JOURNAL OF MECHANICS OF CONTINUA AND
MATHEMATICAL SCIENCES
www.journalimcms.org

ISSN (Online) : 2454 -7190 Vol.-21, No.-06, June (2026) pp 178-195 ISSN (Print) 0973-8975

NOVEL APPROACH FOR ENERGY EFFICIENT ROUTING AND CLUSTERING IN WSN USING FCM-IDEO WITH EC^2-SRP

Esha Rani[1], **Ashwani Kush**[2]

[1,2] Department of Computer Science, Kurukshetra University,
Kurukshetra,Haryana, India.

Email: [1]esha.iihs@kuk.ac.in, [2]akush@kuk.ac.in

Corresponding Author: **Esha Rani**

https://doi.org/10.26782/jmcms.2026.06.00010

(Received: March27, 2026; Revised: May29, 2026; Accepted: June10, 2026)

Abstract

Wireless Sensor Networks have become increasingly significant in the 21st century, enabling a wide spectrum of critical applications. However, energy efficiency remains a fundamental limitation affecting their scalability, reliability, and sustainability. This study introduces a novel framework that integrates Intelligent Dolphin Echolocation Optimization (IDEO) with Fuzzy C-Means clustering for adaptive Cluster Head (CH) selection. The proposed method employs a multi-criteria strategy considering residual energy, transmission distance to the Base Station (BS), and latency minimization, thereby ensuring efficient data aggregation in dynamic environments. Furthermore, an Energy-Conscious Cognitive Smart Routing Protocol (EC^2-SRP) is developed to establish both energy-efficient and shortest routing paths, reducing communication overhead and extending network longevity. The novelty of this work lies in (i) the hybrid integration of IDEO with FCM for adaptive clustering, (ii) multi-criteria CH selection for enhanced energy efficiency, (iii) the design of a cognitive routing protocol balancing energy awareness with path optimality, and (iv) a comprehensive QoS-based evaluation. Simulation results demonstrate superiority over existing methods in terms of energy consumption, network lifetime, packet delivery ratio (PDR), End-to-End Delay, routing overhead, and Fault Tolerance, thereby achieving higher energy efficiency, reliability, and sustainability in Wireless Sensor Networks.

Keywords: Clustering; Cross-layer routing; Fuzzy-C Means; Optimization; Wireless Sensor Network; Optimization

I. Introduction

The 21stcentury has witnessed wireless sensor networks (WSNs) as one of the most transformative technologies, enabling critical applications in environmental monitoring, smart agriculture [XXII], healthcare, industrial automation [XVIII], disaster management, and military surveillance [XVI]. A WSN typically consists of spatially distributed nodes that sense, process, and transmit information to a Base

Station (BS). Despite their promise, WSNs are severely constrained by limited battery resources, communication bandwidth, and processing capabilities [IX]. Energy efficiency is considered the foremost challenge, since battery replacement is infeasible due to the deployment of sensor nodes in remote or inaccessible areas [XIV]. Node energy depletion leads to coverage gaps, diminished reliability, and premature network failure, underscoring the energy-aware clustering and routing mechanism to ensure network longevity and scalability.

Clustering is an effective method to reduce redundant transmissions and balance node energy, wherein sensor nodes transmit data to a Cluster Head (CH) that subsequently forwards aggregated information to the BS. Nonetheless, the CH selection process remains a non-trivial task as it depends upon certain factors like residual energy, communication distance, and network dynamics [XXIV].

To improve WSN performance, various approaches have been proposed with emphasis on latency reduction, energy efficiency, and effective cluster head selection. The Latency-Aware Heterogeneous Cluster-based Data Acquisition (LA-HCDA) [VI] technique was developed to lower end-to-end delay and improve coverage. When integrated with quartile aggregation, it further enhances data collection and extends network lifetime. In addressing energy-related challenges, the Bionic Cross-Layer Routing (BiCLR) protocol [IV] operates across multiple layers—physical, data, and transport—employs an optimized CH selection method to achieve energy-efficient communication, and performance is evaluated using Quality-of-Service (QoS) indicators like transmission mobility and latency. Further, the Energy-aware Adaptive Fuzzy Neural Clustering (EAANFC-MR) algorithm [XIX] chooses CHs based on residual energy, node proximity, and centrality while leveraging Quantum Optimized Bacterial Foraging Optimization (QOBFO) for efficient multi-hop routing. Similarly, the MOFIS-BFO model [I]integrates with Bacterial Foraging Optimization with a Multi-Objective Fuzzy Inference System, incorporates parameters energy, hop-count, and flexibility for CH selection, improving network longevity. In addition, the Nature-Inspired Cross-layer Clustering (NICC) method [XII] also exhibited superior energy management. The Improved Sunflower Optimization (ISFO) algorithm [VII] further diminished energy use and prolonged node activity. Some other metaheuristic algorithms like WOA, GA, etc., were evaluated in [VIII], confirming their effectiveness in energy use, latency, and overall WSN efficiency. The existing routing protocols discussed above were unable to concurrently achieve energy efficiency and path reliability, particularly in large-scale or highly dynamic deployments. These shortcomings have driven the adoption of intelligent bio-inspired optimization techniques to address challenges in both clustering and routing.

This study proposes a novel framework that integrates Intelligent Dolphin Echolocation Optimization (IDEO) with Fuzzy C-Means clustering for adaptive CH selection and introduces Energy-Conscious Cognitive Smart Routing Protocol (EC^2-SRP) for efficient data communication. The IDEO–FCM hybrid improves CH selection by jointly considering residual energy, minimal transmission distance to the BS, and latency reduction, while EC^2-SRP dynamically identifies energy-efficient and shortest routing paths to reduce overhead and extend lifetime. The novelty of this work lies in hybrid IDEO–FCM clustering, multi-criteria CH selection, and cross-layer routing design. Performance is rigorously evaluated across average energy consumption, residual energy, network lifetime, and packet delivery ratio (PDR). Simulation results confirm that the proposed framework significantly outperforms existing techniques, delivering superior energy efficiency, reliability, and sustainability for WSNs.

