



Energy Efficient Clustering in Wireless Sensor Networks Using Arithmetic Optimization Algorithm (AOA)

Abrar Ryadh

Medical Laboratory Techniques Department, Al-Mustaqbal University College, Hillah, Babylon,
Iraq

Corresponding Author

abrarreyadh80@gmail.com

Abstract:

Wireless Sensor Networks (WSNs) are collections of small, low-value nodes prepared with sensors, processor, transceiver, and power gadgets that may set up wi-fi communication. One of the primary demanding situations in WSNs is electricity intake. Clustering is an powerful method for reducing strength intake in wireless sensor networks with the aid of grouping nodes into clusters and choosing a subset of nodes as cluster heads liable for records aggregation and transmission.

In this research, an energy-inexperienced clustering technique is proposed for wireless sensor networks the usage of an optimization set of regulations to cope with the electricity consumption hassle. The proposed approach makes use of the Arithmetic Optimization Algorithm (AOA) to optimize the clustering approach and reduce power intake. The set of rules starts via randomly assigning nodes to clusters and iteratively improves the answer via mathematics operators together with addition, subtraction, multiplication, and department.

The efficiency of the solution is evaluated based on the fitness function which considers the energy consumption of each node and the distance between nodes. Experimental results show that the proposed method outperforms the existing clustering algorithms in terms of energy efficiency, and maintains high network availability and connectivity The proposed method has the potential to be controlled role in applications in WSNs where energy efficiency is an important factor.

Keywords: Wireless Sensor Networks, Clustering, Arithmetic Optimization Algorithm, Energy Efficiency.

Introduction

Wireless sensor networks (WSNs) are a form of network of interconnected sensor nodes that might experience, hold, and transmit information from their surroundings. These nodes have the potential to set up wi-fi links with each one-of-a-kind and transmit information to a applicable node for processing. WSNs commonly encompass many small energy-saving gadgets embedded with sensors,

microcontrollers and wireless conversation interfaces[1] WSNs are also susceptible to safety assaults due to their allotted and absence of centralized control nature. Various protection mechanisms were proposed to address those vulnerabilities, which include encryption, key distribution, and authentication. Research in WSNs is actively addressing disturbing situations which includes scalability, reliability, and cooperation. In favored, WSNs have the capability to transform facts series and processing strategies, making them a large place of research and development in wi-fi communications and sensor networks[2] Wireless Sensor Networks (WSNs) are small, wireless devices that collect and transmit information to specific locations. These networks are crucial due to their ability to transmit real-time data and address environmental factors. Sensor nodes, equipped with sensing, processing, and communication capabilities, gather and transmit data to the ground station. Wireless communication protocols, such as ZigBee, Bluetooth Low Energy, and Wi-Fi, are commonly used.[3]

WSNs require power sources, data aggregation, and security to ensure optimal performance. Sensor nodes run on batteries, and researchers have developed methods for energy efficiency. Data aggregation and routing techniques reduce data transmission and save energy. Security measures include encryption, authentication, and access control. Network management ensures node connectivity, machine updates, and fault detection.[3] Wireless sensor networks (WSNs) are interconnected devices that use Wi-Fi connectivity and sensing capabilities to collect data from their environment. These networks have a great variety of applications in different industries such as healthcare, agriculture, environmental monitoring, automation and home automation[4] Scalability is a significant concern in wireless sensor networks (WSNs), which can have varying node numbers. However, increasing node numbers can lead to increased data usage, connection complexity, performance degradation, and energy inefficiency.[5]

