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Hybrid EECS Framework: Reinforcement Learning-Driven Collaborative Sensing with Grey Wolf Optimized Routing for Energy-Efficient Wireless Sensor Networks

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Abstract -Wireless Sensor Networks (WSNs) play a pivotal role in monitoring and data collection across diverse application domains. As these networks scale in size and complexity, the demand for intelligent and energy-efficient sensing mechanisms becomes increasingly critical. This paper presents an enhanced Energy-Efficient Collaborative Sensing (EECS) framework for WSNs that integrates game-theoretic decision making with reinforcement learning and Grey Wolf Optimization (GWO)-based routing. The proposed model is designed to minimize energy consumption while maintaining high quality of service through adaptive and intelligent cooperation among sensor nodes. A key contribution of this work is the Selection Propensity Index (SPI), which guides the optimal selection of sensing nodes based on their dynamic utility and network conditions. In addition, the framework incorporates a Distributed Anticipatory Time-slot Allocation (DATA) algorithm based on reinforcement learning to enable efficient and collision-aware time-slot selection for collaborative communication. To further enhance network performance, GWO-driven neighbor selection is employed to achieve energy-aware and distance-efficient routing. Extensive simulations demonstrate that the proposed hybrid EECS framework significantly outperforms existing methods in terms of energy efficiency, packet drop ratio, throughput, and network stability. Specifically, the model achieves up to 202% improvement in network lifetime, approximately 30% higher throughput, and more than 60% faster operation under full-load conditions

Key Words: Energy efficiency, Grey Wolf Optimization (GWO), reinforcement learning, Selection Propensity Index (SPI), wireless sensor networks.

1. INTRODUCTION

The rapid advancement of the Fourth Industrial Revolution (IR4.0) has significantly increased the demand for intelligent systems capable of collecting, processing, and transmitting large amounts of data in real time. Technologies such as the Internet of Things (IoT) and Wireless Sensor Networks (WSNs) play a vital role in enabling smart environments, industrial automation, environmental monitoring, healthcare systems, and many other applications. WSNs consist of a large number of small sensor nodes that sense environmental parameters
such as temperature, humidity, pressure, and motion, processing and communicating data wirelessly to a base station. In most real-world applications, sensor nodes are deployed in remote or harsh environments and are powered by batteries, making energy efficiency one of the most critical design considerations. Collaborative sensing allows sensor nodes to share information and coordinate their sensing activities, reducing redundant data collection, minimizing unnecessary communication, and ultimately saving energy. Since communication consumes more energy than sensing or computation, reducing transmitted messages significantly improves the overall network lifetime. Despite the advantages of collaborative sensing, several challenges remain: determining how sensor nodes should coordinate in a decentralized network, balancing energy consumption to avoid early battery depletion, and maintaining reliable communication while minimizing latency. To address these challenges, researchers have explored Game Theory, Reinforcement Learning (RL), and metaheuristic optimization in WSNs. This paper proposes a hybrid EECS framework integrating all three approaches for robust and scalable energy-efficient wireless sensor network operation.

2.LITERATURE SURVEY

Koo e tal. [1] introduced a control-theoretic consensus-based time synchronization algorithm for industrial WSNs, offering rapid convergence and high reliability. Osamy et al. [2] presented the Intelligent Data Collection Technique (IDCT) for

IoT-enabled heterogeneous WSNs, integrating machine learning with dynamic clustering to optimize data gathering and reduce energy consumption. Alkalemia. [3] proposed an energy efficient path planning strate gyusing multiple mobile sinks to collect data from sensor nodes, demonstrating significant improvementsin energy savings and network lifetime. Samara etal. [4] surveyed energy-efficient protocols for WSNs, categorizing them by routing mechanisms and data aggregation techniques. XiaoYan etal. [5] proposed a game theory- based energy-efficient clustering algorithm for WSNs. None of the existing approaches combine game theory, reinforcement learning, and GWO-based routing.

