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Energy-Efficient Clustering in Wireless Sensor Networks through Firefly–Gradient Descent Hybrid Optimization

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Abstract

The Wireless Sensor Networks (WSNs) are utilized by many monitoring applications, and it is widely accessible. Restricted node energy and dynamic network backgrounds limits the effectiveness of WSN. Thus, premature node failures and shorter network lifetime (NL) may result from these limitations. For Cluster Head (CH) selection, conventional clustering methods are ineffective, because these conventional methods mostly utilized static metrics. So, these conventional methods fail to adapt to dynamic topologies and energy patterns. An AI-enhanced Firefly–Gradient Descent Hybrid Optimization (AI-FGDHO) model is suggested in this study for the purpose of resolving those issues. In the network structure, intelligent decision-making is integrated by AI-FGDHO model. The node-level local CH candidacy scoring with lightweight machine learning (ML) algorithms and CH level collaborative model updates without raw data sharing using federated learning (FL) are utilized by this suggested model. The CH rotation schedules and routing strategies are dynamically refined by the Reinforcement learning (RL). For enhancing CH placement, and exploiting network topology, graph neural networks (GNNs) are used. In the exploration ability of Firefly optimization and the exploitation strength of gradient descent, these AI components are integrated, and it facilitate in adaptive and energy-aware clustering. Then, simulation was conducted with the suggested AI-FGDHO and conventional methods. With higher residual energy (0.70 J), delivery ratio (80), NL (950 rounds), throughput (900 packets), lower overhead (120 packets), latency (200 ms), reduced CH rotations (22), and improved coverage (75), the suggested AI-FGDHO model executes better than conventional methods, and it was demonstrated by the simulation outcomes.

Keywords: *Wireless Sensor Networks, Firefly Optimization, Gradient Descent, Federated Learning, Reinforcement Learning, Energy Efficiency.*

Introduction

Wireless Sensor Network Background

To monitor objects in the real-world or within a plant, distributed nodes operate together in a wireless network. These nodes are operated using batteries, so energy efficiency is crucial [1]. An effective technique for reducing communication cost is clustering. This clustering segregates nodes into groups, and CH aggregates the data and then send it to the base station (BS) [2]. Without resulting energy inconsistencies and shortening the NL, dynamic nature of WSN are not effectively managed by this conventional clustering method despite its effectiveness [3].

Challenges in Achieving Efficient Clustering Results

For an effective clustering, CH selection and rotation must be executed properly [4]. Static metrics like residual energy or distance are mostly utilized by the conventional methods, so it fails to adapt to evolving network backgrounds [5]. When energy consumption (EC) of the CH is excessively high, it experiences network splitting. However, remaining unsolved are routing overhead and unbalanced

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energy distribution among clusters issues, which call for more intelligent, scalable clustering approaches [6].

The Significance of AI in Optimizing WSN

- The recent advancements in AI and ML suggest some promising fresh avenues towards addressing the clustering issues in WSNs.
- Distributed training can be achieved with low communication overhead and assured data privacy through Federated Learning [7].
- CH rotation and routing algorithm decisions can be dynamically taken through the assistance of Reinforcement Learning.
- To optimize topology-aware GNNs and leverage WSNs' graph-based nature [8].
- Hybridization with care is required for an optimal combination of the methods in the WSNs' resource-limited scenario.

Hybrid Optimization: Firefly and Gradient Descent

Unlike gradient descent (GD), which provides fast local exploitation and the risk of getting trapped in local minima, metaheuristic algorithms like the Firefly Algorithm (FA) excel in global exploration and can converge slowly [9]. By blending FA and GD, a compromise between exploration and exploitation can be maintained, giving rise to adaptive and energy-efficient CH selection. By integrating AI-based decision mechanisms, this hybridization can significantly enhance efficiency and extend the lifetime of networks [10].

Research Contributions

There exist many clustering algorithms, and they are mostly unable to deal with dynamic energy patterns or network dynamics, nor can they scale. To that effect, this research introduces an AI-FGDHO system that:

- The node-level CH candidacy is evaluated using ML.
- Combines federated learning with CHs to allow for collaborative model updates while protecting user privacy.
- Makes use of reinforcement learning and GNNs to implement topology-aware placement, routing, and adaptive CH rotation.
- Integrates FA and GD to guarantee clustering that is both resilient and energy-efficient.

The following is an overview of the remainder of the paper: Section 2 covers related works from traditional clustering techniques that have been utilized in WSNs. In Section 3, the proposed AI-FGDHO framework is presented. Section 4 covers the simulation findings and comparisons. Section 5 provides insights and suggestions for future work.

Background study

Due to the dynamic nature of WSN environments and the resource-constrained nature of nodes, it is crucial to have energy-efficient routing and clustering algorithms. Selection of the cluster head and routing optimization have seen the spotlight shine on bio-inspired optimization in the form of the Firefly Algorithm and its hybrid forms. In this literature review, ten state-of-the-art hybrid FA approaches are compared and contrasted, highlighting their methods, improvements, and applicability to long-term sustainability in WSN operations.

Optimized cluster head selection in WSNs became a reality with the Hybrid Firefly Algorithm with Particle Swarm Optimization, or HFA-PSO. This HFA-PSO integrates the global exploration of firefly and exploitation of PSO. To improve the well-distributed CH and reduce communication overhead, HFA-PSO is used. The network become more energy-efficient and maintains longer lifetime when compared to conventional methods like LEACH and basic PSO [11].

Hybrid Grey Wolf Optimizer and FA (HGWO-FA) was suggested for routing in heterogeneous WSN. The convergence of Firefly (exploitation) and leadership-based exploration of GWO are utilized by this HGWO-FA, and it supports in enhancing durability and adaptability. In terms of energy consumption, packet delivery ratio (PDR), and stability time, this framework executes well than distinct GWO and FA models for large-scale heterogeneous network backgrounds [12].

For enhancing energy efficiency in WSN clustering, he Hybrid Eagle Strategy using Firefly Optimization, or HES-FA is used. The eagle strategy was utilized for more effective global exploration, and the FA was utilized for enhancing the local CH selection. Throughput was improved, lifetime was extended, and the energy variance of this hybrid was much reduced. In varying energy patterns and dynamic topologies, the efficiency of FA is compared to distinct LEACH and FA [13].

For energy-efficient clustering and routing in IoT-assisted WSN, a novel method named FA and Aquila Optimization (FA-AO) is used. To effectively distribute CH and maintaining low communication costs, the collaboration of hunting-inspired exploration of Aquila and the swarm intelligence of Firefly is utilized. Improved Quality of Service (QoS), longer lifetime, and low EC are attained by the performance evaluation of FA-AO in IoT-based sensor network applications [14].

The FA with Ant Colony Optimization (FA-ACO) is used, and this application ensures energy-efficient cluster-based routing in WSN. Reliable routing paths are offered by this FA-ACO via integrating global search of firefly and pheromone-based path searching of ACO. This hybrid model is highly adaptable to evolving network backgrounds, and it executes better than ACO, FA, and LEACH by average energy consumption, packet delivery, and stability.

Hybrid artificial bee colony with FA named ABC-FA is suggested for WSN CH election. The foraging behavior of ABC offers an effective exploration. For CH selection, local exploration is balanced, and it was ensured by firefly. This ABC-FA improves network stability, minimizes packet loss, and extending the NL when compared to ABC, FA, and LEACH, so it is considered to be an effective clustering technique, and it was demonstrated by the outcomes of the simulation [16].

An energy-efficient CH selection in WSN named Hesitant Fuzzy with FA (HF-FA) is suggested. Hesitant fuzzy sets are used in decision making and also manages uncertainty. The CH selection is improved by this firefly optimization. In terms of accuracy, energy balancing, and prolonged lifetime, the HF-FA executes well when compared to FA-alone and fuzzy-alone models. Thus, the robustness of HF-FA in improving the dependability and energy balancing in clustered WSN is proved.