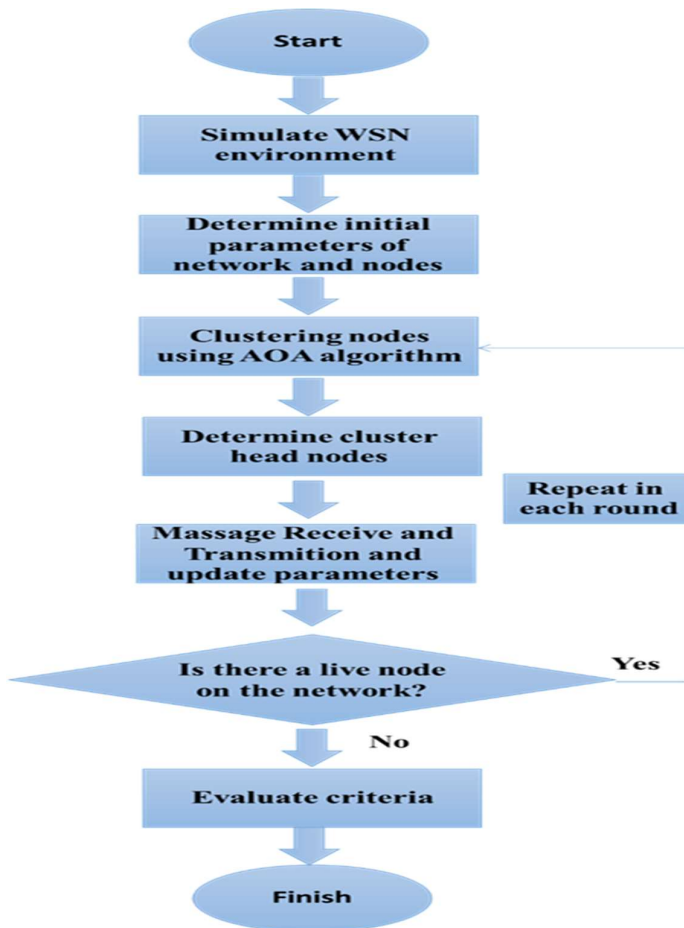
Arithmetic optimization algorithm (AOA) is a machine learning technique used to optimize arithmetic performance in neural networks. This algorithm is specifically designed to optimize computation in convolutional neural networks, with matrix properties and many convolutions[6] The Arithmetic Optimization Algorithm (AOA) is a technique that breaks down complex arithmetic operations into smaller, more efficient sub-operations, reducing computational time and memory usage. It also enhances the accuracy of neural networks, ensuring higher computations and better results. AOA can be applied to feedforward, recurrent, and convolutional neural networks, and has shown promising results in improving convolutional network performance in image popularity tasks. [7]Wireless sensor community (WSN) is a network used for tracking and controlling specific environments. It consists of low-cost sensor nodes, each with a sensor, data processor, and wireless record transmitter. These nodes collect, process, and transmit data to a base station for analysis. The power supply must meet the needs of processors, transmitters, and sensors.[8, 9]

MATERIALS AND METHODS

The research aims to enhance energy efficiency in wireless sensor networks using the Arithmetic Optimization Algorithm (AOA). A novel technique is proposed to select cluster heads (CHs) based

on distance among records and energy intake, aiming to improve overall performance and reduce energy consumption in sensor networks.

This study enhances energy performance of sensor networks using clustering strategies and an arithmetic optimization set of policies (AOA), which uses numerically modeled functions for optimization in various research areas. The efficiency of a wireless sensor network relies heavily on the selection of the optimal cluster centers, which can lead to increased node energy consumption and shorter lifetimes. the paintings **figure.1**. utilize the AOA optimization set of rules, which offers superior performance in clustering problems due to its parallel and high-speed search capabilities and minimizes local



The AOA algorithm is an optimization method utilizing addition, subtraction, multiplication, and division. It consists of two main phases: exploitation and exploration. The aim is to minimize the total distance between nodes, enhancing energy efficiency and network lifetime. The algorithm's steps are detailed below.

1. The AOA optimization algorithm initializes variables α and μ , with α being a control parameter determining exploitation accuracy in each iteration, set at 5.[10]
2. The AOA algorithm generates candidate solutions (X) randomly, with the best solution considered the optimal in each iteration, considering the position of nodes in the sensor network.

$$X = \begin{bmatrix} x_{1,1} & \cdots & \cdots & x_{1,j} & x_{1,n-1} & x_{1,n-1} \\ x_{2,1} & \cdots & \cdots & x_{2,j} & \cdots & x_{2,n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{N-1,1} & \cdots & \cdots & x_{N-1,j} & \cdots & x_{N-1,n} \\ x_{N,1} & \cdots & \cdots & x_{N,j} & x_{N,n-1} & x_{N,n} \end{bmatrix} \quad (1)$$

In the continuation of the algorithm, the following steps are repeated in a loop.