The organization of this paper is done as follows: Section 2 describes the model behaviour of clustering and routing. Section 3 details the proposed hybrid methodology, including the design and implementation of the Intelligent Dolphin Echolocation Optimization (IDEO) algorithm for cluster head selection and Energy-Conscious Cognitive Smart Routing Protocol (EC^2-SRP) for efficient data transmission. Section 4 offers an in-depth analysis of the proposed framework through simulations, highlighting performance metrics such as energy consumption, residual energy, packet delivery ratio, end-to-end delay, fault tolerance, and network lifetime. The last section describes the conclusion in terms of outlining future directions for sustainable and intelligent routing solutions for WSN.

II. System Model

In WSNs, multiple sensor nodes continuously monitor and record environmental parameters within their surroundings, forwarding the aggregated data to the BS. To comprehensively analyze this process, the system model is categorized into two components: the network model, which defines the spatial deployment and communication structure of the nodes, and the energy model, which characterizes the power consumption associated with data transmission, reception, and processing.

Network Model

Energy consumption in WSN is optimized by organizing sensor nodes into distinct clusters. Normal sensor nodes monitor the environment, collect the data, and forward it to the designated CH. Only CHs are authorized to aggregate data from cluster members and transmit it to the BS. Various factors are included in the selection of CHs, such as residual energy, node proximity, and sensing range, etc. So, energy is conserved by the clustering mechanism as direct communication is not required between sensors and the BS. The WSN structural representation is discussed in Figure 1.

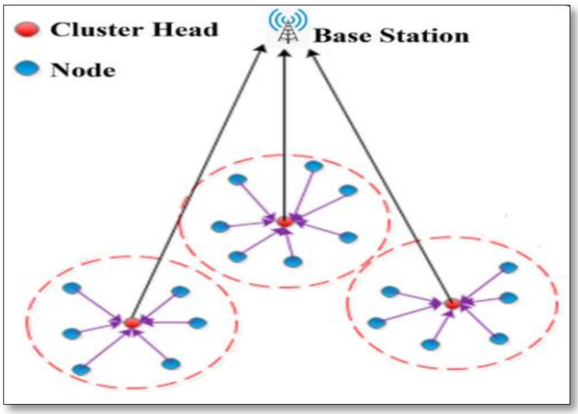

Fig. 1. Framework scenario of WSN

Radio Energy Model

Let:E_{elec} = Electronic energy/bit,$\in_{fs}$ = Amplifier coefficient for free-space
$\in_{mp}$ = Amplifier coefficient for multipath, d = link distance,
$d_0 = \sqrt{\in_{fs}/\in_{mp}}$ = threshold distance

Then the transmit energy to send an N-bit packet over a distance$'d'$ is

$$E_{tx}(N,d) = \begin{cases} NE_{elec} + N \in_{fs} d^2, & d < d_0 \\ NE_{elec} + N \in_{mp} d^4, & d \geq d_0 \end{cases} \tag{1}$$

The reception energy is:$E_{rx}(N) = NE_{elec}$ (2)

III. Proposed Algorithm

The proposed work presents a hybrid, intelligent framework for sustainable WSNs by incorporating Intelligent Dolphin Echolocation Optimization (IDEO)with an Energy-Conscious Cognitive Smart Routing Protocol (EC^2-SRP). The framework exploits the echolocation-inspired behaviour of dolphins to develop a dynamic and adaptive clustering mechanism, enabling optimal CH selection based on multi-objective criteria such as residual energy, node centrality, and communication cost. Through efficient exploration and exploitation of the solution space, the IDEO algorithm addresses the inherent limitations of conventional meta-heuristics approaches. In parallel, the EC^2-SRP protocol leverages cross-layer information—encompassing the physical, MAC, and network layers—to enable real-time, energy-aware routing decisions that adapt to network dynamics and traffic conditions. Collectively, the IDEO and EC^2-SRP modules establish a unified system that enhances network lifetime, balances energy consumption, and improves data reliability. This synergistic integration effectively addresses the critical need for sustainability, adaptability, and scalability in WSNs, particularly within energy-constrained and heterogeneous deployment scenarios.

A) Fuzzy C-Means with Intelligent Dolphin Echolocation Optimization (FCM-IDEO) for Cluster Head Selection

Efficient energy utilization is possible in WSNs with clustering by placing sensor nodes in clusters or groups and revealing one node as the CH, which will be responsible for all activities of that group,from the collection of data to transmitting data to the BS. In this study, to optimize CH selection,the IDEO algorithm is integrated with FCM clustering by dividing sensor nodes into fuzzy clusters. Each node is not restricted to belong to one cluster only, but nodes with membership degree variance can belong to multiple clusters. FCM also offers a probabilistic approach in cluster formation to upgrade efficiency and flexibility. Dynamic adjustment of cluster centroid is performed to reduce the gap within the cluster, influencing the energy-efficient communication. Further advancement in CH selection is performed by IDEO algorithm. By taking the motivation from dolphins' echolocation experience used for object detection, navigation, and path experience, the IDEO algorithm sets up this behaviour to make optimal CH selection by determining factors like consumption rate, communication range, and stability of the network. Although applied in a hybrid manner, the integration of FCM clustering with IDEO not only optimizes CH selection but also balances energy consumption, reduces packet delays, and prolongs network lifetime. The FCM-IDEO-based integration for clustering encompasses the following steps:

I. Input: Initialize the number of clusters and fuzzy membership matrix for each sensor node.
II. Cluster Centroids Estimation: Based on the weighted membership of nodes, upgrade the cluster centroid.
III. Membership Value Modification: Iteratively adjust node memberships to clusters to reduce intra-cluster variance.
IV. IDEO Optimization: Employ dolphins' echolocation-inspired intelligence to extend CH selection by assessing node energy levels, hop-count to the BS, and overall network stability.
V. Convergence Confirmation: Continue repeating steps 2 through 4 until the cluster centers and CH selections reach stability.

The proposed algorithm integrates FCM clustering with the IDEO algorithm to attain optimal CH selection. To determine the absolute number of clusters (C), two factors are taken into account. One is the area of deployment (A),and the otheris the sensing range (R) of the sensor nodes. The total clusters are estimated using the equation $C = A/\pi \mathrm{R}^2$, where A represents the network's coverage area, and R is the communication radius of a sensor node. This calculation ensures that sensor nodes are adequately divided into clusters, optimizing both network connectivity and energy conservation.

