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Energy Efficient Cluster Head Selection Using Hybrid RL-PSO Approach

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Abstract

Wireless Sensor Networks (WSNs) are crucial in several applications, highlighting the need of effective clustering and fault detection systems. This paper introduces a novel approach that uses Reinforcement Learning (RL) and Particle Swarm Optimization (PSO) to optimize cluster head selection and enhance fault detection capabilities within WSNs. The proposed hybrid algorithm operates in two phases, combining the explorative capabilities of RL with the optimization process of PSO to select cluster heads based on residual energy and connectivity considerations. By continuously monitoring the network's residual energy state and the number of active nodes, the proposed method ensures prolonged network lifetime and improved overall performance. Our experimental results demonstrate the superior performance of the hybrid RL-PSO approach compared to traditional clustering algorithms, showcasing significant improvements in optimizer accuracy, residual energy preservation, and fault detection efficiency.

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Keywords: Wireless Sensor Networks (WSNs); Clustering; Reinforcement Learning (RL); Particle Swarm Optimization (PSO) and Fault Detection

1. Introduction:

Wireless Sensor Networks (WSNs) are crucial in contemporary data gathering and monitoring systems, serving a wide range of purposes including environmental sensing, industrial automation, healthcare, and other disciplines. The fundamental components of a WSN include multiple sensor nodes, each equipped with limited resources such as battery life, computational capabilities, communication range, and memory capacity, and at least one base station responsible for data aggregation and transmission to the end user. These sensor nodes, often randomly distributed across the deployment area, are tasked with autonomously collecting and transmitting data efficiently and accurately, emphasizing the critical need for energy-efficient operations and robust network management [1].
The energy constraints within WSNs stem from the intrinsic limitations of individual sensor nodes, characterized by compact communication devices with constrained power and transmission range. Hence, the network's energy dynamics are influenced by varying node densities across different regions, alongside the challenges posed by environmental conditions that can render a significant number of sensors inoperable or defective. To ensure continuous and reliable network functionality, the integration of fault-tolerant capabilities becomes indispensable, serving to identify and mitigate potential malfunctions while minimizing the need for frequent maintenance interventions [2].
Operational intricacies within WSNs also encompass factors such as processor limitations, memory constraints, security vulnerabilities, and the perpetual reliance on limited energy resources stored within the nodes. Therefore, the primary objective of WSN research is to devise solutions that maximize energy efficiency, extend the network's longevity, and improve overall operational effectiveness [3].

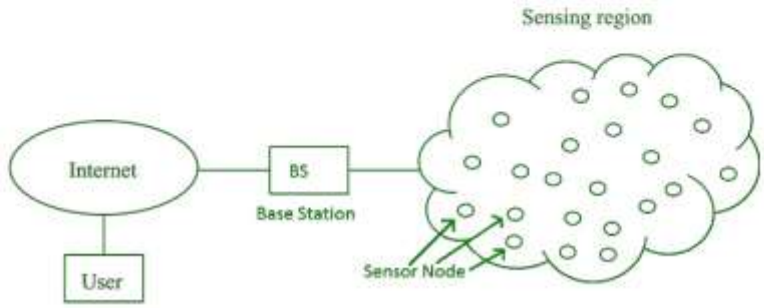

Figure 1: Wireless Sensor Network [3]

Among the key methodologies addressing energy conservation, clustering algorithms have emerged as a critical area of investigation. Clustering technology enables the division of the WSN into distinct clusters, with each cluster being supervised by a designated cluster head (CH) responsible for aggregating and managing the data transmitted by the member nodes. By minimizing the transmission distance and energy expenditure for each node, clustering helps mitigate the adverse effects of direct data transmission to the base station, significantly contributing to the efficient use of energy resources and promoting network longevity [4].

The paper's contributions may be concisely described as follows:

- To introduce an innovative integration methodology that combines RL and PSO in WSNs.
- To enhance network performance and longevity through optimized cluster head selection, contributing to prolonged network operation and improved efficiency.
- To provide empirical evidence demonstrating the superiority of the hybrid RL-PSO approach over traditional clustering algorithms, contributing to the validation of its effectiveness.