3. By choosing cluster heads using a weighted multi-objective minimization function, this work seeks to improve energy efficiency in wireless sensor networks. The function chooses the head with the most energy left after minimizing the distance to cluster heads and sink distance.

The standard deviation of the distance between the cluster members and related cluster heads (f_1) is defined according to Eq.

$$f_1 = \frac{\text{Max}(\text{std}(\text{dis}(M_i \cdot CH_i)))}{\text{worst}(\text{std})} \quad i \in 1, m \quad (2)$$

The cluster head's distance from the base station increases energy consumption, potentially leading to its sudden death. Shorter distances are more suitable for cluster heads, as minimizing the distance between cluster heads and sinks reduces network energy consumption.

$$f_2 = \frac{\sum_{i=1}^m \text{dis}(CH_i \cdot BS)}{\text{Maxdis}(CH \cdot BS) * m} \quad (3)$$

The cluster head in a network collects data from sensor nodes and sends it to the base station, consuming more energy than other nodes, so the node with the highest remaining energy is chosen.

$$f_3 = \frac{\sum_{i=1}^m E_{CHi}}{E_{ini} * m} \quad (4)$$

4. Determining the best answer based on the fitness values calculated in the previous step
5. Updating the Math Optimizer Accelerated function (MOA)
6. Updating the Math Optimizer probability (MOP)

This probability is calculated according to the following equation.

$$MOP(C_Iter + 1) = 1 - \frac{C_Iter^{\frac{1}{\alpha}}}{M_Iter^{\frac{1}{\alpha}}} \quad (5)$$

7. If the value of $r1$ is greater than MOA for each answer, the exploration phase is performed, and otherwise, the exploitation phase is performed.

In the exploration phase:

If $r2$ is greater than 0.5, the mathematical division operator (D) is applied. That is, the position of the answer is updated according to the first law of the following relationship. Otherwise, the mathematical operator multiplication (M) is applied. That is, the position of the answer is updated according to the second law of the following equation.

$$x_{i,j}(C_Iter + 1) = \begin{cases} best(x_i) \div (MOP + \epsilon) \times ((UB_j) - LB_i) \times \mu \times LB_i, & r_2 < 0.5 \\ best(x_j) \times MOP \times ((UB_j) - LB_i) \times \mu \times LB_i, & otherwise \end{cases} \quad (6)$$

In the exploitation phase:

If the value of $r3$ is greater than half, then the mathematical operator minus (S) is applied. That is, the position of the answer is updated according to the first law of Eq. (3-9). Otherwise, the addition arithmetic operator (A) is applied. That is, the position of the answer is updated according to the second law of Eq.

$$x_{i,j}(C - Iter + 1) = \begin{cases} best(x_j) - MOP \times ((UB_j) - LB_j) \times \mu + LB_j, & r3 < 0.5 \\ best(x_j) + MOP \times ((UB_j) - LB_j) \times \mu \times LB_j, & otherwise \end{cases} \quad (7)$$

Solutions are updated during exploration and exploitation stages to obtain the optimal solution.

RESULTS AND DISCUSSION

This bankruptcy presents numerical findings from a MATLAB 2021 simulation of a proposed approach for wireless sensor networks, examining initial parameters, evaluation parameters, and comparative assessment results with different strategies.

The proposed technique's performance is evaluated using network lifetime and residual energy metrics, which measure the number of rounds community nodes remain alive.

In this study, a wireless sensor network is initially created for simulation with parameters such as network size, number of sensors, spatial coordinates, packet size, etc. The initial parameters and their values are presented in **table .1**.