The FCM clustering algorithm assigns all sensor nodes to clusters with respect to a fuzzy membership function. For every node i, a membership degree (μ_{ij}) to cluster j is estimated as follows:

$$\mu_{ij} = \frac{1}{\left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}} \tag{3}$$

Where d_{ij} denotes the gap between node i and cluster centroid j, which is called Euclidean distance, and m represents the fuzziness factor, ranging between 1.5 and 3. The repetitive process refines the cluster centroids using eqs(4):

$$V_j = \frac{\sum_{i=1}^{n} \mu_{ij}{}^{m}.X_i}{\sum_{i=1}^{n} \mu_{ij}{}^{m}} \tag{4}$$

Where X_i denotes spatial coordinates of sensor node i. In this way, clusters are dynamically modified to express the spatial adjustment of nodes, thereby upgrading clustering precision and diminishing energy usage. After finishing the process of clustering, it is time to select CHs, which are refined through the IDEO algorithm, and assess sensor nodes on the basis of their remaining energy, hop-count to the base station (BS), and intra-cluster communication range. The fitness function for CH selection is defined by eqs(5):

$$F_{CH}(i) = w_1.\frac{E_i^{res}}{E_{max}} - w_2.\frac{d_{i,BS}}{d_{max}} - w_3.\frac{d_{ij}}{d_{max}} \tag{5}$$

Where E_i denotes the residual energy of node i, the hop-count from node i to BS is denoted by d_{ij}, BS and d_{ij} is the intra-cluster distance. The coefficients w_1, w_2 and w_3 are weighting factors set to balance energy efficiency, network lifetime, and communication overhead. The highest fitness score sensor node is chosen as the initial cluster head (CH).

B) Energy-Conscious Cognitive Smart Routing Protocol (EC^2-SRP)

Energy conservation and scalability are critical challenges in determining the most efficient data transmission paths from source to destination. These objectives can be achieved through the proposed Energy-Conscious Cognitive Smart Routing Protocol (EC^2-SRP)**,** which enhances communication reliability and reduces packet delays.

In contrast, the existing Cross-Layer Opportunistic Routing Protocol (CLORP) [XXIII] encounters several limitations:

- As the number of constraints increases, the processing capability of WSNs limits the complexity of data transmission.
- Difficulties in integrating with other network protocols.
- Excessive energy consumption, packet loss, reduced delivery rate, and considerable communication delays all impair overall network efficiency.

Cross-Layer Cognitive Decision Framework

The proposed EC^2-SRP employs a cross-layer architecture in which routing decisions are generated using information collected from the Physical Layer, MAC Layer, and Network Layer. Unlike traditional routing protocols that rely on static metrics, the proposed framework continuously exchanges information among protocol layers to support adaptive and energy-aware routing decisions.

At the Physical Layer, each node provides residual energy (E_j) and link quality (LQ_{ij}). The MAC Layer supplies packet delay (D_{ij}) and channel contention information, while the Network Layer contributes hop distance (Hop_{ij}) and neighborhood topology information. These parameters are combined to form a cross-layer state vector: $S_t=[E_j, LQ_{ij}, D_{ij}, Hop_{ij}]$ where (S_t) represents the network state observed at time (t).

The cognitive decision engine periodically monitors the state vector and evaluates network conditions. Based on the observed state, routing decisions are generated by selecting the forwarding node with the highest fitness value. The routing fitness function is expressed as:

$$F_j = \alpha.\frac{E_j^{res}}{E_0} + \beta.\frac{1}{d_{ij}} + \gamma.LQ_{ij} - \delta.D_{ij} \tag{6}$$

where:

E_j^{res} is the residual energy of neighboring node j,
E_0 is the initial node energy,
d_{ij} is the distance between nodes i and j,
LQ_{ij} denotes the link quality,
D_{ij} represents packet delay, and
(α,β,γ,δ) are adaptive weighting coefficients.

The routing action at time t is defined as: $A_t = \arg\max_j F_{ij}$ where the neighboring node with the maximum fitness value is selected as the next-hop forwarding node.
The next-hop selection is therefore given by: $NextHop(i) = \arg\max_{j \in C_i} F_j$ where C_i represents the set of candidate neighboring nodes available for forwarding.
Unlike heuristic routing schemes that use fixed parameter values, the cognitive engine dynamically adjusts the weighting coefficients according to current network conditions. When residual energy decreases significantly, the coefficient (α) is increased to prioritize energy-efficient routes. During congestion periods, the coefficient (γ) is increased to reduce routing delay. Similarly, (δ) is strengthened when communication reliability becomes critical. This adaptive behavior enables the protocol to respond intelligently to topology variations, energy depletion, and traffic fluctuations.During packet transmission, energy consumption is estimated using equations (1) and (2).
The residual energy of each node is continuously updated as:

$$E_j^{res}(t+1) = E_j^{res}(t) - E_{tx} - E_{rx} \tag{7}$$

Nodes whose residual energy falls below a predefined threshold E_{th} are excluded from future forwarding decisions: $E_j^{res} < E_{th}$

This cross-layer cognitive framework enables the routing protocol to adapt proactively to changing network conditions, thereby improving packet delivery, reducing communication delay, balancing energy consumption, and extending network lifetime.

