW), Sydney, Australia, 14 December 2010, pp. 1–8.

Akyildiz, I. F., Su, W., Sankarasubramaniam, Y., & Cayirci, E. (2002). A survey on sensor networks. IEEE Communications magazine, 40(8), 102-114.

Alia, Osama. (2018). A dynamic harmony search-based fuzzy clustering protocol for energy-efficient wireless sensor networks. annals of telecommunications - annales des télécommunications. 73. 353–365. 10.1007/s12243-017-0611-6.

Ben Fradj, H., Anane, R. & Bouallegue, R. Opportunistic Routing Protocols in Wireless Sensor Networks. Wireless Pers Commun 104, 921–933 (2019). https://doi.org/10.1007/s11277-018-6060-3

Bruckner, D., Picus, C., Velik, R., Herzner, W., & Zucker, G. (2012). Hierarchical semantic processing architecture for smart sensors in surveillance networks. IEEE Transactions on Industrial Informatics, 8(2), 291-301.

Cheng, L., Niu, J., Cao, J., Das, S. K., & Gu, Y. (2013). QoS aware geographic opportunistic routing in wireless sensor networks. IEEE Transactions on Parallel and Distributed Systems, 25(7), 1864-1875.

Han, G., Jiang, J., Bao, N., Wan, L., & Guizani, M. (2015). Routing protocols for underwater wireless sensor networks. IEEE Communications Magazine, 53(11), 72-78.

Kavitha, K., Thamaraimanalan, T., & Kumar, M. S. (2014). An optimized heal algorithm for hole detection and healing in wireless sensor networks. International Journal of Advanced Engineering Research and Technology (IJAERT), 2(3), 243-249.

Kumarawadu, P.; Dechene, D.J.; Luccini, M.; Sauer, A. Algorithms for Node Clustering in Wireless Sensor Networks: A Survey. In Proceedings of 4th International Conference on Information and Automation for Sustainability, Colombo, Sri Lanka, 12–14 December 2008; pp. 295–300.

Lindsey S, Raghavendra C, Sivalingam KM (2002) Data gathering algorithms in sensor networks using energy metrics. IEEE Trans Parallel Distributed Syst 13(9):924–935

Liu X (2012) A survey on clustering routing protocols in wireless sensor networks. Sensors 12(8):11113–11153

Manjeshwar A, Agrawal DP (2001) TEEN: a routing protocol for enhanced efficiency in wireless sensor networks. In: Proceedings of the 15th International Parallel and Distributed Processing Symposium (IPDPS), San Francisco, CA, USA, pp 2009–2015

Qing L, Zhu Q, Wang M (2006) Design of a distributed energy efficient clustering algorithm for heterogeneous wireless sensor networks. Comput Commun 29(12):2230–2237

Ran, G.; Zhang, H.; Gong, S. Improving on LEACH protocol of wireless sensor networks using fuzzy logic. J. Inf. Comput. Sci. 2010, 7, 767–775.

Smaragdakis G, Matta I, Bestavros A (2004) SEP: a stable election protocol for clustered heterogeneous wireless sensor networks. In: Proceedings of the International Workshop on SANPA, pp 251– 261

Thamaraimanalan, T., & Sampath, P. (2019). A low power fuzzy logic based variable resolution ADC for wireless ECG monitoring systems. Cognitive Systems Research, 57, 236-245.

Wang, F., & Liu, J. (2010). Networked wireless sensor data collection: issues, challenges, and approaches. IEEE Communications Surveys & Tutorials, 13(4), 673-687.

Yetgin, H., Cheung, K. T. K., El-Hajjar, M., & Hanzo, L. (2015). Network-lifetime maximization of wireless sensor networks. IEEE Access, 3, 2191-2226.

Yick, J., Mukherjee, B., & Ghosal, D. (2008). Wireless sensor network survey. Computer networks, 52(12), 2292-2330.

Younis O, Fahmy S (2004) HEED: A hybrid, energy-efficient, distributed clustering approach for ad-hoc sensor networks. IEEE Trans Mob Comput 3(4):366–379

Yue, J. Zhang, W.; Xiao, W.; Tang, D.; Tang, J. Energy efficient and balanced cluster-based data aggregation algorithm for wireless sensor networks. Procedia Eng. 2012, 19, 2009–2015.