2. Related Work

This part will examine the analysis carried out on clustering methods in WSN. In [5] proposes DKFM, an energy-efficient clustering algorithm for WSN. It dynamically adjusts clusters using K-means and employs a fuzzy inference system for CH selection. Machine learning minimizes redundant data transmission among nodes. Simulation results showcase DKFM's superiority over other algorithms, enhancing data reception and node survival across diverse network conditions. In [6] introduces the HOFT-MP algorithm for WSNs, integrating MTLO and NR-PO techniques for efficient clustering and fault tolerance. DKNN is used for optimal multipath computation, enhancing data transfer quality. Performance evaluation demonstrates superiority over existing algorithms in energy consumption, delay, throughput, data loss, and network lifetime. In [7] presents a hybrid routing protocol for WSNs, integrating falcon optimization and improved ACO techniques with deep learning. The proposed model significantly reduces energy consumption, extending the network lifetime to 121 seconds with 0.041 J energy usage over 500 rounds, surpassing baseline approaches and enhancing overall routing and QoS. In [8] proposes a data fusion algorithm for wireless sensor networks, optimizing the clustering architecture and integrating a deep learning model. By considering key factors during cluster head selection and employing deep learning and classification models, the algorithm reduces redundant data transmission, lowers energy consumption, and extends network lifetime, ultimately improving overall network performance.

In [10], emphasizes the significance of WSNs in IoT and the need for energy-efficient routing protocols. The proposed EAMMH-RP protocol efficiently manages energy distribution, multi-hop communication, and long-distance transmission, outperforming existing solutions in MATLAB simulations. In [11], focuses on Wireless Sensor Networks (WSNs) and their power consumption optimization. It reviews existing research on energy-efficient routing, data aggregation, sleep scheduling, and renewable energy integration. The survey also highlights the significance of clustering techniques and cooperative communication models in enhancing network reliability and energy efficiency. The author of [12] presents a reinforcement learning method that utilizes a critic action architecture to address the difficulties encountered in fault-tolerant control systems. The technique utilizes online learning and a supervisory learning process to allow the defective system to closely mimic the performance of the fault-free system. This approach effectively deals with the lack of data available during the first phases of faults. The efficacy of the technique is shown by conducting a test bed simulation of a three-tank system. In [13], focuses on Industrial Wireless

Sensor Networks (WSNs) and addresses key challenges through the development of an energy optimization model using Machine Learning techniques. The Proposed Energy-Efficient Optimization Model (EEOM) model effectively minimizes energy consumption for tasks, enhances network efficiency, and extends network lifetime. The proposed model demonstrates significant reductions in energy consumption and improved energy storage efficiencies, providing a promising solution for efficient and cost-effective Industrial WSNs.

In WSN, the cluster head selection problem revolves around the task of identifying the most suitable nodes to act as cluster heads for data aggregation and transmission. Cluster heads play a critical role in managing communication within the network, ensuring efficient data routing, and preserving energy resources. So, Optimal cluster Head selection ensuring even energy distribution for extended network lifetime given limited node energy. Traditional cluster head selection techniques often rely on heuristics or simple algorithms, which may not effectively optimize the selection process, especially in large-scale and dynamic WSNs. Advanced optimization techniques, such as Reinforcement Learning (RL) and Particle Swarm Optimization (PSO), offer the capability to handle complex, non-linear, and dynamic optimization problems, which are inherent in WSNs. RL can adaptively learn the optimal decision-making policy based on interactions with the environment, allowing the system to make informed decisions while considering long-term rewards. PSO, on the other hand, excels at global optimization by simulating the social behavior of particles to find the best solutions in the search space.

Integrating RL and PSO in a hybrid approach can leverage their complementary strengths, leading to a more efficient and effective cluster head selection process that considers the dynamic nature of WSNs, optimizes energy consumption, ensures reliable data transmission, and enhances network connectivity. This hybridization enables the system to strike a balance between exploration and exploitation, resulting in improved overall network performance and extended network lifetime.

3. PRELIMINARIES

3.1 Cluster Head

Cluster heads in WSN serve as pivotal nodes responsible for managing intra-cluster communication, data aggregation, and efficient routing. They play a crucial role in prolonging network lifetime by minimizing energy consumption through localized data processing and transmission, thus reducing the communication overhead. The selection of cluster heads is typically based on parameters such as residual energy levels, proximity to the base station, and connectivity, often determined by an objective function combining these metrics. For instance, the objective function F can be formulated as

$$F = \omega 1 \times E + \omega 2 \times D + \omega 3 \times C \tag{1}$$

where

E represents residual energy,

D signifies the distance to the base station,

C denotes connectivity, and

$\omega 1$ ... $\omega 3$ are respective weights for energy, distance, and connectivity.