The FA with Fuzzy Logic (FA-FL) is utilized for multipath routing in WSN. In route decisions, uncertainty is managed by this FL. For path selection, global optimization is handled by FA. When compared to conventional multipath routing methods, this integrated method FA-FL effectively manages the challenges of evolving sensor network backgrounds, and it also improves reliability, energy-efficiency, and reducing delay [18].

The Levy-Guided Grey Wolf Optimizer with Cuckoo Search (LGWO-CS) is introduced for selecting CH with considerable energy. Here, Levy flights are used to improve exploration, the command hierarchy of GWO supports in ensuring balance, and exploitation was then improved by the application of CS. For long-term WSN clustering, this LGWO-CS has become an effective hybrid optimization method. In terms of throughput, conserved energy, and extended lifetime, this LGWO-CS method executes better than conventional GWO, CS, and FA [19].

For clustering, FA and its variants, such as FA-Fuzzy, FA-ACO, and FA-PSO, were considered in CR-FA, which is the Comprehensive Review of Firefly Algorithms. FA's exploration power and weaknesses in large-scale optimization came out in the assessment. Differences between native FA implementations and hybrid FA models indicated that the latter improved WSN scalability, energy efficiency, and clustering accuracy substantially [20].

Research gaps and motivation

Recent hybrid approaches incorporating Firefly have improved WSN clustering, routing reliability, and energy efficiency. However, they suffer from scalability issues, high computing costs, limited mobility flexibility, and minimal field test validation. Rather than concentrating on both exploration and exploitation, most models only perform one of them. This paper introduces Firefly-Gradient Descent Hybrid Optimization (AI-FGDHO), a remedy for these issues that enables energy-conscious clustering that is both adaptive and scalable, which is pivotal for the long-term sustainability of WSNs [21].

All factors being considered, the studies indicate that hybrid FA-based algorithms enhance energy efficiency, routing reliability, and network lifetime when coupled with PSO, GWO, ACO, ABC, fuzzy logic, and reinforcement approaches, as compared in Table 1. While these studies indicate that FA is versatile, they indicate that it has constraints in terms of scalability. The proposed Firefly-Gradient

Descent Hybrid Optimization, where exploration and exploitation are brought together for adaptive WSN clustering, is motivated by this necessity.

Table 1. Related work summary

Ref	Technique / Hybrid Model	Key Focus	Major Findings	Limitations
[11]	Firefly Algorithm + Particle Swarm Optimization (HFA-PSO)	Cluster Head (CH) selection	Reduced energy consumption, balanced CH distribution, and extended lifetime.	Lacked adaptability under high node mobility and varying traffic patterns.
[12]	Grey Wolf Optimizer + Firefly Algorithm (HGWO-FA)	Energy-efficient routing	Improved packet delivery ratio and stability in heterogeneous WSNs.	High computational cost limits scalability for large-scale WSNs.
[13]	Eagle Strategy + Firefly Algorithm (HES-FA)	Energy optimization in clustering	Reduced energy variance and improved throughput compared to LEACH.	Focused mainly on static networks; less effective in dynamic topologies.
[14]	Firefly Algorithm + Aquila Optimization (FA-AO)	IoT-assisted clustering & routing	Enhanced QoS, reduced communication cost, and longer lifetime.	Performance validation is limited to small IoT-driven test cases.
[15]	Firefly Algorithm + Ant Colony Optimization (FA-ACO)	Cluster-based routing	Optimized path discovery with reduced energy and higher packet delivery.	Scalability issues with pheromone updating under dense deployments.
[16]	Artificial Bee Colony + Firefly Algorithm (ABC-FA)	Cluster Head election	Extended lifetime and stability; minimized packet loss.	Complex computations lead to higher overhead during CH election.
[17]	Hesitant Fuzzy + Firefly Algorithm (HF-FA)	Energy-aware CH selection	Balanced energy distribution and improved reliability.	Increased delay due to fuzzy decision-making at each iteration.
[18]	Firefly Algorithm + Fuzzy Logic (FA-FL)	Multipath routing	Reduced latency, increased reliability, and improved adaptability.	Lack of robustness in highly dynamic and large-scale networks.
[19]	Grey Wolf Optimizer + Cuckoo Search (LGWO-CS)	Energy-aware CH selection	Achieved superior throughput and energy efficiency.	Levy flights increase convergence time in dense WSN scenarios.
[20]	Review of Firefly Algorithms & Hybrids (CR-FA)	Survey on FA for clustering	Highlighted FA limitations; hybrids outperform standalone FA.	Did not provide real-world deployment validation of hybrid models.

Methodology

The proposed AI-FGDHO method achieves adaptive, energy-aware clustering in WSNs using federated learning, reinforcement learning, graph neural networks, and a Firefly-Gradient Descent hybrid optimizer, extending the life, reliability, and communication efficiency of networks through topology-aware CH placement, dynamic routing, privacy preservation during local computations, and iterative global optimization.

Node-Level CH Candidacy Scoring

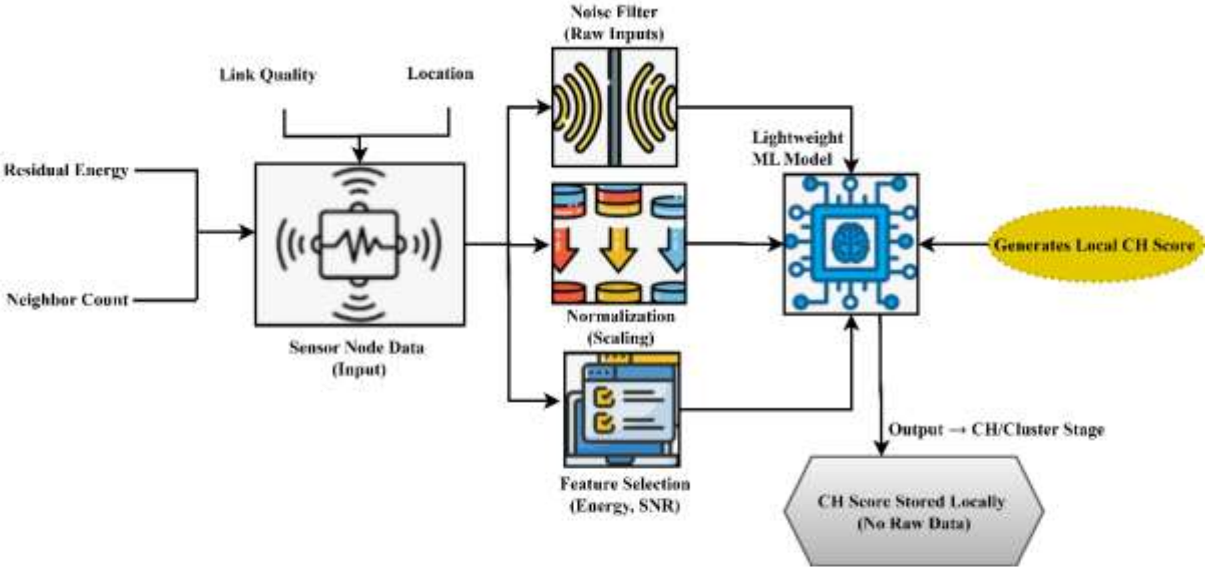

Fig.1. Node-Level CH Candidacy Scoring Overview

Fig.1 demonstrates how sensor nodes perform localized processing to determine if they are suitable candidates to become CH. Each node begins the process by acquiring raw data, which may contain information such as location data, signal-to-noise ratio (SNR), neighbour count, and residual energy. Normalization and lightweight feature extraction are performed on these parameters following a preprocessing step to remove noise and reduce dimensionality. The nodes almost always develop lightweight machine learning models, such as logistic regression or support vector machines, as opposed to sending raw information, which may be expensive in energy usage and potentially lead to privacy violations. The outputs of the models are then used to compute the CH candidacy score. More importantly, there is built-in communication strength because the process is fully local. The CH scores are computed locally on the node while shared aggregated for higher-level decision-making, which provides a node-centric efficacy of distributed and intelligent CH selection in resource-constrained networks and which enables scalability, low energy usage, and privacy preservation.

