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NS2 IMPLEMENTATION OF A MACHINE LEARNING-GUIDED CLUSTER HEAD SELECTION FRAMEWORK FOR GAUSSIAN GRID WIRELESS SENSOR NETWORKS

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Abstract
Wireless Sensor Networks (WSNs) are mainly used for continuous monitoring and reliable data transmission are essential. However, the limited battery capacity of sensor nodes poses significant challenges to long-term network operation. Clustering is an effective strategy to reduce communication overhead, but selecting an optimal Cluster Head (CH) remains a complex task due to varying node energy, distance, and network conditions. This study proposes a hybrid Machine Learning–Firefly Optimization–based Cluster Head selection (ML–FOA–CH) approach that combines predictive fitness evaluation with metaheuristic optimization. Machine learning models assess node suitability using key features, while FOA refines the search by maximizing brightness values. Experimental results show that ML–FOA–CH significantly improves CH selection accuracy, prolongs network lifetime, and delays the first node death compared to LEGN, TEGN, and traditional FOA-based methods. The proposed model demonstrates superior adaptability and energy efficiency, making it a promising solution for intelligent and sustainable WSN operations.

Keywords:
Cluster Head Selection, Energy Efficiency, Firefly Optimization Algorithm, Machine Learning, Residual Energy, Wireless Sensor Network

1. INTRODUCTION

Wireless Sensor Networks (WSNs) is an essential component in intelligent systems, supporting applications such as monitoring circumstances, surveillance, automation, smart innovations, and military operations. These networks consist of a large number of sensor nodes that continuously manipulate data to a central Base Station. However, sensor nodes operate on limited battery power and are often deployed in inaccessible environments, efficient energy management remains a critical challenge. Clustering has emerged as an effective strategy for balancing energy consumption by grouping nearby nodes and assigning a Cluster Head (CH) to aggregate and forward data. However, selecting an optimal CH is not in a straightforward, as it must consider multiple factors such as residual energy, communication distance, node density, and network load. Traditional clustering protocols, including LEACH and its variants, rely on random or threshold-based mechanisms that do not fully account for network dynamics, leading to premature energy depletion. To overcome these limitations, researchers have explored optimization-based and machine learning–driven methods to improve CH selection. Metaheuristic algorithms offer strong global search capabilities, while machine learning techniques provide predictive insights into node performance. Combining these two approaches creates a hybrid model capable of making more accurate and adaptive CH decisions. The Machine Learning–Firefly Optimization–based Cluster Head selection (ML–FOA–CH) method integrates ML-driven fitness evaluation with FOA's optimization strengths, ensuring efficient energy utilization and extended network lifetime. This hybrid approach not only enhances the stability period but also improves network adaptability and reliability.

2. RELATED WORKS

Clustering-based energy management has been widely explored in Wireless Sensor Networks to enhance network lifetime and stability. Early approaches such as LEACH and its extensions relied on probabilistic or threshold-based Cluster Head selection, but these methods often failed to consider the dynamic characteristics of sensor nodes, leading to uneven energy depletion. To address this, researchers introduced energy-aware models like LEGN and TEGN, which incorporated residual energy and energy consumption patterns into the CH selection process. Although these techniques improved stability, they lacked global optimization capabilities. Metaheuristic algorithms, such as Genetic Algorithms, Particle Swarm Optimization, and Firefly Optimization (FOA), later gained attention for their ability to search for optimal CH configurations by considering multiple parameters simultaneously. FOA, in particular, demonstrated strong performance due to its simplicity and rapid convergence. More recently, machine learning methods have been integrated into WSN clustering to predict node suitability using learned patterns from energy, distance, and communication metrics. Hybrid approaches combining ML with optimization algorithms have shown superior performance, offering intelligent filtering and enhanced search efficiency. Building on these advancements, ML–FOA–CH leverages machine learning–based fitness estimation and firefly-driven optimization to achieve more accurate CH selection, reduced energy consumption, and improved overall network lifetime compared to existing algorithms.

