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A Novel Fuzzy Cluster Head Selection and Adaptive Hawk Optimisation Routing Framework for Energy Efficient Wireless Sensor Networks

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Abstract: Wireless Sensor Networks (WSNs) have revolutionized various industries by enabling remote monitoring and data collection from inaccessible locations. However, they face significant challenges in data routing and cluster head selection due to limitations such as energy constraints, bandwidth, and dynamic environments. These challenges arise as nodes may fail due to energy depletion, causing changes in network topology. Efficient communication between cluster heads and the base station is essential, as long-distance data transmission consumes substantial energy, leading to rapid node depletion and reduced network lifetime. To address these issues, this paper proposes a novel Fuzzy-based Cluster Head Selection (FCHS) algorithm that dynamically elects cluster heads based on multiple criteria, including residual energy, distance to the base station, and node density. The FCHS algorithm ensures that cluster heads are selected in a manner that optimizes energy utilization, considering the diverse conditions in a WSN. In addition, an Adaptive Hawk Optimization (AHO) algorithm is employed to optimize data routing between cluster heads and the base station. The AHO algorithm dynamically adapts to changes in network topology, selecting the most energy-efficient paths for data transmission, thereby reducing overall energy consumption. The proposed FCHS-AHO approach is evaluated against existing cluster head selection and routing methods. Simulation results demonstrate that the FCHS-AHO method outperforms traditional techniques in terms of energy efficiency, network lifetime, and data delivery reliability. By optimizing both cluster head selection and routing, this framework significantly enhances the overall performance of WSNs, particularly in dynamic and resource-constrained environments. The proposed method provides a robust solution for improving the sustainability and reliability of WSNs in real-world applications.

Keywords: adaptive hawk optimization (AHO); cluster head selection; energy efficiency; fuzzy logic; wireless sensor networks (WSN)

1 INTRODUCTION

Wireless Sensor Network (WSN) [1] is the most critical and crucial category of the network, composed of randomly distributed sensors. The sensors are the nodes of the network intended to collect the data from the environment in which it has been deployed. The data collected by the sensor is communicated to the base station in various strategies [2]. Due the diversified advantages and features of the WSN, it has been an inevitable technology in the Internet of Things (IoT) [3]. The nodes of the WSN shall be easily deployable in any remote location or in any intended challenging environment like national or international borders. The nodes are tiny in physical dimension and are connected by means of wireless technology, enabling them to monitor, gather the data and to communicate the data. The sensors have been provided with the initial power, such that the energy is consumed during the communication and data routing process. Once the power has been drained, the node is considered as the dead node, leading to the end of the lifetime for the nodes as well as the network. This is the major challenge in the WSN, and this power limitation in the WSN, encourages the design of optimization techniques in performing routing process for data forwarding mechanism.

To overcome the early draining the sensor nodes, the WSN employs multi path routing principle, such that the data traffic is distributed over the entire network, thus distributing the power consumption over the entire nodes of network. The data packets in the WSN have a dual option of single hop or multi hop propagation to save the energy consumption by the sensors during the communication process. To overcome the energy concern, the clustering has been introduced, in which the sensor are formed in a group based on the location, measuring parameter and similar factors. In this group of sensor nodes, a node is designated as the Cluster Head (CH), receives the data from the member sensors. This strategy reduces the workload of the member sensors, as the entire communication is performed by the CH. Once the CH energy is drained, a new sensor with high residual energy is designated as the Cluster Head. The concept of designating the nodes as cluster head, had enhanced the lifetime of the network from "*n*" duration to "*n* + *a*" duration, as the factor "*a*" is the number of nodes in a cluster. This strategy of cluster head based WSN is depicted in Fig. 1.

Low Energy Adaptive Clustering Hierarchy (LEACH) [4], Distributed Energy Efficient Clustering (DEEC) [5], Stable Election Protocol (SEP) [6], Threshold Sensitive Energy Efficient Clustering Protocol (TEEN) [7], and Hybrid Energy Efficient Distributed Clustering Protocol (HEED) [8] are among the strategies that have been introduced for cluster head selection. These strategies were selected based on the network topology, traffic pattern, and dynamic environment.

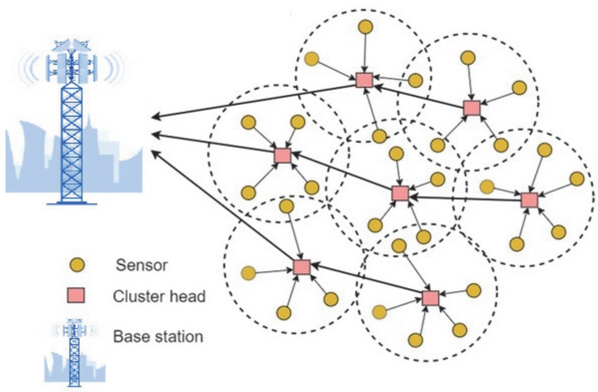

Figure 1 Wireless sensor networks with cluster head based routing strategy

2 LITERATURE REVIEW

The Wireless Sensor Network is an attractive domain, due to its applications in IoT, smart city and for monitoring purposes. This had attracted numerous researchers to actively involves in designing novel methodologies in enhancing the network lifetime. This section describes some of the novel methodologies involved in energy saving and lifetime enhancement objectives. Based on the literature review, the objectives of the proposed work are defined at the end of this section.

Gupta et al. (2024) had enhanced the lifetime of the sensor nodes of the WSN by employing Cluster Head Section using Integrated Butterfly Optimization technique [9]. In this process, the cluster head is designated to the member node based on the butterfly optimization process and by determining the residue energy levels of the sensor nodes. The energy efficient routing in the WSN using the Cluster based Genetic Harris Hawk eye Optimization algorithm (EER0 CGHHOA) [10]. This process had enhanced the routing mechanism, however due to the lack of cluster head mechanism; the proposed work had experienced latency in the data communication process. An intelligent clustering mechanism using Multi Criteria Decision Making (MCDM) technique [11] for energy efficient data communication in the WSN. The proposed technique employed a data driven approach, and the clustering is done based on the type of the data communicated over the network.