Algorithm 1: Cross-Layer Cognitive Routing in EC²-SRP

Input: Network Nodes N, Initial Energy E_0, Weight Coefficients (α, β, γ, δ), Energy Threshold E_{th}

Output: Adaptive Energy-Efficient Routing Path

```
1. Initialize the network and discover neighboring nodes.
2. Repeat until data reaches Base Station:
3. Collect Physical Layer information: Residual Energy ($E_j$), Link Quality ($LQ_{ij}$)
```

```
    Collect MAC Layer information: Packet Delay ($D_{ij}$), Channel Contention
    Collect Network Layer information: Hop Count ($Hop_{ij}$), Neighbor Topology
    Construct state vector: $S_t = [E_j, LQ_{ij}, D_{ij}, Hop_{ij}]$
    Evaluate current network state.
    Dynamically update α, β, γ, δ according to: • Energy depletion • Congestion level • Link reliability • Delay requirements
    For each neighboring node j:
        Compute routing fitness $F_j$
    End For
    Select forwarding node: $NextHop(i) = \arg\max_{j \in C_i} F_j$
    Transmit packet to selected node.
    Compute transmission and reception energy.
    Update residual energy of nodes.
    If $E_j^{res} < E_{th}$ then
        Remove node j from forwarding set.
    End If
    Update state vector $S_t$.
End Repeat
Return optimal routing path.
```

IV. Scenario Generation

To assess the performance of the proposed Bio-Inspired Clustering and Multi-Objective Routing Framework—combining FCM-IDEO with EC^2-SRP —a detailed simulation was conducted using a custom-built script in the programming language Python. The simulation environment covers a 500 m × 500 m area with 100 randomly placed wireless sensor nodes, each initialized with 0.5 joules of energy. A base station is positioned outside the sensing area, mimicking real-world remote communication challenges. Initial node grouping is performed using the FCM algorithm based on spatial and data similarity. IDEO then optimizes CH selection by considering residual energy, intra-cluster distance, and node centrality. The number of CHs dynamically ranges from 2 to 10, adapting to energy and network conditions. EC^2-SRP performs multi-hop routing using cross-layer parameters. Simulation uses realistic data from the Energy Efficiency Detection Dataset. Metrics include residual energy, average energy consumption, packet delivery ratio, end-to-end delay, routing overhead,fault tolerance, and network lifetime.For fair comparison, all benchmark algorithms are evaluated under the above-mentioned simulation settings. The transmission of data packets from

The start node to Destination via CHs is shown in Fig.2, in which six cluster heads supervise all sensor nodes within their respective clusters while conserving energy and providing efficient data collection and transmission.

The efficiency of the proposed FCM-IDEO clustering approach in terms of network performance is evaluated against K-means [XIV], FCM clustering, and EAANFC-MR on metrics like average energy consumption and residual energy.

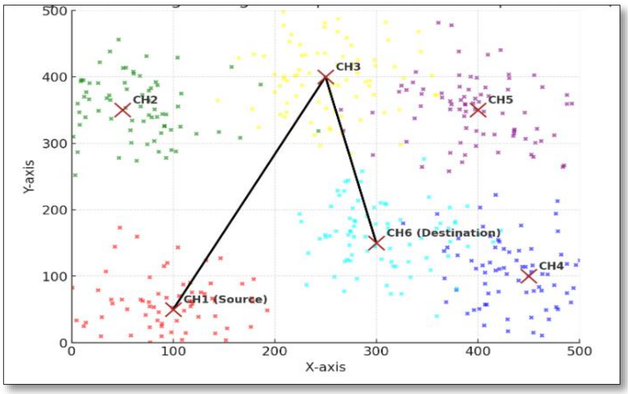

Fig.2. Data packet transmission from Source (CH1) to Destination (CH6)

Evaluation of Clustering and Routing Performance

A WSN comprises of multiple sensor nodes, which can either be active or inactive. The proposed clustering technique continuously monitors the nodes to determine their distances and form clusters accordingly. Instead of utilizing the K-means algorithm, this method applies FCM clustering to group neighboring nodes into clusters. An energy-efficient SN is dynamically selected as CH on the basis of energy consumption levels of all SNs, and CH is periodically updated in every subsequent round, giving adaptability.

Performance Evaluation of Clustering

A crucial technique for guaranteeing effective data transfer is clustering. Based on the average energy usage of each node, the suggested work clustered similar data into a single group using the FCM technique. The efficiency of the proposed FCM-IDEO clustering approach in terms of average energy consumption is evaluated against K-means [III] and FCM clustering and shown statistically in Table 1.

In Figure 3, a comparison of the proposed clustering approach with existing approaches like K-means, Fuzzy C-means, and EAANFC-MR clustering approaches in terms of average energy consumption has been displayed. Therefore, for different cluster sizes, the proposed methodology consumed less power on average in comparison with K-means, Fuzzy C-Means,and the EAANFC-MR method.

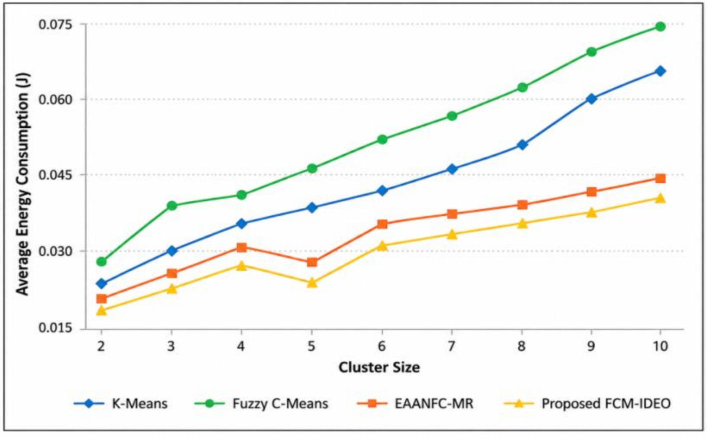

Fig. 3. Performance evaluation of the average energy consumption

Table 1:Average Energy Consumption Comparison of the Proposed Algorithm

Cluster Size	Average Energy Consumption (J)			
	K-Means	Fuzzy-C Means	EAANFC-MR	Proposed FCM-IDEO
2	0.023	0.028	0.0210	0.019
3	0.030	0.040	0.0260	0.023
4	0.035	0.042	0.0310	0.028
5	0.039	0.047	0.0280	0.025
6	0.042	0.053	0.0360	0.033
7	0.046	0.057	0.0380	0.035
8	0.050	0.062	0.0400	0.037
9	0.060	0.070	0.0430	0.039
10	0.0648	0.075	0.0460	0.0423

The statistical data in Table 2 shows the CH selection comparison of the proposed FCM-IDEO method using two traditional techniques:Improved Vertical Clustering - Low Energy Adaptive Clustering Hierarchy (IVC-LEACH) [XI], Whale Optimization Algorithm (WOA), and EAANFC-MR. The CH selection in 200 rounds by the proposed method based on the average residual energy is 42.23 J, whereas the existing methods, IVC-LEACH, WOA, EAANFC-MR have 37.33 J, 32.37 J, and 39.84J, respectively.