Equation 1 allows for a fair comparison of CH; this equation truncates the residual energy to the range [0,1].

$$E_{norm}(i) = \frac{E_{res}(i) - E_{min}}{E_{max} - E_{min} + \epsilon} \qquad (1)$$

The residual energy of node i is denoted as $E_{res}(i)$, the energy boundaries for the entire network are E_{max} and E_{min}, and instability is prevented by ϵ. The normalization $E_{norm}(i)$allows energy to flow seamlessly with other aspects of CH candidacy, and so it ensures fairness by equation 1.

A deterministic count of CH appropriateness using equation 2 that considers energy, link quality, and connectivity is computed by $S_{CH}(i)$.

$$S_{CH}(i) = \alpha \cdot E_{norm}(i) + \beta \cdot \frac{1}{1 + e^{-\gamma \cdot (SNR(i) - \theta)}} + \delta \cdot \frac{N_{nbr}(i)}{N_{tot}} \qquad (2)$$

In equation 2, $E_{norm}(i)$ indicates normalized energy, $SNR(i)$ refers to link reliability, θ indicates SNR threshold, $N_{nbr}(i)$ refers to neighboring count, and α, β, and γ refers to weights. This measure allocates CH responsibilities δ to nodes that are energetic as N_{tot}, have solid connections and are strong in reliability.

The likelihood of a node being CH in a logistic regression form is indicated by equation 3.

$$PCH(i) = \frac{1}{1 + \exp\left(-\left(w_0 + w_1 \cdot E_{norm}(i) + w_2 \cdot SNR(i) + w_3 \cdot \frac{N_{nbr}(i)}{N_{tot}} + w_4 \cdot LQ(i)\right)\right)} \qquad (3)$$

Energy is represented by $E_{norm}(i)$; link strength is represented by $SNR(i)$; node degree of connectivity by $\frac{N_{nbr}(i)}{N_{tot}}$; link quality by $LQ(i)$; and ML weights by $w_0 \ldots\ldots w_4$. This likelihood supports adaptive, for a variety of conditions, data-driven selections of CHs by equation 3.

Federated Learning at Cluster Heads

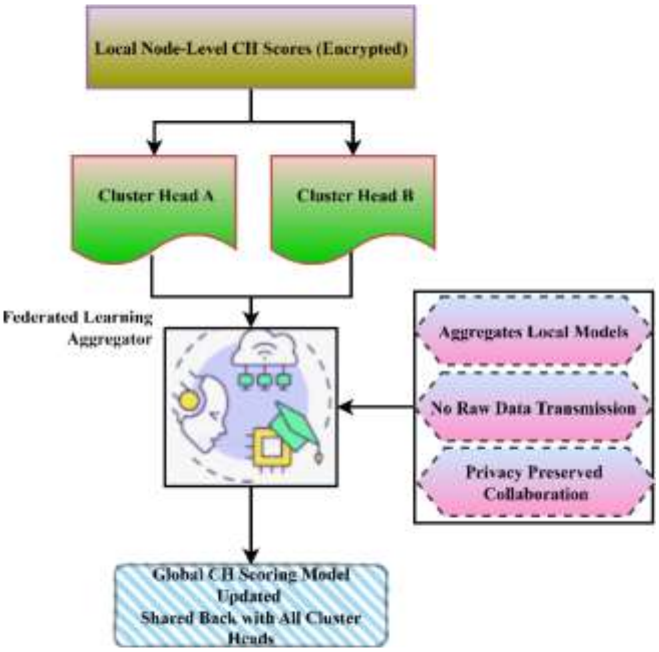

Fig.2. Federated Learning at Cluster Heads

Learn how federated learning operates through the diagram to train models in collaboration with the clusters present without the necessity of exposing any raw sensor data, as shown in Fig.2. The sensor nodes securely pass their CH (cheapness, honesty, and high confidence) candidacy ratings back to their respective CHs. As a means of training the initial models, the action of the cluster nodes is to combine these encrypted models to act as local learners. Central hubs do not receive raw data from the CHs; only the changes made to the models. The change to the model is received at the federated learning aggregator and is utilized to update an improved global model in a time-efficient and secure fashion. The updated, improved model parameters are routed back to the CHs, enforcing a better future set of CH evaluations network-wide. This process enables adaptation to changing network scenarios, decreased cost of communications, and increased intelligence and protection of privacy. The federated learning architecture excels in wireless sensor networks where energy consumption, security, and bandwidth are a priority.

Each cluster head utilizes the node-level CH scores acquired to update its own underlying model as w_k^{t+1} expressed in equation 4.

$$w_k^{t+1} = w_k^t - \eta \cdot \nabla L(w_k^t; D_k) \qquad (4)$$

The model weight at the cluster head in round w_k^t, the learning rate η, loss function as ∇L, and local dataset are denoted by D_k, respectively. This allows us to now provide learning within clusters and for users' privacy, by Equation 4.

The aggregation of all the cluster heads into the global federated model can be expressed with equation 5.

$$w^{t+1} = \sum_{k=1}^{k} \frac{|D_k|}{\sum_{j=1}^{k} D_j} . w_k^{t+1} \qquad (5)$$

In this case, w^{t+1} is the updated global model, k is the total number of cluster heads, $|D_k|$ is the data size for the CH k, and w_k^{t+1} is its updated weight in equation 5. To ensure fair treatment of different clusters, here apply weighted averaging.

The cost of communication for the CHs transmitting model changes to the aggregator can be estimated using equation 6.

$$C_{comm}(k) = \lambda \cdot (\mid w^{t+1} \mid + H_{enc}(w^{t+1})) \qquad (6)$$

In this case, $C_{comm}(k)$ is the communication cost for the CH k, $\mid w^{t+1} \mid$ is the size of the model parameters, H_{enc} is the overhead of encryption, and λ is the energy per bit sent using equation 7. This ensures that the federated aggregation is communication-efficient.

Reinforcement Learning for CH Rotation and Routing

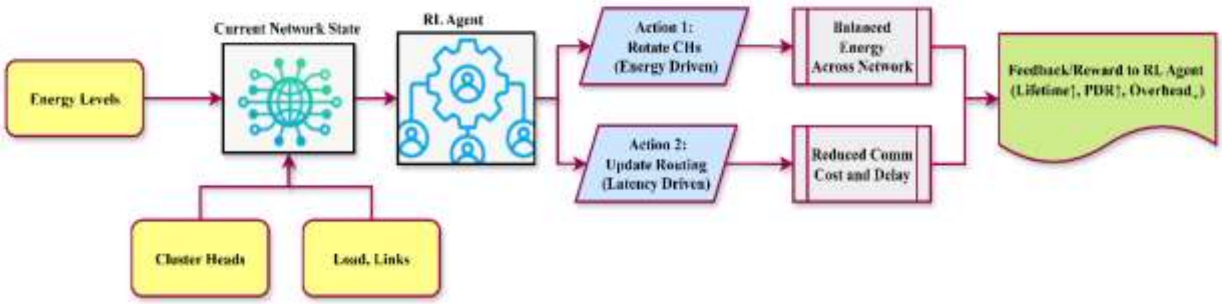

Fig.3. Representation of RL for CH Rotation and Routing

From Fig.3, it can be observed how RL can manage the routing and rotation of CH during dynamic times. The process begins with an assessment of the current state of the network, including: remaining node energy; CH placement; communication load; and link quality. Once the RL agent has received a representation of the state, it uses policy and value functions to determine what action to take next. There are two main actions: CH rotation for energy balancing, and the optimization of routing for latency and cost. Time on network, packet delivery ratio (PDR), communication overhead, and latency are the metrics that demonstrate the results of CH rotation and routing optimization. They are perceived by the RL agent to provide rewards for iteratively improving its dynamic decision-making policy. By being adaptive, RL achieves extended sensor network life by optimizing energy efficiency versus network performance.