Table (1) The Initial Parameters of The Network

Parameters	Values
Network size	100*100
Number of nodes	100
Initial placement of nodes	Randomly
Data transmission energy	5 nJ/bit
Packet size	500 bytes

The proposed method's evaluation parameters include overall network lifetime and residual energy in the wireless sensor network, which are evaluated and compared with other methods. The study examines the impact of network dimensions on its lifetime and energy consumption. Networks with 50*50 dimensions have a longer lifetime, but all nodes are dead after 12,000 rounds, while 150*150 networks have all nodes dead after 8,000 rounds. The energy for a 50*50 network reaches zero after 10,000 rounds, while for a 150*150 network, it reaches zero after 7,000 rounds.

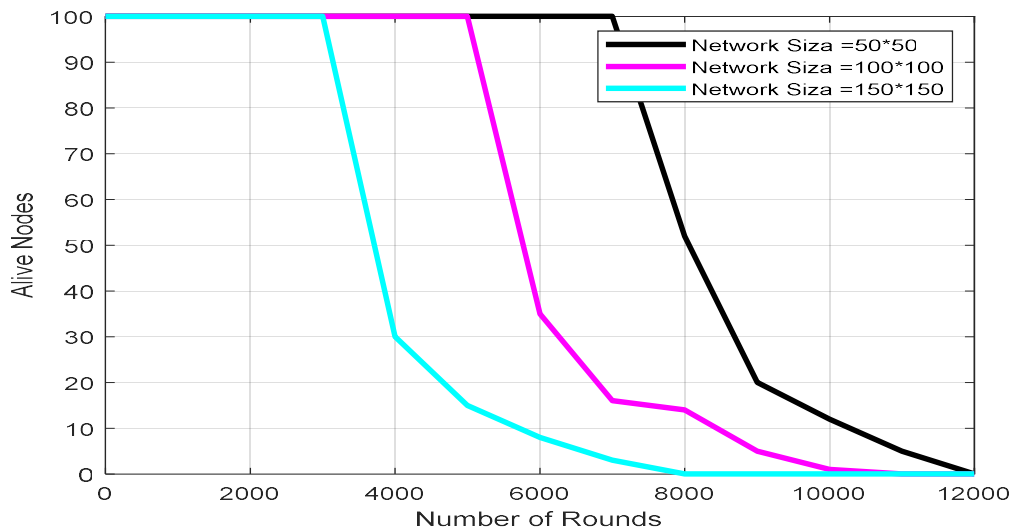


Figure .2. The Effect of Network Size on The Number of Alive Nodes

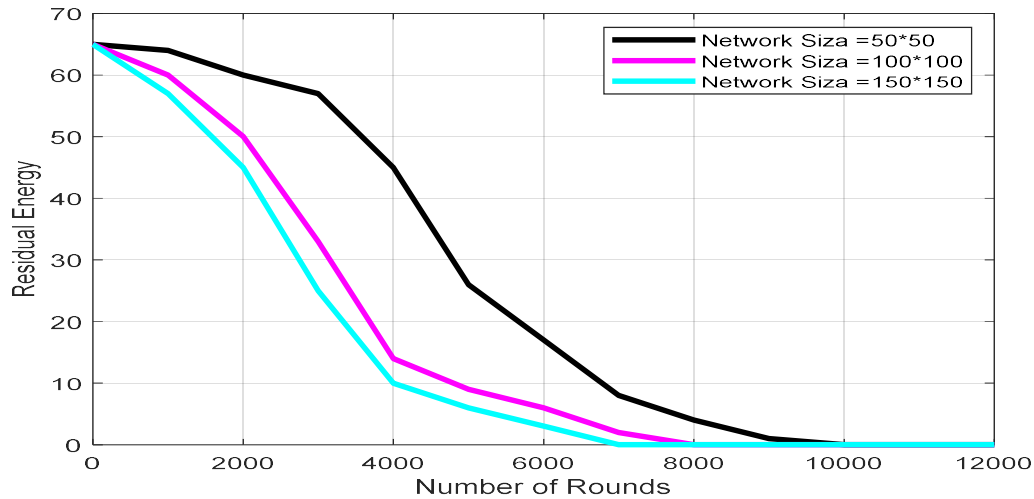


Figure.3. The Effect of Network Size On Residual Energy

The number of active nodes in the network directly affects the network lifetime metric. In fact, we perform multiple rounds of investigation on the number of alive nodes in the network to determine the network lifetime. The stability of the network is demonstrated through this evaluation. The network lifetime, measured as the time from the death of the first node