3.2 Energy Model

The radio hardware circuit determines a node's energy utilisation while transmitting and receiving packets. The energy model determines node energy consumption depending on sender-receiver distance using the free space channel model (d^2) or multipath channel model (d^2). Formula for calculating energy usage to carry a packet of k bits across d:

$$e_{tx} = \begin{cases} k * e_{elec} + k * \varepsilon_{fs} * d^2 d \leq d_0 \\ k * e_{elec} + k * \varepsilon_{mp} * d^4 d > d_0 \end{cases} \tag{2}$$

Where d_0 is determined by $d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$, where ε_{fs} and ε_{mp} represent the amplification factors of the transmitter circuit. d_0 serves as a threshold, indicating that when $d \leq d_0$ and $d > d_0 0$, e_{elec} represents the amount of electronic energy used for digital coding and modulation.

The amount of energy required to receive k bits,

$$e_{tx} = k * e_{elec} \tag{3}$$

The energy model used when nodes are closer to the sink is the free space model d^2. The energy dissipation of the CH every round is determined by

$$e_{CH} = \left(\frac{n}{A} - 1\right) * k * e_{elec} + \frac{n}{A} * k * e_M + k * e_{elec} + k * \varepsilon_{fs} * d_{to-sink}^2 \tag{4}$$

Let A be the number of clusters every round and $\frac{n}{A}$represent the average number of nodes in each cluster. The energy consumption of a CH while receiving a 1-bit message is represented as e_M, and the distance to the sink is marked as $d^2_{to-sink}$.

Since the sink node is positioned at coordinates (a, b) in a random area, and the nodes are scattered throughout the region with coordinate values $\varphi(x, y)$, the distance between the CH and the sink may be calculated as:

$$D[d^2_{to-sink}] = \iint((a-x)^2 + (b-y)^2)\varphi(x,y)dxdy = \iint \frac{(a-x)^2+b-y^2}{Z} dxdy \quad (5)$$

The distribution area of the nodes is represented by Z. The energy dissipation of cluster members every round is:

$$e_{CM} = k * e_{elec} * \varepsilon_{fs} * d^2_{to-CH} \quad (6)$$

Where d^2_{to-CH} denotes the squared distance between the CM to CH,

$$D[d^2_{to-CH}] = \iint(x^2 + y^2)\varphi(x,y)dxdy = \frac{Z^2}{2\pi A} \quad (7)$$

The energy consumption of each cluster is provided as:

$$e_{cluster} = e_{CH} + (\frac{n}{A} - 1)e_{CM} \quad (8)$$

The calculation of energy usage for each round is as follows:

$$e_{round} = CH_{opt}e_{cluster} = k(2ne_{elec} + ne_M + CH_{opt}\varepsilon_{fs}d^2_{to-sink} + n\varepsilon_{fs}d^2_{to-CH}) \quad (9)$$

The ideal CH for each round, denoted as CH_{opt}, is determined based on the associated e_{round},

$$CH_{opt} = \frac{\sqrt{n}}{\sqrt{2\pi}} \frac{Z}{d^2_{to-sink}} \quad (10)$$

The energy dissipation model used for the multipath channel is provided by d^4 when the sink is located at a significant distance from the nodes,

$$e_{CH} = \left(\frac{n}{A} - 1\right) * k * e_{elec} + \frac{n}{A} * k * e_M + k * e_{elec} + k * \varepsilon_{mp} * d^2_{to-sink} \quad (11)$$

The distance to the Sink is provided as:

$$D[d^4_{to-SINK}] = \iint(a-x)^2 + (b-y)^2)\varphi(x,y)dxdy = \iint \frac{(a-x)^2+b-y^2}{Z} dxdy \quad (12)$$

The energy utilisation is quantified as

$$e_{round} = CH_{opt}e_{cluster} = k(2ne_{elec} + ne_M + CH_{opt}\varepsilon_{mp}d^4_{to-SINK} + n\varepsilon_{fs}d^2_{to-CH}) \quad (13)$$