This equation 7 incorporates energy, connections, and routing scenarios states S_t of reinforcement learning.

$$S_t = \left[E_{avg}(t), D_{CH}(t), LQ_{avg}(t), H_{delay}(t)\right] \qquad (7)$$

It contains average residual energy $E_{avg}(t)$, mean link quality as $LQ_{avg}(t)$ mentioned in equation 7, the CH distribution metric as $D_{CH}(t)$and average hop delay. As $H_{delay}(t)$ This defines the state vector for the RL agent's view of the network.

Equation 8 gives a simple rule of thumb for value updates for the RL agent's actions in CH rotation and routing choices.

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right] \qquad (8)$$

In this context, $Q(s,a)$is the value of acting at state a, r is the instantaneous reward, α is the learning rate, γ is the discount rate, with s' being the next state as a' in this equation 8. It ensures the best policies can be learned in an adaptive way.

GNN-Based CH Placement Optimization

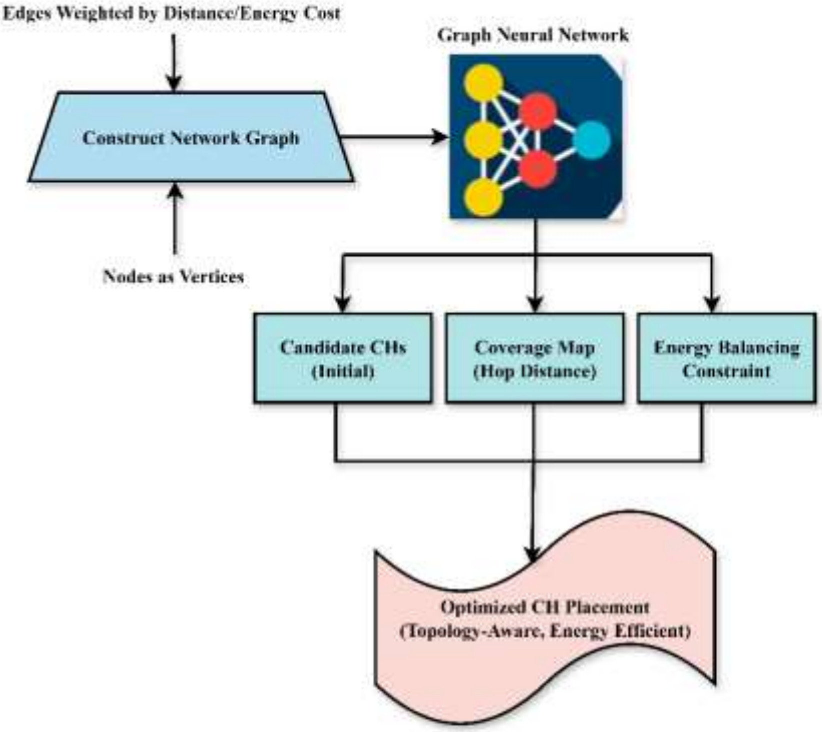

Fig.4. Placement Optimization Process by GNN

Graph Neural Networks optimize the location of cluster heads with the topology of the network, as illustrated in Fig.4. The WSN is represented as an edge-weighted graph using either distance or energy cost as edge weights, where the nodes represent the vertices and lines are the edges. The GNN performs aggregation over both the node characteristics of the graph and the neighbours to generate a topology-aware embedding. This format allows for the assessment of possible CHs: coverage maps, hop distance, reachability, and energy balancing constraints. GNNs indicate structural constraints and unnecessary overlaps and are a more intricate method to capture dependencies than previous algorithms. This leads to better connectivity, workload balance across nodes, and essentially energy efficiency from the optimized placement method. The GNN deals with the topology of the network and, in so doing, guarantees scalable and adaptable clustering without the difficulty of reconfiguration in dense and dynamic deployments. In terms of effective lifetime, stability of performance, and ultimately real-world deployments of the WSN, this methodology vastly improves the operational efficiency.

The WSN can be represented 9 as a weighted graph in this equation $G,$ representing both the topology and the announcement communication costs.

$$G = (V, E, W), \quad W_{ij} = \frac{d_{ij}}{E_{res}(i) \cdot LQ_{(i,j)}} \qquad (9)$$

Here, V refers to the set of nodes, E represents the set of edges, W_{ij} signifies the edge weight as W between the nodes i and j, d indicates the distance from the origin in degrees, $E_{res}(i)$ defines the residual energy of node i, and $LQ_{(i,j)}$ dictates the quality of the communication channel from node i to node b by equation 9, topology codes some notion of energy-awareness.

Utilizing neighbouring features, this equation 10 develops embeddings of nodes by $h_i^{(l+1)}$.

$$h_i^{(l+1)} = \sigma.\left(W^{(l)}.\frac{1}{|N_i|}.\sum_{j \in N(i)} h_i^{(l)} + b^{(l)}\right) \qquad (10)$$

Specifically, σ is the activation, $W^{(l)}$ and $b^{(l)}$ refers to the set of learnable parameters, and $N(i)$, is the neighbour set of nodes i to layer l. As a result of this embedding given in equation 10, topology is considered while determining where to assign CHs.