A Game Theory based Fuzzy Routing (GTFR) [12] for optimizing the operation of the network. This method used the Intra Cluster Communication Distance for optimizing and determining the shortest path for the communication process. A CH election process based on the game theory and a two level management cluster head protocol [13] for the energy efficient data communication process. The nodes in the WSN undergo two level assessment process to perform the local clustering process and multiple rounds of screening for election based cluster head selection process.

A new routing protocol named Environment Fusion Routing Protocol (EFRP) [14] for performing routing in the WSN. The protocol aims in enhancing the energy efficiency of the node by considering the dynamic environment conditions of the nodes. The selected path using the EFRP protocol, experienced a minimized delay in the routing path and had improved the data transmission process. A routing protocol for the IoT environment using the Link Quality based Energy Efficient Protocol [15] for mitigating the latency and for enhancing the packet delivery ratio. The energy consumption using Davies Biuldin K Nearest Neighbor (DBKNN) algorithm and the Radial Adaptive Neuro Fuzzy Interference System (Radial ANFIS) model [16] for performing energy efficient and reduced delay data communication in the WSN. MHCF- CECSO protocol [17] for enhancing the Quality of Service in the WSN. To enhance the Clustering efficiency, the chaos optimization process is performed to enhance the lifetime of the network, reduce the energy consumption and for enhanced reliability.

3 METHODOLOGY

The novelty of the proposed Fuzzy Cluster Head Selection and Adaptive Hawk Optimization (FCHS-AHO) framework lies in its hybrid approach that integrates fuzzy logic-based cluster head selection with an adaptive optimization technique, significantly improving energy efficiency in Wireless Sensor Networks (WSNs). Unlike conventional clustering algorithms, which often rely on static or probabilistic methods for cluster head selection, the proposed framework employs fuzzy logic to dynamically evaluate multiple critical parameters, such as residual energy, node centrality, and distance to the base station, ensuring an optimal and balanced selection of cluster heads. The incorporation of the Adaptive Hawk Optimization (AHO) algorithm further refines the routing process by dynamically adjusting search and exploration behaviors, leading to improved network lifetime and energy utilization. The selection of fuzzy parameters is crucial to the performance of the FCHS-AHO framework. Residual energy is chosen to prevent premature depletion of nodes, node centrality ensures well-distributed clusters, and distance to the base station reduces communication overhead. These parameters collectively enhance the robustness and adaptability of the network, outperforming traditional clustering approaches that often overlook these multifaceted selection criteria. The synergy of fuzzy logic and adaptive optimization in FCHS-AHO introduces a novel paradigm for energy-efficient and scalable WSNs, setting it apart from existing methodologies. The proposed Fuzzy based Cluster Head Selection (FCHS) integrated with the Adaptive Hawk Optimization (AHO) model is composed of two phases namely, the fuzzy based cluster head designation process, followed by the energy efficient routing using the Adaptive Hawk Optimization algorithm. The major objective of these two research phase is to enhance the lifetime of the network, by consuming minimal energy during the data transmission process. The proposed Wireless Sensor network is composed of homogenous sensors, deployed randomly with a uniform level of initial energy level. The Base Station (BS) is positioned at a static point with an unlimited energy level.

3.1 Fuzzy Based Cluster Head Selection (FCHS)

The sensors woven into the network gather intentional data from their environment and relay it to the receiver, either in a single leap or through the intricate dance of multi-hop communication via intermediary sensor nodes. A majority of Wireless Sensor Network (WSN) applications prefer the multi-hop communication method, aiming to bolster reliability, extend network longevity, enhance scalability, and curtail power consumption by alleviating data congestion. The allure of multi-hop communication over single hop lies in its broader bandwidth and the communication overhead intricately woven into the data transfer tapestry. To prolong the network's vitality, clustering emerges as a potent and impactful strategy within the WSN realm, enhancing the operational lifespan of sensor networks. This clustering endeavor entails segmenting the network by grouping sensors based on their logical functions, inherent characteristics, specific needs, and intended applications. By incorporating the clustering approach in the WSN, the network gains a plethora of benefits, including energy efficiency, resilience, and a significantly extended network lifespan. Fig. 1 illustrates the clustering-based architecture for the WSN, showcasing a sensor node with a superior residual energy level and an optimal distance from fellow nodes, designated as the Cluster Head (CH) for its respective cluster. Data from the member sensor nodes is transmitted through the Cluster Head to the base station, traversing the intermediary Cluster Heads of adjacent clusters. This innovative work unveils a groundbreaking Fuzzy-based Cluster Head Selection (FCHS) method for designating a member node as the Cluster Head. The energy consumed from free space and multipath amplification is defined as per Eq. (1).

$$E_S(n, d) = \begin{cases} nE_{ini} + nd^n \varepsilon_{fs}; \, d < d_T \\ nE_{ini} + nd^n E_{ma}; \, d \geq d_T \end{cases} \tag{1}$$

where, the $E_S(n, d)$ is the net energy to the 'n' number of sensor node at a distance 'd' from the base station.