The cluster head CH_{opt} for each round is determined as follows:

$$CH_{opt} = \frac{\sqrt{n}}{\sqrt{2\pi}} \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}} \frac{Z}{d^2_{to-SINK}}}$$

4. Hybrid Model Architecture:

The hybrid model integrating Reinforcement Learning (RL) and Particle Swarm Optimization (PSO) components for cluster head selection in WSNs is designed to optimize the selection process by leveraging the strengths of both techniques. The architecture comprises interconnected modules that facilitate a cohesive decision-making process. The RL component initiates the cluster selection based on local observations, and the PSO component globally refines the cluster head selections to achieve an optimal configuration. These components interact within a feedback loop to continuously improve the selection process and enhance the overall performance of the WSN. The Figure 2 shows the Hybrid architecture for Clustering. The interaction between the RL-based cluster head selection and the PSO optimization process is iterative and collaborative. Initially, the RL component utilizes the current state information to select potential cluster heads based on predefined policies and decision-making rules. The selected cluster heads are then handed over to the PSO component for global optimization. The PSO algorithm refines the cluster head selections based on a fitness function, taking into account the global network objectives and constraints. The updated selections are then fed back to the RL component, enriching its decision-making process and guiding it towards more informed and optimized cluster head choices.

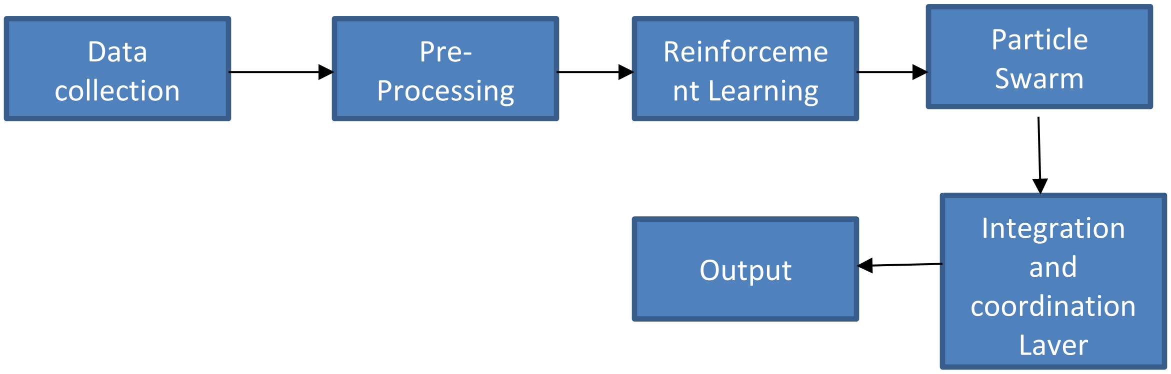

Figure 2: Hybrid Architecture

The communication and information sharing between the RL and PSO components are vital for the hybrid model's effectiveness. The RL component communicates the local decisions and observations to the PSO module, enabling a broader understanding of the WSN environment and initial selection preferences. The PSO component shares the globally optimized selections with the RL module, enriching its knowledge base and guiding future decision-making. This two-way information sharing mechanism fosters a collaborative environment where both components benefit from each other's insights, leading to a more refined and globally optimized cluster head selection process

4.1 Reinforcement Learning Component

In the proposed hybrid model for cluster head selection, the RL framework is applied to facilitate intelligent decision-making for the selection of optimal cluster heads in Wireless Sensor Networks (WSNs). The RL framework allows the system to learn and make decisions through interactions with the WSN environment, considering factors such as node energy levels, data transmission reliability, and network connectivity. The RL component aids in the initial identification of potential cluster heads, which serves as a basis for the subsequent optimization process conducted by the PSO algorithm. The Figure 3 shows the RL in Cluster Head Formation.