Firefly–Gradient Descent Hybrid Optimization

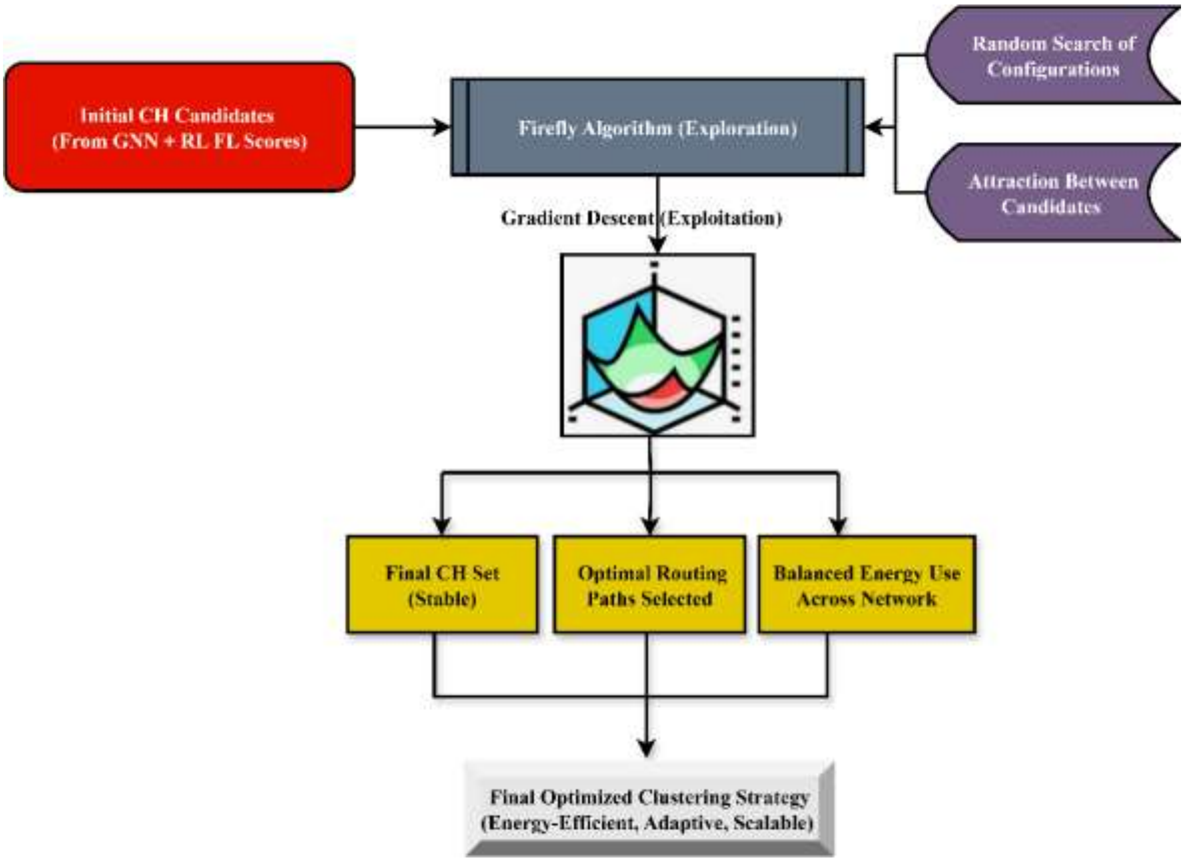

Fig.5. Firefly–Gradient Descent Hybrid Optimization

Fig.5 depicts a hybrid optimization method that unites the exploration strength of the Firefly Algorithm and the accuracy of Gradient Descent when successfully formalizing CH and routing configurations. First, CH candidates are evaluated by RL, FL, and GNN scoring. The journey involves simulating a set population of CH candidates via Firefly Algorithm iterations to guarantee diminishing early convergence and retention of diversity in the exploration of the search space, specifically, calculations driven by attraction-based movements. Additionally, with the shotgun of confirmed CH candidates, next apply the Gradient Descent approach for parameter optimization guided towards reducing energy consumption and improving routing efficiency. Therefore, this two-phase technique provides accuracy and reliability by amalgamating global exploratory abilities with local exploitability. Consistent set of CH, energy-efficient routing paths, and evenly distributed load over the network may result. Promoting durability towards dynamic changes, scalability in larger WSN, and convergence are all facilitated by this hybrid method. Thus, an adaptive and energy-efficiency clustering method was offered. Here, the NL is prolonged, and stability of network's efficiency is maintained by this adaptive and energy-efficiency clustering method.

Equation 11 facilitates the global exploration by xi^{t+1} for the CH/routing search space by selectively updating the positions of candidate solutions based on attraction.

$$xi^{t+1} = xi^t + {\beta_0}^{e-\gamma rij^2}(xj^t - xi^t) + \alpha_t.\varepsilon_i^t \qquad (11)$$

In equation 11 xi^t designates the solution vector of firefly i found at iteration j, xj^t indicates a neighbor that is brighter, β_0 is base attractiveness, α_t refers to the light absorption coefficient, rij^2 stands for the Euclidean distance between solutions, xi^t indicates the amplitude of randomization, and ε_i^t indicates a random vector. This is implemented to reduce the potential of solutions that lead to local minima while optimizing for CH/routing configurations, facilitate exploration of the population, and retain diversity.

For the optimization, whatever strategy of Firefly and GD, this equation 12 measures potential combinations of solutions that they may optimize regarding energy, coverage distance, and load balance.

$$F(x) = \lambda_1 \sum_{c \in CH_{(x)}} \frac{1}{E_{res}(c)} + \lambda_2 \sum_{u \in V^{c \in CH_{(x)}}} min\, d(u,c) + \lambda_3 Var_{c \in CH(x)}(Lc) \qquad (12)$$

Variables in Equation 12 are for the cost function used are $E_{res}(c)$ residual energy; $d(u,c)$ distance node u from CH c; (Lc) load at CH; $\lambda_{1,}\lambda_{2,}\lambda_3$ trade-off weights; and $F(x)$ indicates the cost of solution x. The equation output here provides the benefits of measures of energy efficiency, coverage, and load balancing to guide optimization.

Algorithm 1: AI-FGDHO for WSN Clustering and Routing

```
Input: $N$ nodes $V = \{1, \dots, N\}$, adjacency $A$, residual energy ${E_{res}}^{(0)}$, link quality $LQ(i,j)$,
    hyperparameters $T$, $T_{FL}$, $L$, $M$, $P$, $I_{FF}$, $I_{GD}$, $\eta_{node}$, $\eta_{FL}$, $\eta_{GD}$, $\lambda, \alpha, \gamma, \varepsilon$
Output: Final CH set $CH^{(T)}$, routing table $R^{(T)}$, global model $W^{(T)}$

Initialize node models ${w_{node}}^{(0)}$, CH models ${w_K}^{(0)}$, global model $W^{(0)}$
Initialize RL Q-table or policy $\pi\_\varphi$, GNN params $\Theta^{(0)}$
Initialize firefly population $\{{x_p}^{(0)}\}$ for candidate CHs/routing
$for\ t = 1\ to\ T\ do$
    $for\ each\ node\ i \in V\ do$
        Compute normalized energy $E_{norm}(t)(i)$
        Predict local CH score $P_{CH}(t)(i)$ using $w_{node}(t-1)$
    $end\ for$
    Federated Learning: CHs aggregate local updates to update $W^{(T)}$
    Construct weighted graph $G^{(t)}$ using $E_{res}(t-1)\ and\ LQ$
    Compute GNN embeddings $h_i(L)$ with multi-head attention
    Compute combined CH scores $S_{comb}(t)(i) = \omega_1 P_{CH} + \omega_2 \sigma(h_i(L)) + \omega_3$ proximity
    RL selects action $a_{(t)}$ for CH rotation/routing update
    Firefly exploration: update $\{x_p\}$ using brightness attraction
    Gradient Descent refinement on top solutions $\theta \leftarrow \theta - \eta_{GD}\ g/\sqrt{v} + \varepsilon$
    Select final $CH^{(T)}$ and routing $R^{(T)}$ from best refined solution
    Evaluate network performance and compute RL reward $R^{(T)}$
    Update Q-table/policy $\pi\_\varphi$ and node energies $E_{res}(t)$
    Check termination: fraction nodes dead or $t = T$
end for
Return $CH^{(T)}$, $R^{(T)}$, $W^{(T)}$
```

For an adaptive, and energy-efficient clustering in WSN, various AI components are integrated by this method. The connectivity, connection quality, and normalized residual energy are the main parameters that must be considered while computing CH candidacy scores. This CH candidacy scores are computed from node-level models. Using the federated learning, the CH candidacy scores are aggregated by the CH, as shown in Algorithm 1, and this may ensure data privacy and also allow the CH to collaboratively modify models. To input all three input parameters into a weighted graph representing the WSN, as well as taking into account node connection quality, energy usage, and distance, a Graph Neural Network or multi-head attention will be employed to train a model that outputs topology-aware embeddings capable of improving CH placement decisions across the network. A reinforcement learning agent will optimize and update routing pathways based on performance-based rewards, dynamically rotating CHs as an extension of the routing optimization, and adapting the nodes' energy throughout the routing training process to maximize the life of the WSN. Neighbouring models are evaluated using the firefly algorithm to explore potential global configurations for remodelling CHs and routing configuration possibilities. The best layout will be refined using gradient descent to minimize energy use while maintaining coverage and load limits. Once the global model configuration has been completed, the network will continue this process as scheduling the models, routing pathways, node energetic/energy usage, and CHs are updated or altered. Each iteration will yield messaging for each routing table and energy configuration that optimizes the route, and each must be implemented in the global model configuration. The iterative cycle will produce the new routing tables, the optimization of CHs, as well as new learning on the residual model utilized for the network's continuous operation.

To enable the balance of exploration and exploitation across WSN clustering, the AI-FGDHO framework implements distributed intelligence, multi-agent learning, and hybrid optimization in an effective manner. It combines local scoring, federated aggregation, RL-based rotation, GNN embeddings, and firefly-gradient descent refinement, which provides scalable and energy-efficient CH selection and routing, enhances packet delivery, reduces overhead, and prolongs the overall lifetime of the network.

Experimental Analysis

Through key network metrics, this section will compare the proposed AI-FGDHO framework against three existing clustering techniques: FA-ACO, FA-FL, and LGWO-CS. In dynamic WSN, the way the AI-FGDHO remains adaptable, durable, and energy-aware are analyzed via the simulation with some parameters like network lifetime, energy consumption, packet delivery, latency, coverage, and optimization efficiency.

Dataset Description

The LoRaWAN at the Edge Dataset (LoED) data is collected from nine gateways in a dense urban background, and it is a public dataset. Raw payload data and related gateway metadata are included in this dataset, and it offers a vital data regarding the efficacy of LoRaWAN networks in real-world situations. This LoED allow the researchers in analysing wide range of topics related to data transmission behavior in urban backgrounds, the coverage of a network, and signal strength, among others. Crucial data regarding gateway locations, gateway models, and data statistics for each gateway are given to potential users by the README file [22]. For those interested in exploring the specifics of how LoRaWAN functions in crowded urban environments, the resource also includes a Jupyter notebook and a Python script designed to help in generating basic statistics from the dataset.