3.EXISTING METHOD

The existing game-theory based energy-efficient collaborative sensing model for WSNs uses a non-cooperative game model where each node evaluates its utility based on residual energy, distance from base station, number of neighbouring nodes, and anticipated energy consumption. The game G is defined as G = {N, S, U} where N is the set of players (IoT devices), S is the set of strategies $\{S_L, S_H, S_{CS}, S_{NS}\}$ representing low-resolution sensing, high-resolution sensing, collaborative sensing, and no sensing respectively, and U is the utility function providing payoffs based on chosen strategies.

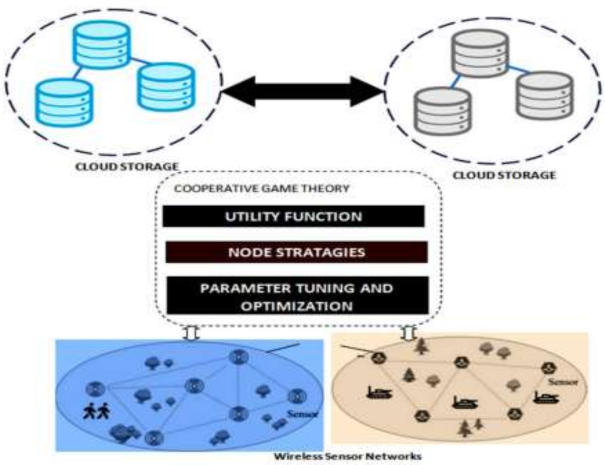

Fig 1: Block diagram of the existing game-theory-based energy efficient sensor network model

The utility function for device i using strategy S on task j is defined as:

$U(i,S,j)=w_1\times A_i(s)-w_2\times E+w_3\times COH_i(s)+w_4\times C(i,S,j)$----→ (1)

where $A_i(s)$ is sensing accuracy, E is energy consumed, $COH_i(s)$ is communication overhead, and C(i,S,j) is the collaborative sensing benefit.The Nash Equilibrium ensures that no node has an incentive to unilaterally change its decision once a stable configuration is reached.

Disadvantages of Existing Method: The existing method suffers from random neighbor selection leading to suboptimal routing and energy waste. Energy imbalance occurs as some nodes are used too frequently.Reinforcement learning convergence is low, causing in efficient routing initially. Indense networks, collisions increase and energy drains faster, reducing network lifetime.

4.PROPOSED METHODOLOGY

The proposed Hybrid EECS-GWO-RL framework enhances the existing EECS model by integrating Grey Wolf Optimization (GWO) for intelligent neighbor selection and routing. The framework operates through the following key components:

Selection Propensity Index (SPI):

A novel parameter, the Selection Propensity Index (SPI), is defined for each node by considering how each node evaluates its utility against potential collaborations. The SPI of node i is the average utility when collaborating with all other nodes:

$SPI_i=(1/|N|-1)\times SU(i,S,j)$,jÎN,j¹i-------→(2)

The SPI uses min-max normalization to convert utility values to a range [0, 1]. A higher SPI indicates a more favorable strategy. Nodes with higher SPI tend to collaborate more, while nodes with low SPI are more energy-efficient when operating independently.

Distributed Anticipatory Time-slot Allocation(DATA): The DATA algorithm is a reinforcement learning-based distributed time-slot selection algorithm. Each node independently selects time slots using an-greedy exploration strategy.

The Q-value for the chosen time slot is updated using the Bellman equation:

$Q(i,S,j)=(1-a)\times Q(i,S,j)+a\times[U(i,S,j)+g\times max_{j'}Q(i,S,j')]$---→(3)

where is the learning rate and is the discount factor. The exploration rate decreases gradually over time, shifting the balance from exploration to exploitation. This ensures collision-aware time-slot selection for collaborative communication.