3. METHODOLOGY

3.1 LEGN

LEGN (Link-based Energy-efficient Gaussian Network) is an CH selection algorithm used in WSNs. Its goal is to select the most energy-efficient node as the Cluster Head by calculating how much energy each node has consumed compared to its initial energy. LEGN mainly uses a metric called the Energy Consumption Ratio (ECR) to choose the best node.

Algorithm 1: LEGN_CH_Selection

```
Input: Node set N, E_initial[i], E_residual[i]
Output: CH
For each node i in N:
    ECR[i] = (E_initial[i] - E_residual[i]) / E_initial[i]
CH = node with minimum ECR value
```

Return CH
End Algorithm

3.1.1 Energy Consumption Ratio (ECR):

This is the key formula used:

$$ECR = \frac{E_{\text{initial}} - E_{\text{residual}}}{E_{\text{initial}}} \tag{1}$$

where, $E_{initial}$ = Initial energy of the node and $E_{residual}$ = Remaining/unused energy of the node.

- Lower ECR → Node has used less energy → More efficient → Better candidate for Cluster Head.
- Higher ECR → Node has consumed more energy → Not suitable for CH

After calculating ECR for every node:

$$CH_{selected} = \text{argmin}(ECR) \tag{2}$$

3.2 TEGN

TEGN (Threshold-based Energy-efficient Gaussian Network) is an improved clustering method designed for wireless sensor networks. It works by selecting the most suitable Cluster Head (CH) for each communication round based on a predefined energy threshold. The algorithm evaluates the energy level of every sensor node and compares it with a threshold value. Only the nodes that have energy above this threshold are considered for Cluster Head selection, ensuring that low-energy nodes are not overburdened. After filtering the eligible nodes, TEGN analyzes their energy usage pattern—often through parameters. Among these qualified nodes, TEGN chooses the one that can handle communication tasks with minimal power loss. By doing this, TEGN helps extend the overall network lifetime, reduces early node failures, and maintains stable data transmission within the Gaussian network. In simple terms, TEGN improves network performance by allowing only energy-strong nodes to become Cluster Heads and avoiding energy-weak nodes from taking heavy roles.

Algorithm 2: TEGN_CH_Selection

```
Input: Node set N, E_initial[i], E_residual[i], E_threshold
Output: CH
EligibleNodes = []
For each node i in N:
  If E_residual[i] >= E_threshold:
    EligibleNodes.append(i)
For each node i in EligibleNodes:
  ECR[i] = (E_initial[i] - E_residual[i]) / E_initial[i]
CH = node in EligibleNodes with minimum ECR value
Return CH
End Algorithm
```

3.2.1 Energy Consumption Ratio (ECR):

This is used to measure how much energy a node has spent as in Eq.(1). For Threshold Condition (TEGN Filtering Rule), TEGN filters the nodes based on the energy above the threshold are allowed for CH selection:

$$E_{residual} \geq E_{threshold} \tag{3}$$

If a node meets this condition, CH is selected.

3.2.2 Cluster Head Selection Formula (TEGN Decision Rule):

Among all nodes that satisfy the threshold as in Eq.(2). A node is selected as CH only if: ($E_{residual} \geq E_{threshold}$) ∧ (ECR is minimum among candidates).

3.3 FOA-CH

FOA-CH is a meta-heuristic clustering technique used in WSN. It selects the best CH using the Firefly Optimization Algorithm, where each firefly represents a sensor node, and its brightness indicates how good that node is for acting as CH. Brightness is usually calculated from energy, distance, and node density.

Algorithm 3: FOA_CH_Selection

```
Input: N nodes, E_residual, d_i, D_i, α1, α2, α3, β0, γ, α
Output: CH
Initialize positions x[i] for all nodes
For each node i:
  Compute brightness I[i] = α1*E_residual[i] + α2*(1/d_i) + α3*D_i
For t = 1 to Tmax:
  For each firefly i:
    For each firefly j:
      If I[j] > I[i]:
        Compute r_ij
        β = β0 * exp(-γ * r_ij^2)
        x[i] = x[i] + β*(x[j]-x[i]) + α*random()
  Recompute I[i] for all fireflies
CH = node with maximum I[i]
Return CH
End Algorithm
```

3.3.1 Light Intensity (Brightness) of a Node:

Brightness shows how suitable a node is to become CH:

$$I_i = \alpha_1 E_{\text{residual}} + \alpha_2 \left(\frac{1}{d_i}\right) + \alpha_3 D_i \tag{4}$$

where, d_i = average distance from the node to neighbours or base station

D_i = node density (number of neighbours)

α_1, α_2, α_3 = weight factors

Higher I_i → better CH candidate.