Analysis of Network Lifetime (NL)

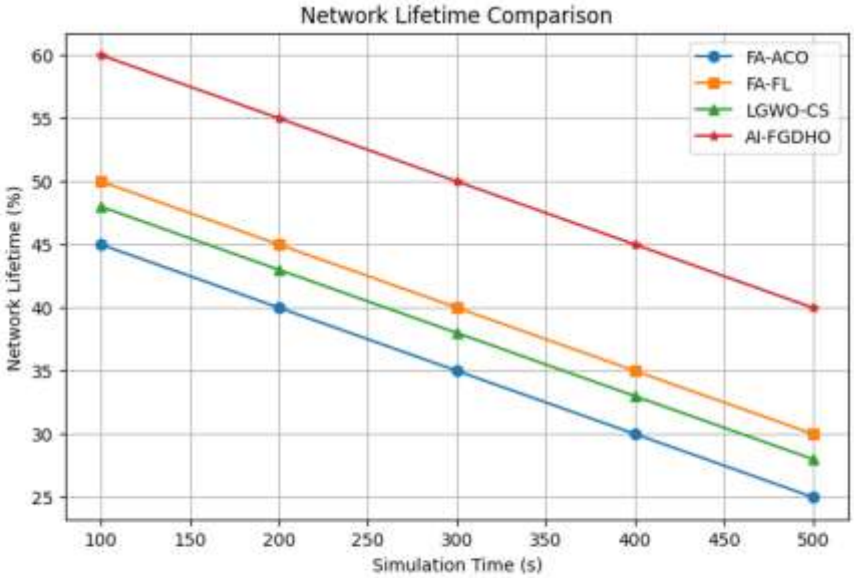

Fig.6. Network Lifetime Analysis

Fig.6 discusses network lifetime, which refers to the duration until most of the nodes deplete their energies. AI-FGDHO is consistently able to deliver its network lifetime beyond FA-ACO, FA-FL, and LGWO-CS as found through these results. This improvement comes from the hybrid optimization method using equation 13, which adapts to a rapidly changing network scenario; rotates the cluster head intelligently, and distributes energy uniformly among nodes. AI-FGDHO is the only algorithm with extended network lifetime, thereby making this methodology scalable to large-scale energy-efficient WSN implementation, which improves performance and reliability.

$$NL = \min_{i \in N}(T_i^{alive}) \qquad (13)$$

Here, (T_i^{alive}) signifies the operational time until energy is exhausted for node i. The network's sensor nodes are designated by N. Equation 13 outputs the system lifetime defined in AI-FGDHO by determining the network lifetime as the minimum time alive across all nodes in the network.

Analysis of Residual Energy Distribution (RED)

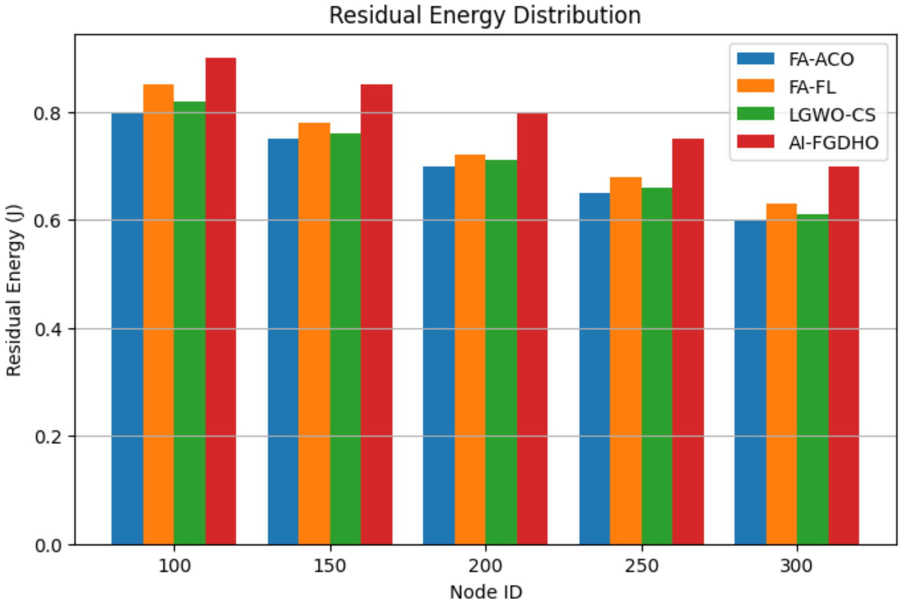

Fig.7. Residual Energy Distribution Analysis

Residual Energy Distribution can be used to observe wasted energy across all sensor nodes, which are analysed in Fig.7. AI-FGDHO displays a better energy zone with the possibility of delaying the degradation of individual nodes as opposed to previous techniques in equation 14. The incorporation of lightweight machine learning at the nodes and federated learning on CH supports adaptive CH selection based on energy zones. This balance tends to assure that energy zones are fairly depleted and hotspot networks are reduced. Because of the stability AI-FGDHO offers to the perception system with the prevention of node failures, the lifetime of the network improves, and the perception continues to perform correctly in dynamic network situations.

$$E_{residual}^{avg} = \frac{1}{N}\sum_{i=1}^{N} E_i \qquad (14)$$

The total number of nodes is denoted by N, while E_i represents the residual energy of node i. The formula determines the average amount of energy as avg that remains as $residual$, which shows how evenly distributed the power is throughout the AI-FGDHO nodes in equation 14.

Analysis of Packet Delivery Ratio (PDR)

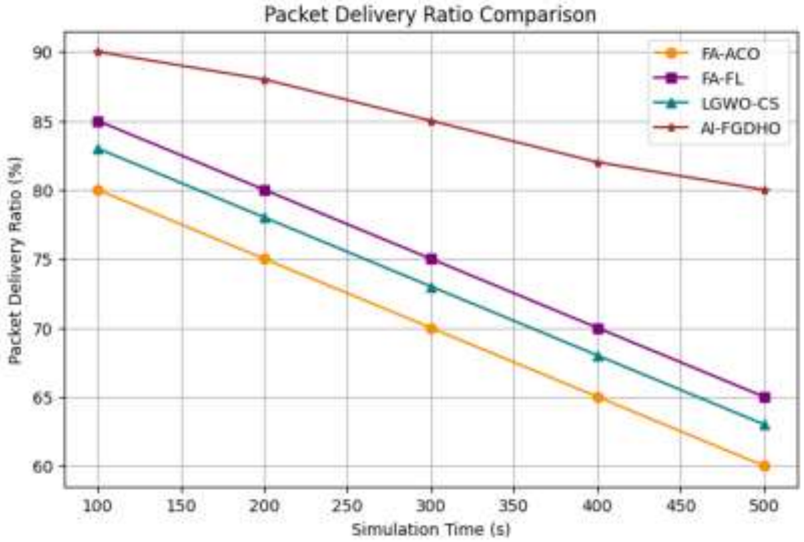

Fig.8. Packet Delivery Ratio Analysis

The packet delivery ratio is the ratio of the number of packets successfully transmitted to the total number of packets in Fig.8. According to the statistics, AI-FGDHO outperforms FA-ACO, FA-FL, and LGWO-CS in terms of PDR over the course of the simulation with no apparent decrease. Equation 15 optimises routing paths using RL, while adaptive CH rotation guarantees network connectivity and minimal packet loss. By reducing link failures, energy-aware clustering when combined with GNN-based placement further enhances data reliability.

Particularly in mission-critical monitoring application systems that depend on complete data supply and timely data delivery in equation 15, a rise in PDR indicates that AI-FGDHO maintains an effective level of communication that is significant.

$$PDR = \frac{\sum_{i=1}^{N} P_i^{received}}{P_i^{sent}} \qquad (15)$$

Node i's transmitted and received packets are indicated by $P_i^{received}$ and P_i^{sent}, respectively. Equation 15 provides an indication of AI-FGDHO's ability to deliver packets while comparing to other methods along the same framework, understanding its role in evaluating data reliability across the network.