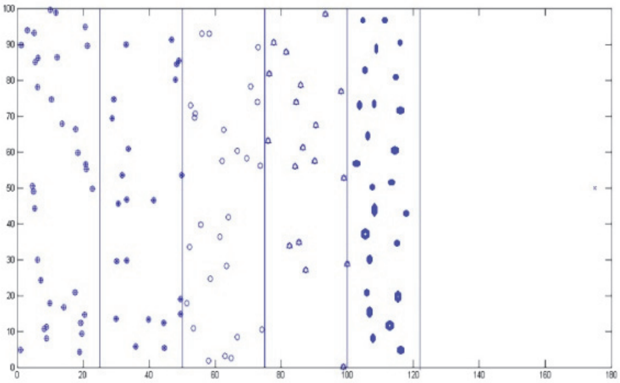

Figure 2 Random node deployment

The term E_{ini} is the initial energy, ε_{fs} is the energy due to free space communication and E_{ma} is the energy for amplification in multi path communication process. The consumed energy for the data communication is defined in Eq. (2).

$$E_{CH} = n\left(E_{ini} + E_{ma} + \varepsilon_{fs}\right) \tag{2}$$

The distance between the Cluster head and the node sensor is defined as in Eq. (3).

$$d_{CH \to S} = \frac{\sum_{i=1}^{n} d_i}{\left(n/T_c\right)} \tag{3}$$

where, $d_{CH \to S}$ is the distance between the cluster head and the sensor nodes, while n is the total number of sensor nodes and T_C is the total number of cluster heads in the network. Initially in the topology building process, the deployed nodes were grouped together based on the distance, (as the sensor were homogenous, the characteristics based separation cannot be done) and all the sensors communicate with the neighboring sensors using the 'hello' packet. Based on the greetings packet, the lingering energy, sensor density, and the span between the sensors to connect with the base station are ascertained. The framework for Fuzzy-based Cluster Head Selection is illustrated in Fig. 3.

The preliminary step of the envisioned FCHS model involves setting the fundamental parameters: lingering energy, the distance from the sensor (S) to the Base Station (BS), and the density of the sensor nodes. The established parameters were channeled into the initial Fuzzifier process. This Fuzzifier accepts crisp inputs of residual energy, node density, and the separation distance between the sensor and the base station. Each fuzzy set is assigned a distinctive degree of membership, and the transformation is executed by the Fuzzifier process.

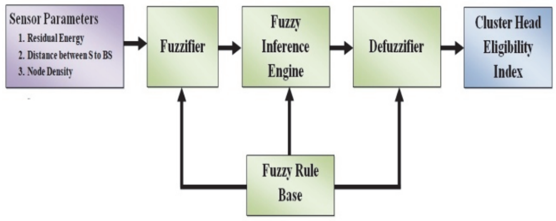

Figure 3 Fuzzy based cluster head selection - architectural process

The Fuzzifier process is steered by the fuzzy rule base, which is a compilation of numerous if-then scenarios crafted by the user. The rule base is meticulously defined and depicted, as it dictates the fluid dynamics of the fuzzy system. The trio of variables, lingering energy, the distance from the sensor to the base station, and node density, are fed into the fuzzification process. This fuzzification process transfigures these crisp values into fuzzy (imprecise) membership values. The fuzzification process entails defining fuzzy sets and calculating membership values. The fuzzy sets are utilized to represent the trio of input variables, while the membership functions depict the extent of membership for any specified crisp values[18-21]. The membership values are calculated for all the crisp input values using the membership functions delineated as the fuzzy set in Tab. 1.

Table 1 Fuzzification Input function and its variables

Crisp Input functions	Variable functions		
Residual Energy	High	Medium	Low
Distance	Far	Medium	Closer
Node Density	Denser	Medium	Sparse

The membership functions of the input variables are defined as in Eq. (4).

$$\mu_{RE}(x) = \begin{cases} 0; \text{ if } x \leq a \\ \dfrac{x-a}{b-a}; \text{ if } a \leq x \leq b \\ 1; \text{ if } x \geq b \end{cases} \tag{4}$$

$$\mu_D(x) = \begin{cases} 0; \text{ if } x \leq c \\ \dfrac{x-c}{d-c}; \text{ if } c \leq x \leq d \\ 1; \text{ if } x \geq c \end{cases} \tag{5}$$

$$\mu_{ND}(x) = \frac{1}{\left(1 + \exp\left(-\left(x-c\right)\right)/\sigma\right)} \tag{6}$$

where, $\mu(x)$ is the membership degree of 'x' in the fuzzy set, while 'a' and 'b' are the left and right edge of the membership curve depicted in Fig. 4 to Fig. 6 for residual energy, distance between sensor to base station and the node density.