to the death of the final node, is shown in **Figure (4)**, where various approaches including the method mentioned in reference[11] are studied. The study compares the PSO-EEC and HSA-PSO approaches for a 100-node network. The proposed technique shows greater stability due to efficient cluster head selection and robust clustering, unlike the referenced paper's loss of first and final nodes.

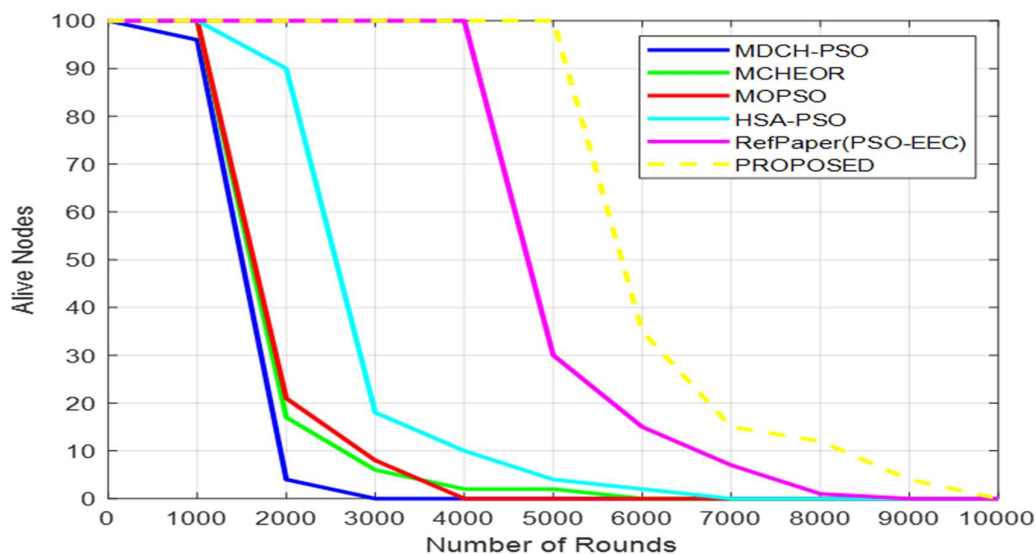


Figure .4. Investigating Network Lifetime Using Different Clustering Methods

The simulation results for the HSA-PSO, PSO-EEC (reference method), and the proposed approach, as presented in **Table (2)** for a deeper analysis of the network lifetime

The Proposed method	PSO-EEC	HSA-PSO	FND (First Node Dead) HND (Half Node Dead) LND (Last Node Dead)	Scenario of nodes with different energy
4950	3990	1050	FND	All nodes 0.5 J energy
5800	4700	2500	HND	
9900	8100	6900	LND	

Table .2. the numerical values of network lifetime for different approaches

This section examines the residual energy of nodes, which is inversely related to network lifetime. Nodes should be placed in clusters close to cluster heads to minimize energy consumption. The proposed method consumes half its energy by round 3000 and depletes all it by round 8000, demonstrating its effectiveness and superiority over other methods.