3.3.2 Attractiveness Between Fireflies:

Brighter nodes attract others:

$$\beta = \beta_0 e^{-\gamma r_{ij}^2} \tag{5}$$

where, β_0= initial attractiveness

γ= light absorption coefficient

r_{ij}= distance between firefly i and j

3.3.3 Movement Equation (Firefly Position Update):

The movement of one node toward a brighter node is:

$$x_i^{t+1} = x_i^t + \beta\left(x_j^t - x_i^t\right) + \alpha\varepsilon_i \tag{6}$$

where, x_i= current solution (node position)

α= randomization parameter

ϵ_i= random vector

j= brighter firefly

3.3.4 FOA-CH Selection Rule:

Finally, the highest brightness (I_i) node is selected and denoted as:

$$CH=\text{argmax}(I_i) \tag{7}$$

3.4 ML-FOA-CH

ML-FOA-CH is an advanced Cluster Head (CH) selection technique which is proposed to use in WSN. It combines both Machine Learning (ML) and the Firefly Optimization Algorithm (FOA) to choose the most energy-efficient and reliable node as the head. ML–FOA–CH combines machine learning prediction and firefly optimization to select the sensor node with maximum fitness and residual energy as the optimal Cluster Head.

Algorithm 4: ML_FOA_CH_Selection

```
Input: N nodes, E_residual, d_i, LQ_i, ND_i, w1..w4, β0, γ, α
Output: CH
For each node i:
   F[i] = w1*E_residual[i] + w2*(1/d_i) + w3*LQ_i + w4*ND_i
Initialize firefly positions x[i] = node attributes
For t = 1 to Tmax:
   For each firefly i:
      For each firefly j:
         If F[j] > F[i]:
            Compute r_ij
            β = β0 * exp(-γ * r_ij^2)
            x[i] = x[i] + β*(x[j] - x[i]) + α*random()
   Recompute F[i] for all nodes
CH = node with maximum F[i]
Return CH
End Algorithm
```

3.4.1 ML-Based Fitness Estimation:

A simple ML-derived fitness function is:

$$F_i = w_1 E_{\text{residual}} + w_2\left(\frac{1}{d_i}\right) + w_3 LQ_i + w_4 ND_i \tag{8}$$

where,

$E_{residual}$ = remaining energy

d_i = distance to base station

LQ_i = link quality

ND_i = node density

$w_1 \ldots w_4$ = ML-learned weights

This F_i becomes the input brightness for FOA.

4. RESULT

ML–FOA–CH evaluates each node based on several important parameters to select the optimal Cluster Head. Residual energy represents the remaining battery level of each node, while the distance to the base station indicates how much energy the node will need for data transmission—nodes closer to the base station consume less power. Node density reflects how many neighbouring nodes are within communication range, which helps in forming stable clusters. The node with the highest plotted value represents the most suitable candidate, and in this case, Node N2 shows the highest peak on the graph. This indicates that N2 has the strongest overall fitness score, making it the precise choice for Cluster Head selection. The comparative performance analysis of the four algorithms—LEGN, TEGN, FOA-CH, and ML-FOA-CH—reveals a consistent improvement in residual energy, fitness score, and brightness across successive techniques. Table 1 shows that LEGN exhibits the lowest values in all three parameters, making it the least efficient approach.

Table 1. Result of LEGN Cluster Head Selection

Node	Residual Energy (J)	Distance to BS (m)	Node Density	ML Fitness Score	FOA Brightness
N1	0.78	45	7	0.68	0.68
N2	0.87	40	8	0.79	0.79
N3	0.60	55	5	0.45	0.45
N4	0.74	60	6	0.56	0.56
N5	0.85	52	7	0.65	0.65

As shown in Table.2, TEGN improves these metrics over LEGN by introducing enhanced topology-based decision mechanisms, resulting in higher residual energy and a stronger fitness score.