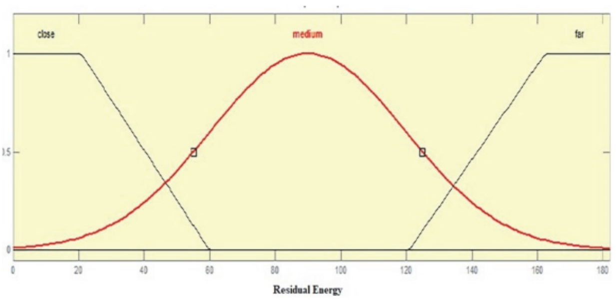

Figure 4 Membership function - residual energy

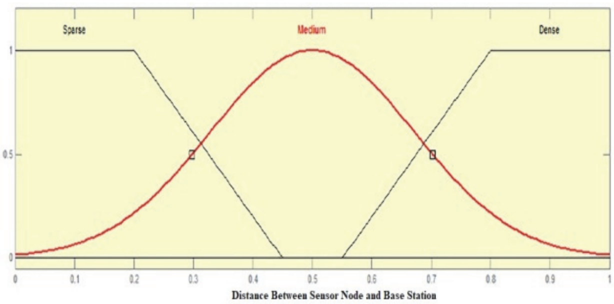

Figure 5 Membership function - distance between sensor and base station

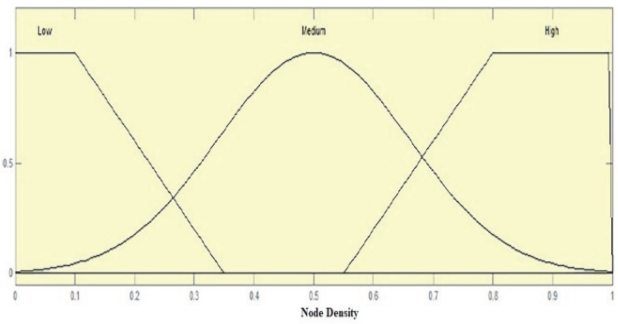

Figure 6 Membership function - node density

The enchanting fuzzification journey is guided by the mystical fuzzy rule base, artfully crafted from the If-then propositions of variable functions showcased in Tab. 1. The fuzzy logic criteria weights for cluster head selection are determined through an empirical and heuristic approach, ensuring a balanced trade-off between energy efficiency and network stability. Key parameters such as residual energy, node centrality, and distance to the base station are assigned weights based on their relative impact on network lifetime and communication efficiency. Residual energy receives the highest weight to prevent premature node depletion, node centrality ensures well-distributed clusters, and distance to the base station minimizes communication overhead. These weights are fine-tuned through simulations and sensitivity analysis to optimize cluster head selection for prolonged network performance.

The fuzzy membership function for residual energy is expressed with three classes namely, $\mu_{RE}(x) > \mu_T$ (High); $\mu_{RE}(x) = \mu_T$ (Medium) and $\mu_{RE}(x) < \mu_T$ (Low) energy. The fuzzy membership function of the distance is defined with $\mu_D(x) < \mu_T$ (Closer Node); $\mu_D(x) = \mu_T$ (Medium) and $\mu_D(x) > \mu_T$ (Far). While the node density is defined at three levels namely, denser ($\mu_{ND}(x) > \mu_T$); Medium ($\mu_{ND}(x) = \mu_T$) and Sparse ($\mu_{ND}(x) < \mu_T$). The collection of fuzzy rules was crafted based on the eligibility index, which was formulated using the Mamdani inference functions, a frequently utilized method for delineating the traits of fuzzy rules. Following the fuzzification stage, the fuzzy inference engine emerges as a crucial element of the suggested fuzzy-based cluster head selection methodology. The fuzzy inference engine is propelled by the if-then statements established within the fuzzy rule base, facilitating the defuzzification process. Constructed with various membership functions such as the triangular, trapezoidal, sigmoid, or Gaussian functions, the fuzzy inference engine is a sophisticated tool. In this proposed endeavor, the trapezoidal function serves as the chosen membership function, as articulated in Eq. (7).

$$f_M\left(x;\,a;\,b;\,c;\,d\right)=\max\left(\max\left(\frac{x-a}{b-a}\right);\,1;\,\left(\frac{x-c}{d-c}\right);\,0\right) \quad (7)$$

The final process is the defuzzification process which performs the mapping process of the input imprecise values with the fuzzy rule sets to perform a decision making process. The decision making process in the defuzzification is performed based on the centre function defined in Eq. (8).

$$f_C=\frac{\int\mu_{RE}\left(x\right)+\int\mu_D\left(x\right)+\int\mu_{ND}\left(x\right)}{\int\mu\left(x\right)} \quad (8)$$

The defuzzifier process performs the decision process by converting the input crispy input to imprecise values and with the help of fuzzy rule sets, determines the eligibility index of the input variables. The threshold value of the nodes, which is fed as the input to determine the eligibility for designating as cluster head is defined in Eq. (9).

$$f_{TH}=\frac{N_i\times\mathrm{Mean}\left(EI\left(N_i\right)\right)}{1-N_i\times\mathrm{mod}\left(\mu\left(x\right)\right)} \quad (9)$$

where, f_{TH} is the threshold function, N_i is the 'i-th' node considered for the selection as cluster head, EI is the eligibility index, while $\mu(x)$ is the cumulative fuzzy rule of the input crispy functions. The algorithm for cluster head selection method is described below.

Algorithm: Fuzzy based Cluster Head Selection (FCHS)

Input: Node population - N_i; $i = n$; n - number of nodes in the cluster.
Output: N_i-N_{CH}/Cluster Head Designation
Processes:
1: Initialize the crispy parameters, $\mu_{RE}(x)$; $\mu_D(x)$; $\mu_{ND}(x)$ and $\mu(x)$
2: Define the membership functions of parameters as in Eq. (4) to Eq. (6).
3: Node N_i - cluster node member
4: $N_i \cdot P$ - Region based probability
5: $N_i \cdot T_r$ - Region based transmission range
6: While ($N_i \mid i < n$)
7: {
8: Determine the Eligibility Index for node N_i
9: Determine mean (EI)
10: Determine threshold function:

$$f_{TH} = \frac{N_i \times \text{Mean}\left(EI\left(N_i\right)\right)}{1 - N_i \times \text{mod}\left(\mu\left(x\right)\right)}$$

11: If (EI = Extraordinary/Best/Better/Good)
12: Determine centre function for N_i:

$$f_C = \frac{\int \mu_{RE}\left(x\right) + \int \mu_D\left(x\right) + \int \mu_{ND}\left(x\right)}{\int \mu\left(x\right)}$$

13: Designate $N_i \rightarrow N_{CH}$
14: Add N_i to N_{CH} directory
15: Else
16: Repeat process with i++, $i < n$
17: End if
18: End while
19: End processes

The algorithm presented in Tab. 3, describes the processes involved in selecting and designating a member node as the cluster head [22-25].

3.2 Energy Efficient Routing Using Adaptive Hawk Optimization (AHO)

The Adaptive Hawk Optimization (AHO) algorithm demonstrates high adaptability in dynamic environments through its ability to balance exploration and exploitation based on real-time conditions. Unlike traditional metaheuristic algorithms with fixed parameters, AHO employs an adaptive mechanism that dynamically adjusts the intensity of search behaviors, mimicking the cooperative hunting strategies of hawks. This adaptability enables the algorithm to respond effectively to network changes such as node failures, energy depletion, and varying data traffic. By modifying the escape energy and attack strategies based on fitness evaluations, AHO ensures optimal routing paths while minimizing energy consumption. This theoretical flexibility makes AHO well-suited for dynamic wireless sensor networks.