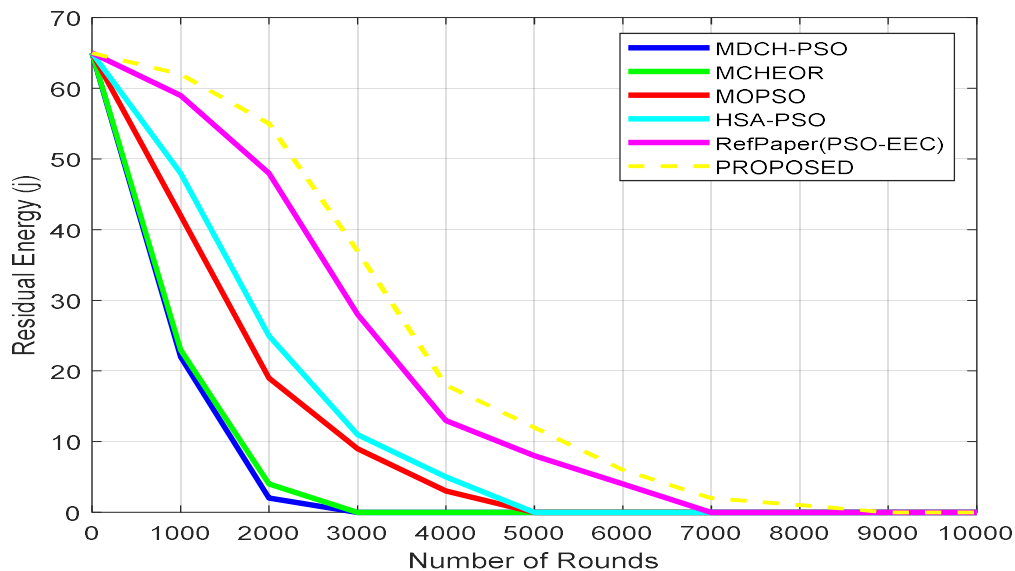


Figure.5. Investigating Network Energy Consumption Using Different Clustering Methods

In **Table (3)**, the numerical results of **Figure (5)** are presented in more detail. This table shows the levels of energy consumed by the reference article and the proposed method at both levels of energy consumption of half nodes and all nodes.

The proposed method	PSO-EEC	HSA-PSO	HEC (Half Energy Consumption) FEC (Full Energy Consumption)	Scenario of nodes with different energy
3200	2600	1500	HEC	All nodes
8300	6990	4990	FEC	0.5 J energy

Table.3. the numerical values of network energy consumption for different approaches

Figure .6. shows node loss over different rounds, demonstrating the proposed technique's stability compared to previous methods. All nodes lost after over 10000 rounds, while the reference paper's method had all nodes dying at around 9000 rounds. The proposed approach outperforms unique strategies in terms of balance.

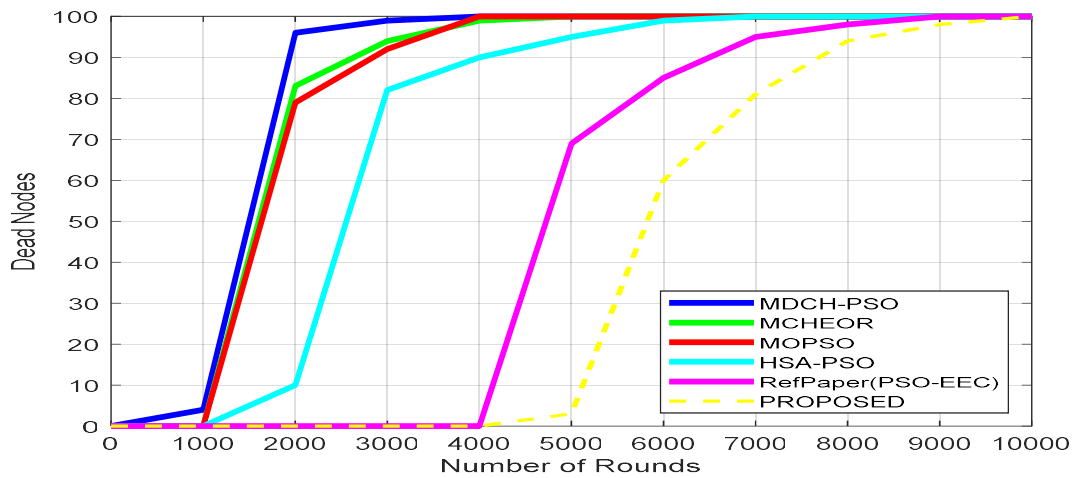


Figure.6. The Death Process of Nodes in Different Rounds for Different Methods

Conclusions

Wireless Sensor Networks (WSNs) are extensively applied in numerous programs along with environmental monitoring, web site traffic manage, and military surveillance. In the ones packages, sensors are deployed to collect data from the environment and transmit it to a base station for processing. However, because of the restrained battery life of sensors, strength performance is a vital element in WSN format. In this take a look at a method is proposed that makes use of an optimization set of guidelines to cluster sensors based totally totally on their residual power stages, predominant to a extra balanced energy consumption amongst clusters. Simulation effects display that the proposed technique outperforms special clustering algorithms in terms of community lifetime and power consumption.