Table 2: Residual Energy Comparison of the Proposed Algorithm

Rounds	Residual Energy (J)			
	IVC-LEACH	WOA	EAANFC-MR	Proposed FCM-IDEO
200	37.33	32.37	39.84	42.23
400	32.43	27.46	34.91	37.33
600	19.62	14.72	22.11	24.53
800	12.76	4.91	12.98	14.72

1000	2.95	0.98	3.94	4.91
1200	2.94	0.98	3.92	4.9
1400	0.49	0.02	0.74	0.98
1600	0	0	0	0

Figure 4 is an interpretation of several rounds,showing residual energy as a parameter. Here, too, it can be inferred that the proposed scheme has more energy left as compared to others. It can be seen that when rounds are above 1000, the performance is almost the same for all.

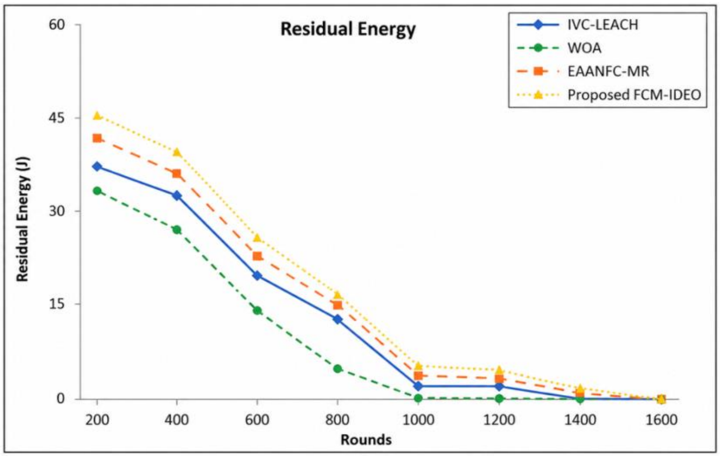

Fig.4. Comparison of the proposed method FCM-IDEO for CH selection

Performance Evaluation of Routing

The efficiency of the proposed routing protocol EC^2-SRP is evaluated in terms of routing performance on metrics like Energy consumption, Network Lifetime, Packet Delivery Ratio, End-to-End Delay, Routing Overhead, and Fault Tolerance in comparison with existing techniques EC-Fuzzy (Energy Aware Cross Layer-based Fuzzy Logic) and EC-adaptive threshold (Energy Aware cross-layer-based adaptive threshold technique).

Energy Consumption

The energy consumption of the proposed methodology is shown in Table 3, along with two existing approaches: EC-Fuzzy (Energy Aware Cross Layer-based Fuzzy Logic), EC-adaptive threshold (Energy Aware cross-layer-based adaptive threshold technique), BiCLR, and CLORP.The comparativeevaluation for energy consumption is shown in Figure 5,and the proposed methodology's energy consumption rate is lower than that of existing techniques for any number of nodes. For example, for 400 nodes, the proposed methodology consumes power 3.8mJ, whereas EC-Fuzzy and EC-adaptive threshold, BiCLR, and CLORP consume 11.75mJ, 7.95mJ, 7.05mJ, and 6.23mJ,respectively. When the number of nodes increases, the performance decreases a bit, which may be because of excessive mathematical computations.

Table3: Comparison of Energy Consumption of Proposed Technique

Techniques	Energy Consumption (mJ) vs. Number of Nodes					
	100	200	300	400	500	600
Proposed EC^2-SRP	1.77	1.01	4.13	3.8	3.19	2.0
EC-Fuzzy	7.95	9.36	9.87	11.75	10.56	10.67
EC-adaptive threshold	7.25	7.89	7.21	7.95	7.43	7.74
BiCLR	5.37	5.92	6.48	7.05	7.61	8.14
CLORP	4.82	5.11	5.74	6.23	6.84	7.16

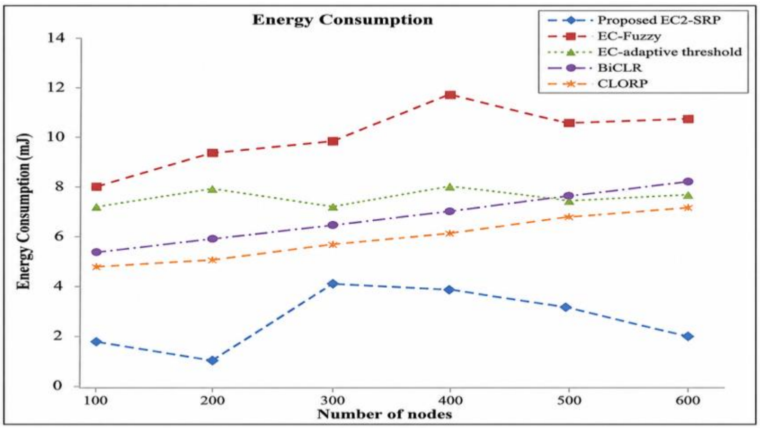

Fig. 5. Energy Consumption Comparison of EC^2-SRP Technique

Network Lifetime

The network lifetime of the proposed EC^2-SRP is evaluated against conventional algorithms, as illustrated in Figure 6. The results indicate that the proposed method achieves a significantly longer network lifetime compared to other approaches, according to the data given in Table 4.

Table 4: Comparison of Network Lifetime Of Proposed Technique EC^2-SRP

Techniques	Network Lifetime (Rounds) vs. Number of					
	100	200	300	400	500	600
Proposed EC^2-SRP	5808	5611	5414	5118	4922	4710
EC-Fuzzy	4804	4608	4510	4118	3921	3618
EC-adaptive	5295	5000	4804	4608	4510	4404
BiCLR	5408	5206	5002	4710	4524	4318
CLORP	5520	5315	5108	4825	4612	4420

The simulation results clearly demonstrate that the proposed method extends the network lifetime to 5808 rounds for 100 nodes. In comparison, the existing cross-layer-based adaptive threshold technique and cross-layer fuzzy logic approach achieve 5295 and 4804 rounds, respectively. Additionally, network lifetime gradually decreases as the number of nodes increases, as shown in Figure 6. Therefore, data transmission efficiency is directly influenced by the extended network lifetime. A denser medium makes network lifetime decline, and this is as per the theory suggested that more nodes will call for more calculations.