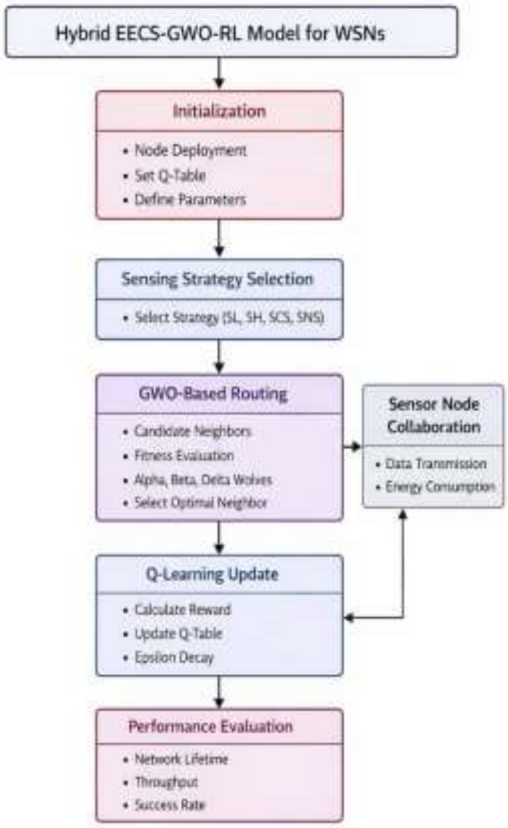

Fig 2: Flow of Proposed Method

GWO-Based Routing:

Grey Wolf Optimization (GWO) is integrated into the EECS routing phase to replace random neighbor selection with an intelligent, fitness-guided routing strategy. The algorithm imitates the leadership hierarchy and cooperative hunting mechanism of grey wolves. Candidate neighbours are treated as search agents evaluated through a multi-metric fitness function considering residual energy.The wolf hierarchy consists of alpha (bestsolution), beta,delta,and omega wolves. The iterative position update mechanism of alpha, beta, and delta wolves guides routing decisions toward high-quality paths, ensuring convergence toward energy-efficient communication routes. This reduces unnecessary energy expenditure and improves network stability.

Hybrid Integration:

The proposed model combines game-theoretic decision making, reinforcement learning-based time-slot allocation, and GWO-based routing. Game theory enables strategic sensing decisions; reinforcement learning enables adaptive learning from previous experiences; and GWO ensures energy-aware, distance-efficient routing. This hybrid approach enhances intelligent coordination among sensor nodes and significantly improves network lifetime and throughput.

5.RESULTS AND DISCUSSION

The proposed Hybrid EECS framework was implemented and simulated in MATLAB R2022b. Performance was evaluated against the existing game-theory based EECS method across four key metrics: average reward, final energy levels, average SPI, and collaboration success rate.

Average Reward Over Time: The proposed methods how scalar advantage in stability and resilience. While both methods begin at similar performance levels, the existing approach experiences a sharp collapse around the midpoint, with rewards plunging dramatically and remaining low. In contrast, the proposed method maintains a relatively steady reward
trajectory with only minor fluctuations, demonstrating significantly greater robustness to changing conditions.

Final Energy Levels of Nodes: The proposed method consistently maintains lower and more efficient energy usage compared to the existing approach. The consistency across nodes implies that the proposed method distributes workload more evenly, preventing energy drain imbalances — a critical advantage for prolonging network lifetime.

Average SPI Over Time: The SPI of the existing method drops sharply after a certain time slot, indicating rapid energy depletion and reduced sensing capability. The proposed method maintains a stable and controlled SPI throughout operation, avoiding sudden degradation. This reflects the classic trade-off where the proposed method prioritizes sustained performance over short-lived peaks, resulting in more reliable and predictable system behavior.

Collaboration Success Rate: The proposed method rapidly reaches a higher collaboration success rate and sustains it, while the existing method improves at a slower pace. This indicates better coordination and interaction among nodes using intelligent decision-making. The system achieves a 202% increase in network lifetime, 30% higher throughput, and more than 60% faster performance compared to the existing approach.

7.CONCLUSION

This paper presented a Hybrid EECS framework effectively enhancing energy-efficient collaborative sensing in wireless sensor networks by integrating game-theoretic learning, reinforcement learning, and Grey Wolf Optimization-based routing. The combined approach enables intelligent sensing strategy selection and adaptive, energy-aware neighbor routing, leading to improved network stability and resource utilization. Simulation results demonstrate significant gains in network lifetime, throughput, and overall communication reliability compared with conventional methods. The lightweight and scalable design makes it well suited for dynamic and large-scale WSN deployments, providing a robust and practical solution for next-generation energy-efficient wireless sensor network applications.

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