The optimal route that links the cluster head to the base station via the Adaptive Hawk Optimization (AHO) algorithm. This innovative optimization algorithm draws its inspiration from the captivating hunting techniques of the hawk. The AHO algorithm is adept at uncovering the most efficient solution for identifying the ideal pathway, ensuring the shortest distance while using the least possible energy during the exchange of information. In this inventive approach, the cluster's location is likened to the hawk's starting point (H_n), while the positions of the neighboring cluster heads situated between the cluster head and the base station are referred to as ($H_{n+1}, H_{n+2}, \ldots, H_{n+N}$). The selection of these intermediary cluster heads is executed at random. The methodology for selecting these random intermediary cluster heads and establishing the routing path is articulated in Eq. (10).

$$h_{n+1} = \begin{cases} h_{\text{rand}(n)} - a; \text{ If } \left(h_{\text{rand}(n)} - a\right) \leq EI_T \\ h_{\text{rand}(n)} + a; \text{ If } \left(h_{\text{rand}(n)} + a\right) > EI_T \end{cases} \tag{10}$$

where, $h_{\text{rand}}(n)$ is the random neighbor cluster head chosen to determine the neighboring cluster head, a is the scaling factor ranging between (0, 1), while EI_T is the minimum threshold value of Eligibility Index. The location of the hawk (Source Cluster Head) is represented by the first iteration process $h_{\text{rand}}(n)$, whereas the initial position of the hawk is defined as h_n. The mean location of the hawk is mathematically represented as defined in Eq. (11).

$$h_{m(n)} = \frac{1}{N}\alpha\sum_{i=0}^{N} h_{i(n)} \tag{11}$$

where, $h_{m(n)}$ is the mean location of the hawk, $h_{i(n)}$ is the location of the hawk at 'i' iterations. The term 'α' is the adaptive factor, which determines the location of the hawk. The next hop for the hawk is determined using the Eq. (12).

$$h_{(n+1)} = \alpha h_{(n)} - \beta\left|H_n - h_n\right| \tag{12}$$

where, $h_{(n+1)}$ is the next cluster head considered as the next hop to reach the Base Station. The term α is the adaptive factor, chosen in random to choose the next hop based on the desired threshold eligibility index. The term β is the sub-adaptation factor while H_n is the destination location. i.e. (location of base station) is presented in Fig. 7.

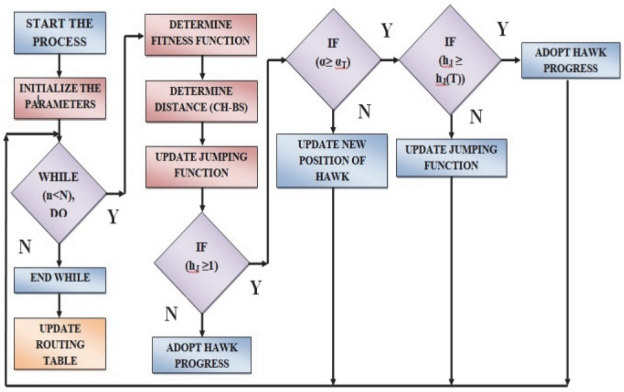

Figure 7 Adaptive hawk optimization - energy efficient routing - flow process

The AHO algorithm for performing the routing process by determining the optimal shortest path satisfying the threshold eligibility index is below

Algorithm 2: Algorithm- Adaptive Hawk Optimization- Optimal Shortest Path Selection

Input: Cluster Head Table ($N_{CH0}, N_{CH1}, N_{CH2}, \ldots, N_{CH1}$)
Output:Optimal Routing path ($P_{CH \rightarrow BS}$)
Processes:
1: Initialize the Cluster Head population
2: Initialize the Eligibility index of all Cluster Head
3: Set number of iterations to 'N'/N is the total number of Cluster Heads
4: While ($n < N$), do
5: Compute the fitness function of the parent cluster head:

$$F_N = \alpha N_C + \beta N_{RE} + \gamma N_{CR} \tag{13}$$

6: Determine the distance

$$D_{CH\to BS}=\sqrt{\left(x_2-x_1\right)^2+\left(y_2-y_1\right)^2+\left(z_2-z\right)^2} \tag{14}$$

7: For (each cluster head (h_i); $i < N$; i++), do
8: Update the jumping strength h_J and residual energy h_{RE}

$$h_J=\frac{E_{RE}-E_T}{4\pi d^2 D_{CH\to BS}} \tag{15}$$

9: Update the Jump function of each Cluster head
10: End if
11: If ($h_J \geq 1$), then
12: Adopt Hawk based progress towards base station
13: End if
14: If ($h_J < 1$), then
15: If ($\alpha \geq \alpha_T$ & $h_J \geq h_{J(T)}$), then
16: Adopt Hawk movement towards the prey (base station)
17: Else if ($\alpha \geq \alpha_T$ & $h_J < h_{J(T)}$), then
18: Update the jump equation defined in Eq. (15).
19: Else if ($\alpha < \alpha_T$ & $h_J \geq h_{J(T)}$), then
20: Update the new position of the hawk (Message from CH) using Eq. (16).

$$h_{(n+1)}=\begin{cases} h_{(n+1)A}; \text{ if } h_J \geq h_T \\ h_{(n+1)B}; \text{ if } h_J < h_T \end{cases} \tag{16}$$

21: Else if ($\alpha < \alpha_T$ & $h_J > h_{J(T)}$), then
22: Update the new position of the hawk (Message from CH) using Eq. (17).

$$h_{(n+1)}=\begin{cases} h_{(n+2)C}; \text{ if } h_J \geq h_T \\ h_{(n+2)D}; \text{ if } h_J < h_T \end{cases} \tag{17}$$

23: End if
24: Return the Routing table:

$$\begin{aligned} P_{CH\to BS} &= h_n \to h_{(n+1)A}/h_{(n+1)B} \to \\ &\to h_{(n+2)C}/h_{(n+2)D} \to h_{(n+N)} \to H_n \end{aligned} \tag{18}$$

25: End while
26: End processes

The subsequent leap of communication from the cluster leader (h_n) is transmitted to the neighboring most suitable cluster function ($h_{(n+i)}$). Consequently, the Optimal Shortest route is established utilizing the innovative Adaptive Hawk Optimization (AHO) algorithm.