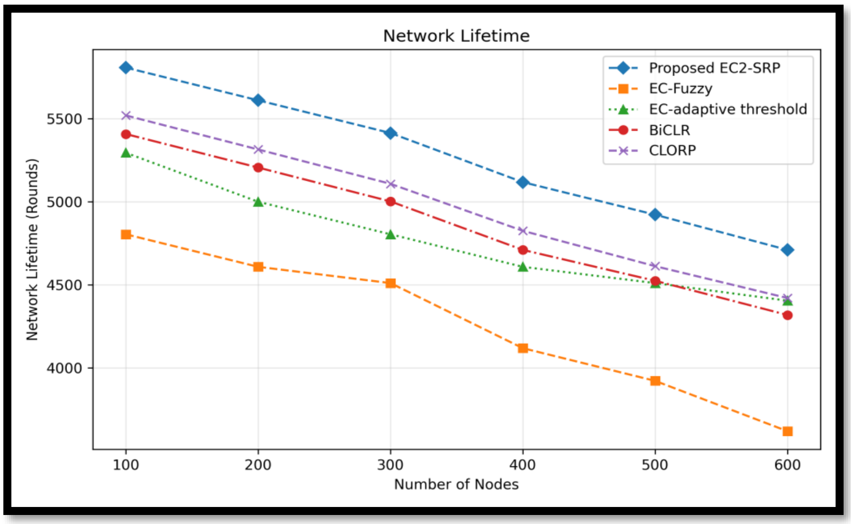

Fig. 6: Network Lifetime Comparison of EC^2-SRP Technique

Packet Delivery Ratio (PDR) and End-to-End Delay

The comparative evaluation data of the proposed technique with the conventional algorithms, cross-layer-based adaptive threshold, and cross-layer fuzzy logic, with respect to Packet Delivery Ratio and End-to-End Delay,are shown in Table 5. The EC^2-SRP approach's packet delivery ratio was high (100%) in 100 nodes as compared to the conventional algorithms, and the end-to-end delay of the proposed approach was much less as compared to others, as shown in Figure 7.

Table5:Comparative Evaluation of PDR and End-to-End Delay of Proposed Technique

Techniques	PDR(%) vs. Number of nodes					End-to-End Delay(ms) vs. Number of Nodes				
	100	200	300	400	500	100	200	300	400	500
Proposed EC^2-SRP	100	100	98	96	96	20	21	24	28	30
EC-Fuzzy	97	96	96	95	94	28	31	33	36	39
EC-adaptive threshold	95	91	90	90	88	35	42	45	47	52
BiCLR	98	97	95	94	92	25	28	30	33	36
CLORP	99	98	97	95	93	23	26	28	31	34

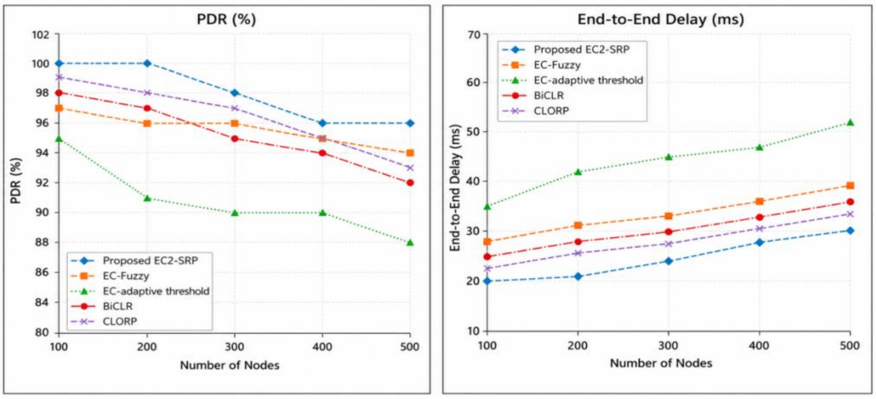

Fig. 7. PDR and End-to-End Delay comparison of EC^2-SRP

Routing Overhead and Fault Tolerance

The comparative evaluation data of the proposed technique with the conventional algorithms,cross-layer-based adaptive threshold, and cross-layer fuzzy logic, with respect to Routing Overhead and Fault Tolerance,are shown in Table 6.

Table 6:Comparative Evaluation of Routing Overhead and Fault Tolerance of Proposed Technique

Techniques	Routing Overhead (%) vs. Number of nodes					Fault Tolerance (%) vs. Number of Nodes				
	100	200	300	400	500	5%	10%	15%	20%	25%
Proposed EC^2-SRP	4.2	5.1	6.4	7.8	8.9	99	97	95	92	89
EC-Fuzzy	9.8	10.7	12.1	13.5	15.2	95	92	88	84	79
EC-adaptive threshold	8.3	9.4	10.6	12.3	13.8	94	90	86	82	77
BiCLR	6.0	6.9	8.1	9.3	10.6	97	94	91	87	83
CLORP	5.1	5.9	6.9	8.0	9.3	96	93	90	85	81

The routing overhead of the proposed EC^2-SRP protocol is significantly lower than EC-Fuzzy, EC-adaptive threshold, BiCLR, and CLORP techniques. The adaptive cross-layer routing mechanism minimizes route rediscovery and control packet generation, thereby reducing overhead. As network density increases, routing overhead increases for all protocols; however, the proposed method maintains the lowest overhead, achieving only 8.9% at 500 nodes, as shown in Figure 8.

Fault tolerance analysis evaluates the ability of the routing protocol to maintain successful communication under node failures. The proposed EC^2-SRP demonstrates superior resilience because alternate routes are dynamically reconstructed using residual energy, link quality, and delay information. Even when 25% of nodes fail, EC^2-SRP maintains an 89% successful packet delivery rate, outperforming EC-Fuzzy (79%), EC-adaptive threshold (77%), BiCLR(83%), and CLORP(81%), as shown in Figure 8.