Analysis of Communication Overhead (CO)

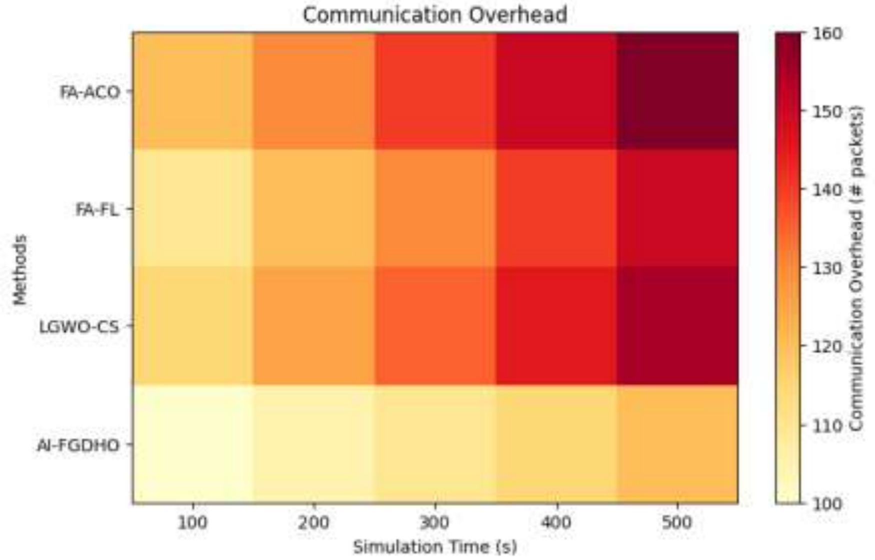

Fig.9. Communication Overhead

The term communication overhead refers to the total number of control packets transmitted across the network, given in Fig.9. When compared to traditional techniques, AI-FGDHO has lower communication overhead, allowing for improved network efficiency. Through federated learning and localized evaluation of CH candidates, nodes eliminate raw data transmissions. The hybrid Firefly-Gradient Descent optimization process additionally results in the reduction of unnecessary routing updates. Such reductions in communication overhead allow AI-FGDHO to save energy and open up bandwidth for critical data communication, thereby increasing network lifetime, improving PDR, and decreasing latency, which is quite appropriate for constrained resource WSN environments by CO in equation 16.

$$CO = \sum_{j=1}^{N} C_i^{control} \qquad (16)$$

The total number of control packets sent by node i is denoted by $C_i^{control}$. This is indicative of a measure of energy and bandwidth efficiency by AI-FGDHO in a comparison with clustering protocols in a general sense, while acting as a total measure of communication overhead in Equation 16.

Analysis of Average Latency / End-to-End Delay (D)

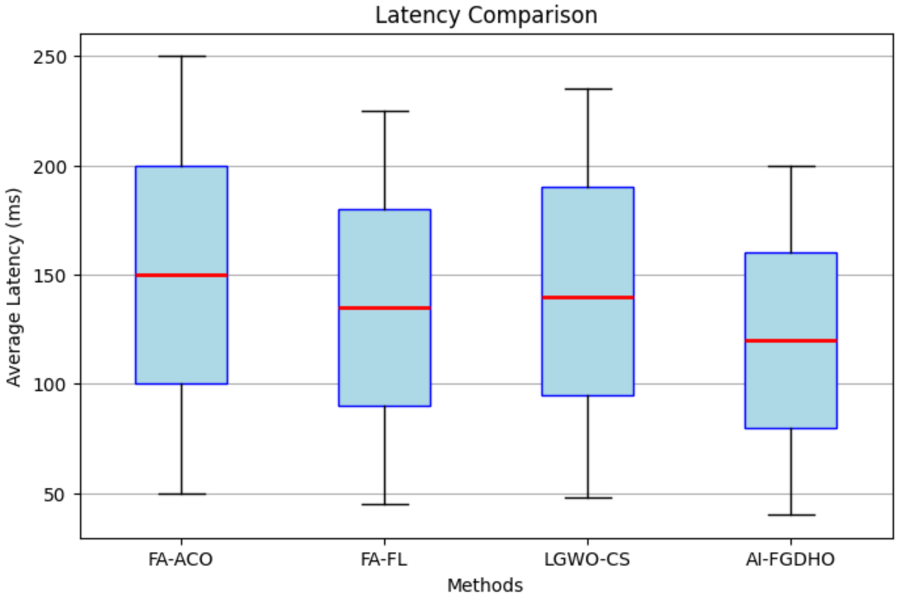

Fig.10. Latency Analysis

Average latency is the total amount of time it takes a packet to transmit from the packet source to the final destination, as shown in Fig.10. In terms of reducing average latency, AI-FGDHO is superior to FA-ACO, FA-FL, and LGWO-CS over a variety of hop counts. This is accomplished in part by using reinforcement learning for adaptive routing and placing efficient CHs using GNNs that not only reduce congestion along with long paths, thus reduce average latency when compared to other methodologies. When considering the different applications of real-time monitoring, reduced latency means data is delivered quickly, and rates of response improve.

Timely information is communicated without compromising reliability or communicational efficiency; therefore, evidence is provided that AI-FGDHO saved energy and improved network performance in equation 17.

$$D_{avg} = \frac{1}{P}\sum_{j=1}^{p} d_j \qquad (17)$$

In equation 17, d_j represents the packet total, and P symbolizes the end-to-end delay for packet p. This formula 17 estimates average latency to measure the speed gains j resulting from AI-FGDHO's improved packet routing.

Analysis of Cluster Head Rotation Frequency (CHR)

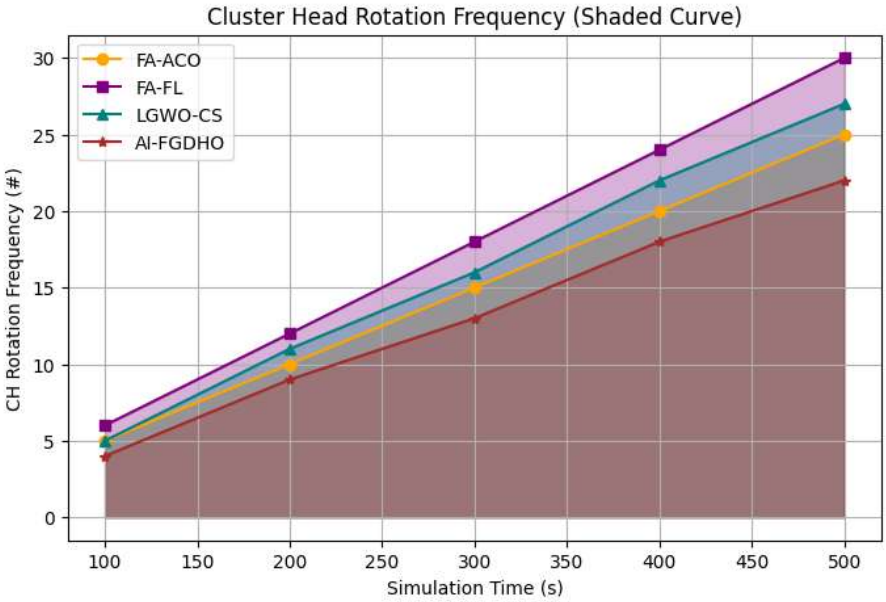

Fig.11. Cluster Head Rotation Frequency Analysis

The Cluster Head Rotation Frequency is a metric defined strategically for effectively creating a continuous supply of energy that reflects the frequency with which the leadership positions rotate. AI-FGDHO structured optimized CH rotation to eliminate unnecessary rotation while enhancing energy fairness in Fig.11. The optimized CH rotation uses node energy and network conditions to create dynamic schedule decisions embedded in the reinforcement learning process to smoothly avoid spikes in energy depletion and extend the life of the network.