4 RESULTS AND DISCUSSION

The efficacy of the proposed Fuzzy-based Cluster Head Selection (FCHS) framework and the Adaptive Hawk Optimization (AHO) is executed using the Network Simulator-2 (NS-2) tool, while a python tool is harnessed for the deployment the model. To enhance the evaluation of the proposed FCHS-AHO framework, additional simulation scenarios should incorporate varying network densities and node mobility. Higher node densities can test the framework's scalability and cluster formation efficiency, ensuring optimal cluster head selection even in congested environments. Mobility scenarios, where sensor nodes or the base station change positions, can assess the adaptability of the Adaptive Hawk Optimization algorithm in dynamic topologies. By simulating diverse real-world conditions, such as varying traffic loads and obstacle-induced communication disruptions, a more comprehensive performance assessment can be conducted, validating the robustness and applicability of the proposed framework in practical WSN deployments. The architecture of the network crafted for the application of the proposed initiative is illustrated in Tab. 2.

Table 2 Proposed network specifications

Network Parameter	Specifications
Simulation Area	100 × 100 m
Count of Sensor Node	125
Initial Energy level	100 mJ
Energy dissipated at free space	10 pJ
Topology	Star
Data packet size	4000 bits
Amplifier Energy	10 pJ/bit/m^2

The simulated network is portrayed in Fig. 1, showcasing the spontaneous deployment of nodes within the coverage expanse. An average of 20-25 sensor nodes was scattered across each 20 sq.mt., thereby creating at least 5 clusters of nodes. This proposed study is examined across a range of rounds, from 500 to 5000 communication rounds, with the residual energy quantified and compared against other works [26-30]. The recorded values of residual energy after 500-5000 communication rounds are cataloged in Tab. 3.

Table 3 Comparison of residual energy / mJ

Rounds	V. B. Patil (2024) [26]	H. Gul (2024) [27]	I. Ahmed (2024) [28]	K. K. Patil (2024) [29]	A. Jalili (2024) [30]	Proposed FCHS + AHO
500	99.29	99.21	98.42	98.87	99.01	99.95
1000	98.29	98.71	97.48	97.06	98.07	99.01
1500	97.48	96.04	96.84	97.18	96.11	98.32
2000	96.24	95.48	95.30	96.84	95.03	97.69
2500	95.91	94.72	94.63	94.75	93.48	95.21
3000	92.05	92.47	91.79	92.64	91.85	94.97
3500	87.02	86.58	87.94	87.03	86.50	90.04
4000	80.36	80.39	80.74	79.56	79.21	80.65
4500	73.59	72.15	71.15	70.68	71.84	74.58
5000	52.02	49.35	51.02	50.03	49.99	62.48

From the tabulated figures of residual energy [30] in Tab. 6, the residual energy of the proposed initiative following 5000 communication rounds stands at 62.48 milli Joules, whereas the existing state-of-the-art methodologies report values of 52.02 mJ, 49.35 mJ, 51.02 mJ, 50.03 mJ, and 49.99 mJ. The graphical juxtaposition of the residual energy between the proposed initiative and existing methodologies [31] is illustrated in Fig. 8.

The main aspect influencing how long the network and sensor nodes last is their energy usage [32]. Tab. 4 tabulates the energy used by the cluster head across a range of 500 to 5000 communication rounds.

For 5000 communication rounds, the suggested technique uses 12.1 mJ, whereas the current methods [33] use 21.57 mJ, 22.8 mJ, 20.13, 20.65 mJ, and 21.85 mJ. Fig. 9 presents a visual illustration of the energy usage comparison.

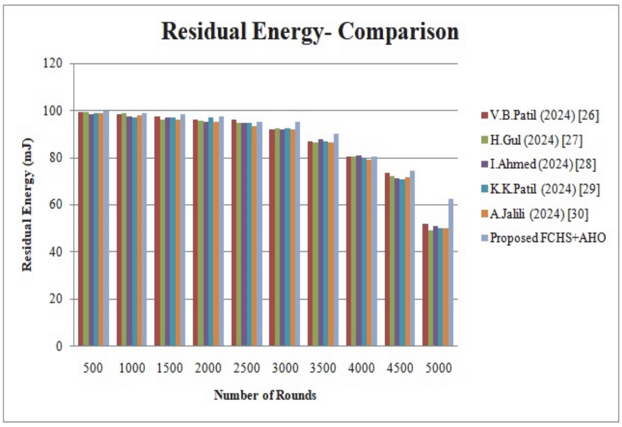

Figure 8 Comparison of E_{Re} - CH

Table 4 Comparison of energy consumption / mJ

Rounds	V. B. Patil (2024) [26]	H. Gul (2024) [27]	I. Ahmed (2024) [28]	K. K. Patil (2024) [29]	A. Jalili (2024) [30]	Proposed FCHS + AHO
500	0.71	0.79	1.58	1.13	0.99	0.05
1000	1	0.5	0.94	1.81	0.94	0.94
1500	0.81	2.67	0.64	0.86	1.96	0.69
2000	1.24	0.56	1.54	0.34	1.08	0.63
2500	0.33	0.76	0.67	2.09	1.55	2.48
3000	3.86	2.25	2.84	2.11	1.63	0.24
3500	5.03	5.89	3.85	5.61	5.35	4.93
4000	6.66	6.19	7.2	7.47	7.29	9.39
4500	6.77	8.24	9.59	8.88	7.37	6.07
5000	21.57	22.8	20.13	20.65	21.85	12.1