This research proposes an efficient clustering algorithm for wi-fi networks that takes into consideration the strength stage of every sensor. By using the optimization algorithm, the proposed technique achieves a extra balanced power consumption amongst clusters, and as a end result the enhanced community lifetime. Simulation consequences highlight the effectiveness of the proposed method in lowering energy intake even as preserving network performance. In conclusion, this studies contributes precious insights to the field of WSNs and can be useful in developing and optimizing energy-green sensor networks for numerous programs.

Future Works

In order to improve the future works, the following recommendations can be taken into consideration:

1. Application of fuzzy clustering techniques: Fuzzy clustering allows more flexible assignment of sensors to clusters considering the number of members rather than rigid This can improve both cluster design and network performance.
2. ombining metaheuristic algorithms: Look for a combination of two or more metaheuristic algorithms such as genetic algorithm (GA) and particle swarm optimization (PSO) to make the cluster head selection more efficient and effective.
3. Combining Fuzzy Clustering with Metaheuristic Algorithm: This hybrid approach can use the simple fuzzy clustering in assigning sensors to clusters while using metaheuristic algorithms search power to optimize the cluster head selection process Thus this combination can improve cluster formation and energy efficiency in WSNs.

References

1. Seah, W.K., Z.A. Eu, and H.-P. Tan. *Wireless sensor networks powered by ambient energy harvesting (WSN-HEAP)-Survey and challenges*. in *2009 1st International Conference on Wireless Communication, Vehicular Technology, Information Theory and Aerospace & Electronic Systems Technology*. 2009. Ieee.
2. Yick, J., B. Mukherjee, and D. Ghosal, *Wireless sensor network survey*. *Computer networks*, 2008. **52**(12): p. 2292-2330.
3. Xu, G., W. Shen, and X. Wang, *Applications of wireless sensor networks in marine environment monitoring: A survey*. *Sensors*, 2014. **14**(9): p. 16932-16954.
4. Losilla, F., et al., *A comprehensive approach to WSN-based ITS applications: A survey*. *Sensors*, 2011. **11**(11): p. 10220-10265.
5. Bala, T., et al., *A survey: issues and challenges in wireless sensor network*. *Int. J. Eng. Technol*, 2018. **7**(2): p. 53-55.
6. Dhal, K.G., et al., *A comprehensive survey on arithmetic optimization algorithm*. *Archives of Computational Methods in Engineering*, 2023. **30**(5): p. 3379-3404.
7. Abualigah, L., et al., *The arithmetic optimization algorithm*. *Computer methods in applied mechanics and engineering*, 2021. **376**: p. 113609.
8. Mazumdar, N., A. Nag, and S. Nandi, *HDDS: Hierarchical Data Dissemination Strategy for energy optimization in dynamic wireless sensor network under harsh environments*. *Ad Hoc Networks*, 2021. **111**: p. 102348.
9. Sathish Kumar, L., et al., *Modern Energy Optimization Approach for Efficient Data Communication in IoT-Based Wireless Sensor Networks*. *Wireless Communications and Mobile Computing*, 2022. **2022**(1): p. 7901587.
10. Han, Y., et al., *Clustering the wireless sensor networks: a meta-heuristic approach*. *IEEE Access*, 2020. **8**: p. 214551-214564.
11. Jha, S.K. and E.M. Eyong, *An energy optimization in wireless sensor networks by using genetic algorithm*. *Telecommunication Systems*, 2018. **67**: p. 113-121.