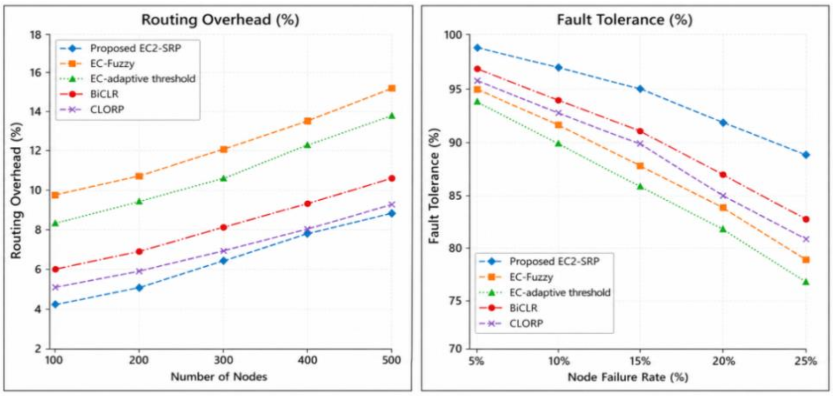

Fig.8. Routing Overhead and Fault Tolerance Comparison of EC^2-SRP Technique

Computational Complexity and Overhead Analysis

To evaluate the feasibility of routing and clustering protocols of WSN, Computational complexity is also an essential parameter. The proposed framework combines Fuzzy C-Means (FCM) clustering, Intelligent Dolphin Echolocation Optimization (IDEO), and the Energy-Conscious Cognitive Smart Routing Protocol (EC^2-SRP).The computational complexity of the FCM clustering stage is expressed as$O(nkI)$,where n is the total number of sensor nodes, k represents the number of clusters, and I is the maximum number of iterations. The IDEO optimization stage introduces an additional complexity of$O(P \times T \times D)$,where P is the dolphin population size, T is the number of optimization iterations, and D is the dimensionality of the search space.Therefore, the overall complexity of the proposed FCM–IDEO clustering framework can be represented as:$O(nkI) + O(P \times T \times D)$**.**For routing, the proposed EC^2-SRP evaluates neighboring nodes using cross-layer information obtained from the Physical Layer, MAC Layer, and Network Layer. Assuming N sensor nodes and M neighboring candidates, the routing decision complexity can be approximated as$O(N \times M)$**.**Although the proposed framework introduces additional optimization and adaptive decision-making operations, the computational complexity remains polynomial and scalable for medium- and large-scale WSN deployments.The proposed EC^2-SRP incurs a slightly higher computational cost because of the integration of IDEO-based optimization and adaptive cross-layer decision making. However, the additional overhead is compensated by substantial improvements in packet delivery ratio, energy consumption, routing, end-to-end delay, fault tolerance, and network lifetime. The results indicate that the proposed framework achieves an effective balance between computational cost and network performance.

V. Conclusion

A new scheme, in essence a hybrid scheme, has been proposed. The scheme performs in two major steps: (i) promotes CH selection using FCM Clustering with IDEO, and (ii) effective routing in WSNs via Energy-aware cross-layer smart routing protocol (EC^2-SRP). The FCM-IDEO method can be applied for the best CH selection from appropriate nodes. The common metrics—Average Energy Consumption, Residual power —were used to compare the results. Lastly, for effective data transmission, the EC^2-SRP algorithm routing protocol is employed. On established node-to-node paths, the routing procedure is allowed. The suggested system works better than other methods, as shown by the simulation results. The suggested methodology's performance is compared with that of the current optimization-based routing techniques. The optimal route from the CH to the BS is selected by EC^2-SRP.The proposed method outperformed those of the current approaches in evaluating PDR, energy consumption, network lifetime, end-to-end delay, routing overhead, and fault tolerance. Performance results for QoS criteria include PDR (100%), power consumption (1.77 mJ), network lifespan (5908 cycles) for 100 nodes, end-to-end delay (20ms), routing overhead (4.2%), and fault tolerance (99%). The overall accuracy of the suggested approach is 93.19%. Consequently, the proposed approach performs more efficiently than current strategies. In all scenariosand metrics, the suggested approach yielded superior outcomes. The present work only lacks the direct implementation of advanced reinforcement-learning and graph-neural-network-based routing approaches in a simulation framework.Future research will investigate the integration of deep reinforcement learning and graph-based optimization. A static sensor node WSN was used to test, implement, and idealize the suggested work. This study can be extended to networks of sensors with real-time mobile sensor nodes, which will further enhance adaptive routing performance under highly dynamic network conditions.

Conflict of Interest

There was no relevant conflict of interest regarding this paper.

References

I. A. Daniel, K. M. Balamurugan, R. Vijay and K. Arjun. :‘Energy Aware Clustering with Multihop Routing Algorithm for Wireless Sensor Networks’. Intelligent Automation & Soft Computing. Vol. 29, No. 1, pp. 233–246, 2021. 10.32604/iasc.2021.016405

II. A. Gupta, D. Riordan and S. Sampalli. :‘Cluster-Head Election Using Fuzzy Logic for Wireless Sensor Networks’. Proceedings of the 3rd Annual Communication Networks and Services Research Conference (CNSR). pp. 255–260, 2005.10.1109/CNSR.2005.27

III. A. Iwendi, P. K. R. Maddikunta, T. R. Gadekallu, K. Lakshmanna, A. K. Bashir and M. J. Piran. :‘A Metaheuristic Optimization Approach for Energy Efficiency in the IoT Networks’. Software: Practice and Experience. Vol. 51, No. 12, pp. 2558–2571, 2021. 10.1002/spe.2797

IV. A. Latha, S. Prasanna, S. Hemalatha and B. Sivakumar. :‘A Harmonized Trust Assisted Energy Efficient Data Aggregation Scheme for Distributed Sensor Networks’. Cognitive Systems Research. Vol. 56, pp. 14–22, 2019. 10.1016/j.cogsys.2018.11.006

V. A. Messaoudi, R. Elkamel, A. Helali and R. Bouallegue. :‘Cross-Layer Based Routing Protocol for Wireless Sensor Networks Using a Fuzzy Logic Module’. Proceedings of the 13th International Wireless Communications and Mobile Computing Conference (IWCMC). pp. 764–769, 2017. 10.1109/IWCMC.2017.7986381