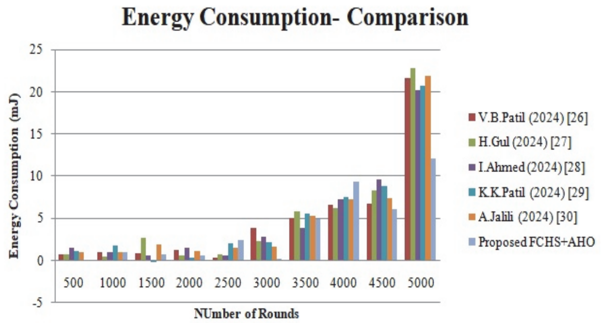

Figure 9 Comparison of energy consumption

The PDR relies on various factors [34] namely, the topology of WSN, energy efficiency, node lifetime, network lifetime, node density etc. The measured values of packet delivery ratio for various rounds are tabulated in Tab. 5.

Table 5 Comparison of packet delivery ratio / %

Rounds	V. B. Patil (2024) [26]	H. Gul (2024) [27]	I. Ahmed (2024) [28]	K. K. Patil (2024) [29]	A. Jalili (2024) [30]	Proposed FCHS + AHO
500	100	100	100	100	100	100
1000	99.99	100	99.98	99.59	99.67	100
1500	97.51	96.02	93.15	93.48	91.58	98.02
2000	83.65	86.54	84.59	86.74	85.26	90.15
2500	80.03	79.04	78.95	78.84	77.02	80.69
3000	76.21	77.02	77.84	76.84	75.5	79.12
3500	70.15	69.84	70.74	70.94	70.61	71.65
4000	68.84	65.84	65.55	64.15	63.18	69.03
4500	60.11	63.48	59.48	58.18	57.84	61.74
5000	50.74	50.01	48.01	49.91	47.07	53.14

The Packet delivery ratio of the proposed work is more than half of percentage, specifically 53.14% for 5000 rounds, while it is 50.74%, 50.01%, 48.01%, 49.91% and 47.07% for the existing methodologies. The graphical comparison of the PDR is depicted in Fig. 10.

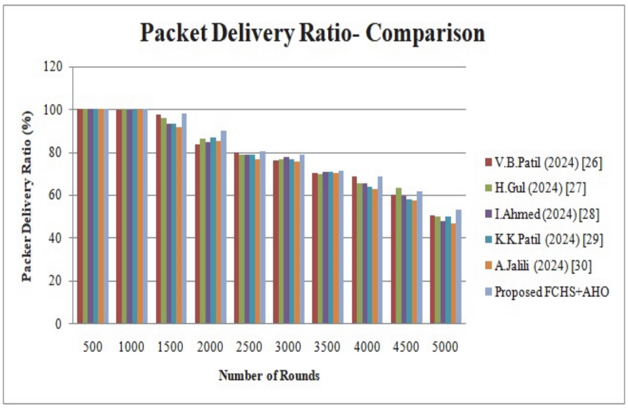

Figure 10 Comparison of packet delivery ratio

The combination of fuzzy-based clustering and hawk optimization can lead to a good packet delivery ratio (PDR) in wireless sensor networks (WSNs) due to flexibility, adaptability, robustness and the rate of convergence. Fuzzy logic allows for gradual transitions between membership degrees, making it suitable for handling the uncertainties and complexities inherent in WSN environments. The proposed FCHS algorithm can adapt to changing network conditions, such as node failures or variations in traffic patterns. HO can rapidly converge to near-optimal solutions with the AHO algorithm, which lowers computing overhead and boosts network performance overall. One important performance parameter that impacts the network's responsiveness and dependability is this latency. Transmission delay, propagation delay, and the kind of protocol used to determine the routing process are the factors affecting the WSN's end-to-end delay. Tab. 6 contains the observed end-to-end delay value.

Table 6 Comparison of end to end delay / µsec

Rounds	V. B. Patil (2024) [26]	H. Gul (2024) [27]	I. Ahmed (2024) [28]	K. K. Patil (2024) [29]	A. Jalili (2024) [30]	Proposed FCHS + AHO
500	1.96	1.84	1.95	1.65	1.84	1.04
1000	2.05	2.48	2.95	2.74	2.95	1.96
1500	3.15	3.48	3.96	3.15	3.08	2.92
2000	5.84	5398	5.47	5.23	5.75	4.95
2500	9.15	9.78	9.16	10.04	10.47	8.48
3000	14.48	14.36	14.02	15.96	15.04	12.01
3500	21.48	20.48	20.66	21.04	20.17	18.4
4000	29.48	28.06	28.48	27.48	29.48	24.06
4500	33.48	32.05	33.19	33.47	32.82	30.07
5000	40.48	39.03	40.4	41.25	41.39	36.21

When comparing the suggested work's end-to-end delay to the current cluster head construction and routing mechanism technique, it is lower. For 5000 communication cycles, the end-to-end latency of the proposed work is 36.21 µs; for the known techniques of cluster head construction and routing principles, it is 40.48 µs, 39.03 µs, 40.4 µs, 41.25 µs, and 41.39 µs. Fig. 11 shows the graphical comparison of the suggested work.