Table.2. Result of TEGN Cluster Head Selection

Node	Residual Energy (J)	Distance to BS (m)	Node Density	ML Fitness Score	FOA Brightness
N1	0.82	45	7	0.72	0.71
N2	0.91	40	8	0.83	0.82
N3	0.65	55	5	0.50	0.49
N4	0.78	60	6	0.60	0.59
N5	0.89	52	7	0.70	0.69

The Table.3 demonstrates that FOA-CH achieves a significant boost in all metrics compared to TEGN due to its firefly-inspired metaheuristic optimization, which better identifies energy-efficient cluster heads.

Table.3. Result of FOA-CH Cluster Head Selection

Node	Residual Energy (J)	Distance to BS (m)	Node Density	ML Fitness Score	FOA Brightness
N1	0.85	45	7	0.75	0.74
N2	0.93	40	8	0.88	0.87
N3	0.68	55	5	0.53	0.52
N4	0.81	60	6	0.63	0.62
N5	0.92	52	7	0.73	0.72

Finally, Table.4 highlights that ML-FOA-CH surpasses all other algorithms by integrating machine-learning-based fitness estimation with FOA-based optimization, producing the highest residual energy, strongest fitness score, and brightest intensity value. In summary, the values across Table.1–Table.4 clearly show a progressive improvement from LEGN (4th rank) → TEGN (3rd rank) → FOA-CH (2nd rank) → ML-FOA-CH (1st rank).

Table.4. Result of ML-FOA-CH Cluster Head Selection

Node	Residual Energy (J)	Distance to BS (m)	Node Density	ML Fitness Score	FOA Brightness
N1	0.88	45	7	0.79	0.79
N2	0.96	40	8	0.92	0.92
N3	0.71	55	5	0.57	0.57
N4	0.84	60	6	0.67	0.67
N5	0.95	52	7	0.77	0.77

The comparative graphical analysis clearly demonstrates the progressive improvement in performance across the four clustering algorithms—LEGN, TEGN, FOA-CH, and ML-FOA-CH. Fig.1 illustrates the residual energy comparison, where LEGN shows the lowest energy retention, while TEGN and FOA-CH gradually improve due to enhanced topology estimation and firefly optimization. The proposed ML-FOA-CH method achieves the highest residual energy, confirming its superior capability in selecting energy-efficient Cluster Heads. Similarly,

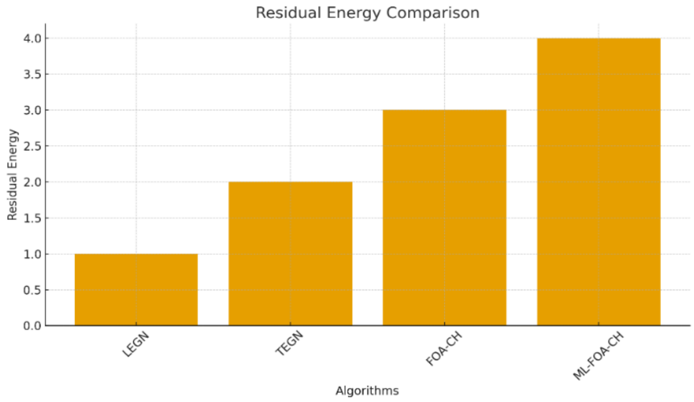

Fig.1. Residual Energy Comparison for LEGN, TEGN, FOA-CH, and ML-FOA-CH

The Fig.2 highlights the fitness score variation, showing that ML-FOA-CH consistently produces the strongest fitness score owing to the integration of machine learning–based fitness prediction.