AI-FGDHO's intelligent and adaptive clustering mechanism shows how to be effective in dynamic WSN situations expressed through balanced CH rotation by equation 18, to avoid overloading of single-nodes, minimize communication overheads, and ensure there is no degradation in network coverage.

$$CHR = \frac{\sum_{t=1}^{T} Rt}{T} \qquad (18)$$

At time interval T, Rt conveys the number of CH rotations, and T encapsulates the amount of time spent in simulation in equation 18. By measuring the average frequency of rotations, AI-FGDHO can highlight the energy-awareness of the adaptive of CH scheduling.

Analysis of Coverage Ratio / Node Connectivity (CR)

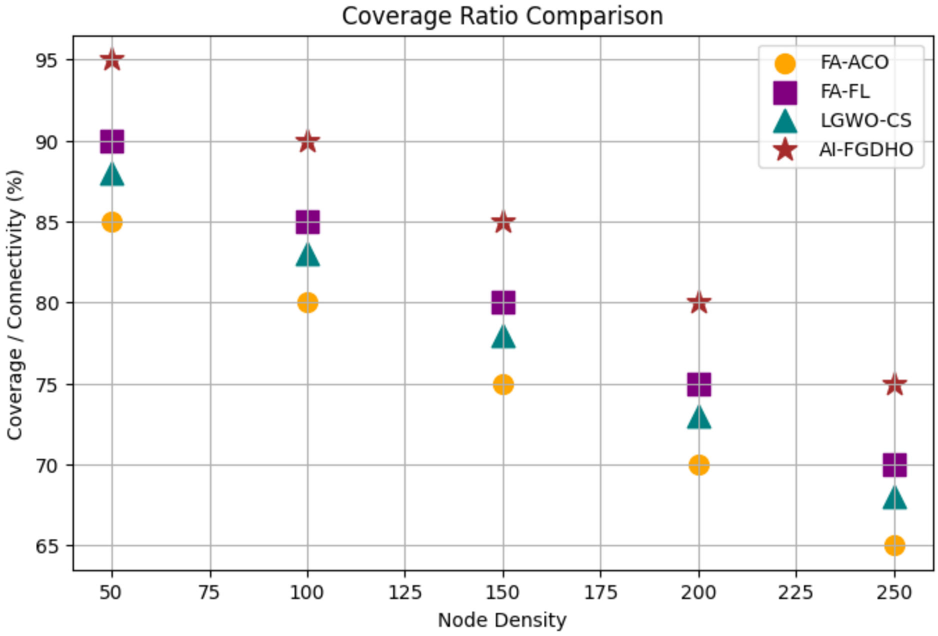

Fig.12. Coverage Ratio Analysis

The Coverage Ratio in Fig.12 indicates the monitored area of the network as well as the connectivity of each node. AI-FGDHO maintains a higher coverage ratio than all methods (FA-ACO, FA-FL, and LGWO-CS) for any node density. The aim of GNN-based CH placement is to minimize redundancy and maximize reachability by the optimal placement of cluster heads in the sensor field. Nodes maintain connectivity for longer due to energy-efficient routing and adaptive energy-aware clustering management. The greater coverage ratio CR through equation 19 achieved means AI-FGDHO will more consistently monitor and sense the environment, which is essential to applications with dense or large-scale WSN deployments, and still maintain the robustness of the network topology.

$$CR = \frac{\mathrm{N}_{covered}}{N_{total}} \qquad (19)$$

$\mathrm{N}_{covered}$ signifies the number of actively monitored or connected nodes, while it is displayed by N_{total} the entire number of deployed nodes. This ratio CR represents AI-FGDHO's ability to continue connectivity and measure sensing efficiency, and is indicative of coverage in a network in equation 19.

Analysis of Convergence Time / Optimization Efficiency (CT)

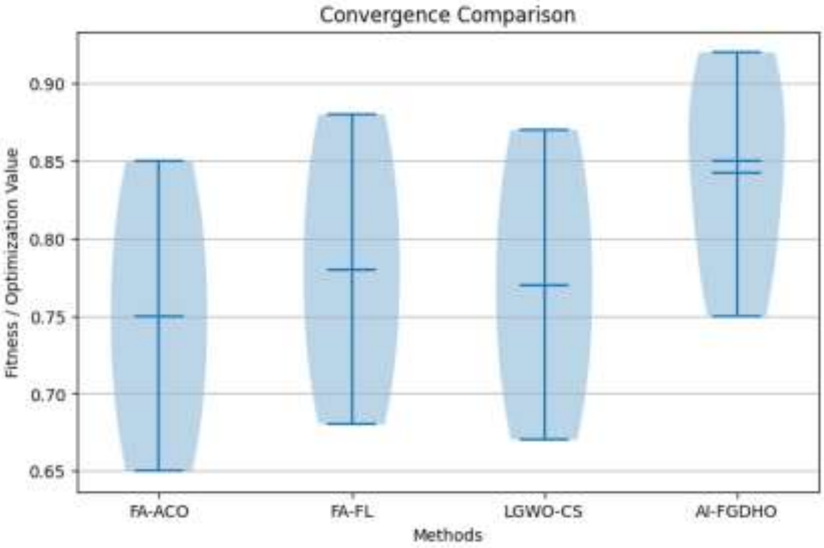

Fig.13. Convergence Time / Optimization Efficiency (CT)

The optimization algorithm is evaluated by speed (time) and stability, shown in Fig.13, and the incorporation of global exploration through the Firefly Algorithm and local exploitation through Gradient Descent allows AI-FGDHO to converge more rapidly than traditional methods. Early convergence allows for quick and cost-effective selection of optimal CHs and routing paths. This efficiency keeps latency and PDR high while reducing the energy required for needless iterations, and enhances overall network responsiveness.

For large-scale, dynamic WSN applications, AI-FGDHO makes the most sense, and the hybrid optimization yields solutions faster, more stable, and energy-aware by CT in equation 20.

$$CT = min\{ t: | f(t) - f^* | \leq \epsilon \} \qquad (20)$$

The fitness value at iteration t is presented as $f(t)$, and the optimal solution is indicated as f^* and ϵ denotes tolerance. This metric determines the rate of convergence of AI-FGDHO to the optimal clustering and routing in equation 20.

By achieving a higher packet delivery ratio, lower latency, balanced residual energy, extended network life, lower communication overhead, it is clear through the results that AI-FGDHO is superior to traditional methodologies, without exception. The hybrid AI-based optimization is demonstrated by high coverage, optimal CH rotation, and increased convergence speed. In conclusion, AI-FGDHO presents a reliable, energy-efficient, and extensible framework that can be useful in dynamic WSN environments.

Conclusion and Future Work

To provide an adaptive and energy-efficient clustering solution in wireless sensor networks and present the AI-FGDHO framework, short for Artificial Intelligence-enhanced Firefly-Gradient Descent Hybrid Optimization. The proposed framework effectively mitigates energy consumption whilst minimizing communication overhead and improving the reliability of the network through a novel technique, which incorporates lightweight node-level machine learning and federated learning at CHs with reinforcement learning for dynamic CH rotation and routing, and Graph Neural Networks for topology-aware CH placement. The simulation was conducted to compare the AI-FGDHO model with conventional clustering methods like FA-ACO, FA-FL, and LGWO-CS using crucial parameters like NL, RED, PDR, latency, coverage ratio, and convergence efficiency. From the outcomes of the simulation, it is clear that the suggested AI-FGDHO model executes better than the conventional clustering methods by NL, RED, PDR, latency, coverage ratio, and convergence efficiency. Thus, secure, scalable, and privacy-preserving decision-making processes in evolving network backgrounds is obtained by integrating global exploration and local exploitation in a hybrid optimization.

Future Works

A heterogeneous sensor network with different energy and processing capacities might be created using this technique. By gathering real-time IoT data for verification and creating adaptive security plans to counteract malicious nodes and possible threats, the framework can be improved. Investigating energy harvesting techniques and multi-objective optimisation algorithms can increase sustainability and operational efficiency. In order to support the development of energy-aware, flexible, and resilient WSN architectures and to better understand the distinctions between simulation and real-world applications of WSN, AI-FGDHO should be used in the field for extensive, real-world operational applications

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