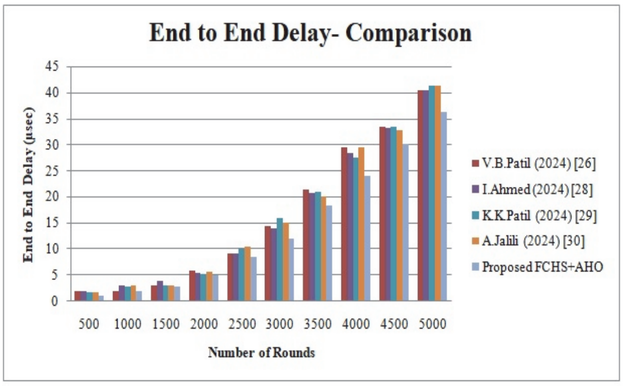

Figure 11 Comparison of end to end delay

Due to its dynamic adaptation, load balancing, and optimized routing pathways, fuzzy-based cluster head selection combined with adaptive hawk optimization can result in a lower end-to-end delay. Flexible decision-making is made possible by fuzzy logic, which enables the algorithm to choose cluster heads depending on variables like node energy, communication quality, and distance to other nodes. This helps the program to adjust to changing network conditions. Fuzzy-based cluster head selection helps to more evenly spread the workload among nodes, lowering congestion and enhancing network efficiency by taking into account a number of criteria. The throughput of a Wireless Sensor Network (WSN) is a measure of the maximum rate at which data can be successfully transmitted through the network. The observed values of throughput for the proposed and existing works are listed in Tab. 7.

Table 7 Comparison of throughput / Bps

Rounds	V. B. Patil (2024) [26]	H. Gul (2024) [27]	I. Ahmed (2024) [28]	K. K. Patil (2024) [29]	A. Jalili (2024) [30]	Proposed FCHS + AHO
500	1000	1000	1000	1000	1000	1000
1000	998	985	984	983	986	999
1500	983	975	971	969	972	985
2000	971	969	963	972	958	975
2500	942	936	933	939	936	953
3000	890	886	884	875	868	900
3500	830	821	810	801	815	842
4000	750	742	736	734	726	779
4500	696	686	687	674	662	698
5000	589	563	584	569	573	602

For 5000 number rounds, the suggested FCHS and AHO algorithm yields 602 bits per second, which is somewhat more than the current routing and cluster head formation algorithms technique. Fig. 12 shows the graphical comparison of the throughput.

Due to its balanced load distribution, dynamic adaptability, and lower routing cost, fuzzy-based cluster head selection and adaptive hawk optimization can result in increased throughput in wireless sensor networks (WSNs). Flexible decision-making is made possible by fuzzy logic, which enables the algorithm to choose cluster heads depending on variables like node energy, communication quality, and distance to other nodes. This helps the program to adjust to changing network conditions. Fuzzy-based cluster head selection helps to more evenly spread the workload among nodes, lowering congestion and enhancing network efficiency by taking into account a number of criteria. By minimizing the number of hops needed for data transmission, the optimal cluster head selection can lower routing overhead and increase network throughput.

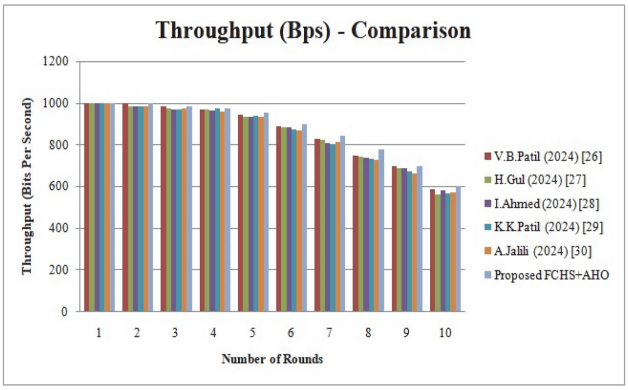

Figure 12 Comparison of throughput / bits per second

The computational complexity of the proposed FCHS-AHO framework is primarily influenced by the fuzzy logic-based cluster head selection and the Adaptive Hawk Optimization (AHO) algorithm. The fuzzy inference system operates with a polynomial time complexity, ensuring efficient decision-making. AHO, as a metaheuristic optimization technique, has a complexity of O(nlogn), making it scalable for larger networks. The framework efficiently balances exploration and exploitation, reducing redundant computations while optimizing routing. Its scalability is evident in its ability to handle varying network sizes and densities without significant degradation in energy efficiency or performance, making it suitable for large-scale WSN deployments.

5 CONCLUSION

Wireless Sensor Networks (WSNs) play a critical role in monitoring and data collection from remote and challenging environments. However, their efficiency is hindered by limited energy resources, leading to reduced network lifespan. To address this, the proposed framework integrates Adaptive Hawk Optimization (AHO) with Fuzzy-based Cluster Head Selection (FCHS) to enhance energy efficiency and network stability. The key technical contributions of this work include an intelligent cluster head selection mechanism leveraging fuzzy logic, an adaptive optimization-driven routing approach, and an improved load-balancing strategy. The proposed framework demonstrates superior performance, achieving 62.58 mJ residual energy, 12.1 mJ energy consumption, 53.14% packet delivery ratio, 36.21 µsec end-to-end delay, and 602 bits/sec throughput for 5000 packet transmissions. These results confirm the effectiveness of FCHS-AHO in optimizing WSN performance under varying network conditions. The proposed FCHS-AHO framework is highly applicable to smart agriculture, environmental monitoring, and industrial IoT, where energy-efficient WSNs are essential. However, real-world deployment challenges include hardware constraints, unpredictable environmental conditions, and network scalability. Additionally, dynamic topology changes may require further optimization to ensure adaptive and robust performance in practical scenarios. Future work will focus on refining fuzzy membership functions and incorporating enhanced adaptive mechanisms to further improve energy efficiency scalability and security considerations, making WSNs more robust for real-world applications.

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