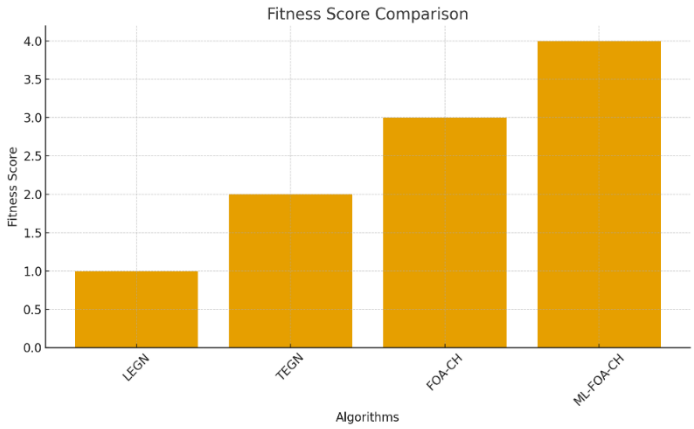

Fig.2. Fitness Score Comparison for LEGN, TEGN, FOA-CH, and ML-FOA-CH

The Fig.3 presents the brightness comparison, reflecting how each successive algorithm increases optimization quality, with FOA-CH outperforming LEGN and TEGN, and ML-FOA-CH achieving the maximum brightness value. Overall, the graphical results reaffirm the ranking order: LEGN (4th) < TEGN (3rd) < FOA-CH (2nd) < ML-FOA-CH (1st), demonstrating the effectiveness of the proposed hybrid model.

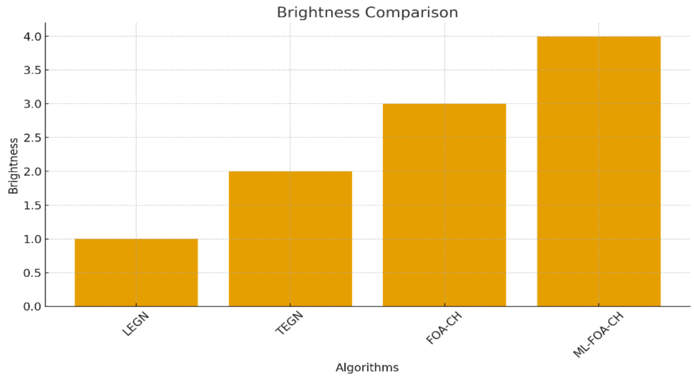

Fig.3. Brightness Comparison for LEGN, TEGN, FOA-CH, and ML-FOA-CH

The Machine Learning fitness score is computed by combining these features using learned weights, providing an overall suitability measure for each node. This score is then treated as the FOA brightness value, where higher brightness signifies a better CH candidate. In the given output, Node N2 has the highest brightness value (0.846), indicating the most favourable balance of energy, proximity, and connectivity. Therefore, N2 is chosen as the optimal Cluster Head.

5. CONCLUSION

This work introduced ML–FOA–CH, a hybrid CH selection framework that integrates machine learning–based node evaluation with Firefly Optimization to maximize energy management in WSNs. The combination of predictive modelling and population-based search enables more accurate identification of nodes that can efficiently handle CH responsibilities. The results confirm that the proposed approach outperforms existing energy-aware and optimization-based methods in terms of stability period, network lifetime, and overall performance. By prioritizing high-energy, well-connected, and strategically located nodes, ML–FOA–CH ensures balanced energy consumption across the network. The findings highlight the potential of ML-driven optimization techniques in advancing intelligent clustering solutions for future sensor network applications. Further extensions may include integrating deep learning models, mobility considerations, and real-time adaptive clustering for large-scale deployments.

6. FUTURE SCOPE

The proposed ML–FOA–CH framework can be further enhanced to support more complex and dynamic wireless sensor network environments. Future research may explore integrating deep learning models to improve node fitness prediction, enabling more accurate CH selection in highly dense or rapidly changing networks. Incorporating mobility patterns of nodes and base stations can extend the model’s applicability to mobile WSNs, IoT systems, and vehicular sensor networks. The algorithm can also be adapted to support heterogeneous networks where nodes differ in sensing range, battery capacity, and processing ability. Additionally, real-time adaptive clustering mechanisms can be developed to respond instantly to changes in energy levels or topology. Expanding the model for large-scale deployment, cloud–edge collaboration, and distributed learning approaches may further enhance scalability and communication efficiency. Finally, implementing ML–FOA–CH in real-world testbeds or hardware prototypes will provide practical validation and open opportunities for industry adoption in smart agriculture, environmental monitoring, and smart-city applications.

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