VI. A. Tandon, P. Kumar, V. Rishiwal, M. Yadav and P. Yadav. :‘A Bio-Inspired Hybrid Cross-Layer Routing Protocol for Energy Preservation in WSN-Assisted IoT’. KSII Transactions on Internet and Information Systems. Vol. 15, No. 4, 2021.10.3837/tiis.2021.04.008

VII. A. Venkatesan, D. Balamurugan, T. Thamaraimanalan and M. Ramkumar. :‘Efficient Machine Learning Technique for Tumor Classification Based on Gene Expression Data’. Proceedings of the 8th International Conference on Advanced Computing and Communication Systems (ICACCS). Vol. 1, pp. 1982–1986, 2022.10.1109/ICACCS54159.2022.9785294

VIII. A. F. Raslan, A. F. Ali, A. Darwish and H. M. El-Sherbiny. :‘An Improved Sunflower Optimization Algorithm for Cluster Head Selection in the Internet of Things’. IEEE Access. Vol. 9, pp. 156171–156186, 2021.10.1109/ACCESS.2021.3126537

IX. E. Rani, A. Kush and B. Bansal. :‘Novel Approach with AI to Increase Life of Wireless Sensor Networks (WSNs) via FCMA: Fuzzy-C Means Clustering with A-Star Approach’. Future Technologies Conference. pp. 531–545, 2024.10.1109/ICCICA60014.2024.10584902

X. G. Samara, M. A. Hassan and Y. Zayed. :‘An Intelligent Vice Cluster Head Election Protocol in WSN’. arXiv Preprint arXiv:2112.01310, 2021. 10.48550/arXiv.2112.01310

XI. H. Echoukairi, A. Kada, K. Bouragba and M. Ouzzif. :‘A Novel Centralized Clustering Approach Based on K-Means Algorithm for Wireless Sensor Network’. IEEE Computing Conference. pp. 1259–1262, 2017.10.1109/SAI.2017.8252252

XII. H. B. Mahajan and A. Badarla. :‘Cross-Layer Protocol for WSN-Assisted IoT Smart Farming Applications Using Nature Inspired Algorithm’. Wireless Personal Communications. Vol. 121, No. 4, pp. 3125–3149, 2021.10.1007/s11277-021-08866-6

XIII. J. Chen, D. Wu, Y. Zhao, N. Sharma, M. Blumenstein and S. Yu. :‘Fooling Intrusion Detection Systems Using Adversarially Autoencoder’. Digital Communications and Networks. Vol. 7, No. 3, pp. 453–460, 2021.10.1016/j.dcan.2020.11.001

XIV. J. Wang, K. Wang, J. Niu and W. Liu. :‘A K-Medoids Based Clustering Algorithm for Wireless Sensor Networks’. International Workshop on Advanced Image Technology (IWAIT). pp. 1–4, 2018.10.1109/IWAIT.2018.8369769

XV. K. Lee, D. Lee and Y. I. Eom. :‘Power-Efficient and High-Performance Block I/O Framework for Mobile Virtualization Systems’. International Conference on Ubiquitous Information Management and Communication. pp. 1–7, 2015.10.1007/s11227-016-1810-z

XVI. K. Maraiya, K. Kant and N. Gupta. :‘Efficient Cluster Head Selection Scheme for Data Aggregation in Wireless Sensor Network’. International Journal of Computer Applications. Vol. 23, No. 9, pp. 10–18, 2011.10.5120/2981-3980

XVII. M. Guerroumi, N. Badache and S. Moussaoui. :‘Mobile Sink and Power Management for Efficient Data Dissemination in Wireless Sensor Networks’. Telecommunication Systems. Vol. 58, No. 4, pp. 279–292, 2015.10.1007/s11235-014-9877-4

XVIII. N. Mittal, U. Singh and R. Salgotra. :‘Tree-Based Threshold-Sensitive Energy-Efficient Routing Approach for Wireless Sensor Networks’. Wireless Personal Communications. Vol. 108, No. 1, pp. 473–492, 2019.10.1007/s11277-019-06413-y

XIX. N. Ramachandran and V. Perumal. :‘Delay-Aware Heterogeneous Cluster-Based Data Acquisition in Internet of Things’. Computers & Electrical Engineering. Vol. 65, pp. 44–58, 2018.10.1016/j.compeleceng.2017.03.018

XX. N. T. Tam, D. T. Hai, L. H. Son and L. T. Vinh. :‘Improving Lifetime and Network Connections of 3D Wireless Sensor Networks Based on Fuzzy Clustering and Particle Swarm Optimization’. Wireless Networks. Vol. 24, No. 5, pp. 1477–1490, 2018.10.1007/s11276-016-1393-y

XXI. R. Singh and A. K. Verma. :‘Energy Efficient Cross Layer Based Adaptive Threshold Routing Protocol for WSN’. AEU-International Journal of Electronics and Communications. Vol. 72, pp. 166–173, 2017.10.1016/j.aeue.2016.11.032

XXII. S. Chand, S. Singh and B. Kumar. :‘Heterogeneous HEED Protocol for Wireless Sensor Networks’. Wireless Personal Communications. Vol. 77, No. 3, pp. 2117–2139, 2014.10.1007/s11277-014-1622-5

XXIII. S. Liu, J. Wang, W. Shi, G. Han, S. Yan and J. Li. :‘CLORP: Cross-Layer Opportunistic Routing Protocol for Underwater Sensor Networks Based on Multiagent Reinforcement Learning’. IEEE Sensors Journal. Vol. 24, No. 10, pp. 17243–17258, 2024.10.1109/JSEN.2024.3384635

XXIV. S. A. Soleymani, S. Goudarzi, N. Kama, S. A. Ismail, M. Ali, Z. M. Zainal and M. Zareei. :‘A Hybrid Prediction Model for Energy-Efficient Data Collection in Wireless Sensor Networks’. Symmetry. Vol. 12, No. 12, Article 2024, 2020.10.3390/sym12122024

XXV. X. Liu, J. Li, Z. Dong and F. Xiong. :‘Joint Design of Energy-Efficient Clustering and Data Recovery for Wireless Sensor Networks’. IEEE Access. Vol. 5, pp. 3646–3656, 2017.10.1109/ACCESS.2017.2678020