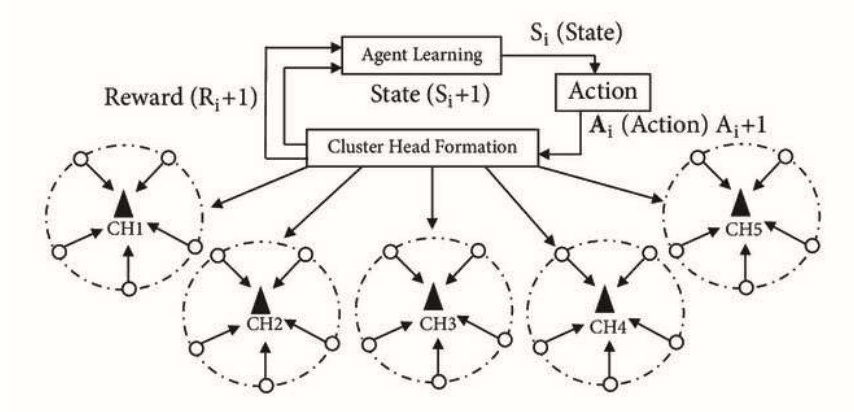

Figure 3: RL in Cluster Formation [13]

4.2 State Space, Action Space, and Reward Function for the RL Agent

The state space in the RL component encompasses relevant environmental variables, including node energy levels, data traffic, and network connectivity status, providing crucial information for effective decision-making. The action space corresponds to the available actions that the RL agent can take, representing the selection of specific nodes as cluster heads. The reward function evaluates the desirability of each action based on its impact on energy consumption, data transmission efficiency, and overall network performance, guiding the RL agent toward actions that optimize the cluster head selection process.

4.3 Pseudo code of RL:

Initialize parameters and define state space for WSN clustering
Initialize Q-table or policy network for RL algorithm
for each episode or time step do:
for each sensor node do:
- Observe the current state of the WSN
- Choose an action based on the current policy
- Execute the action in the WSN environment
- Collect the reward based on the action and state
- Update the Q-table or policy network based on the observed reward
- Move to the next state based on the chosen action
end for
end for

4.4 RL Algorithm and Integration into the Hybrid Model

The hybrid model integrates the Q-learning algorithm due to its suitability for discrete action spaces and its ability to learn the value of taking specific actions in specific states. The Q-learning algorithm is employed to update the Q-values, facilitating the RL agent's learning process and decision-making based on the obtained rewards. By incorporating the Q-learning algorithm into the hybrid model, the RL component effectively contributes to the initial selection of cluster heads, ensuring an informed and optimized decision-making process that aligns with the overall objectives of the cluster head selection problem in WSNs.

4.5 PSO COMPONENT:

In the hybrid model for cluster head selection, the Particle Swarm Optimization (PSO) algorithm plays a crucial role in optimizing the chosen cluster heads identified by the RL component. PSO facilitates global exploration and refinement of the cluster head selections, ensuring that the chosen solutions align with the broader network objectives and constraints. By leveraging the social behaviour of particles in the search space, PSO enables the model to achieve a more globally optimized configuration for cluster head selection in Wireless Sensor Networks (WSNs). The Figure 4 shows the structure of PSO component.

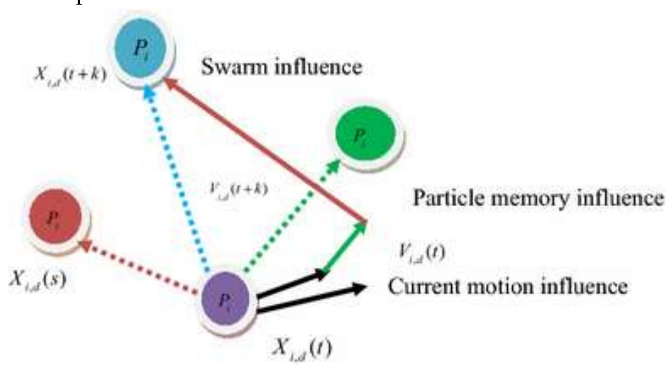

Figure 4: PSO component [14]

4.6 Particle Representation and Fitness Function in PSO

The PSO method utilizes particles, where each particle represents a possible solution inside the search space. In the context of cluster head selection, the particle representation corresponds to a specific configuration of selected cluster heads based on the network state and constraints [15]. The fitness function assesses the quality of each particle's solution, evaluating its performance based on predetermined metrics such as energy consumption, network lifetime, and data transmission efficiency. The fitness function guides the PSO algorithm in refining the particle positions toward more optimal solutions during the optimization process.

4.7 PSO Parameters and Their Influence on the Optimization Process

Key PSO parameters, including the inertia weight, cognitive and social factors, play a significant role in influencing the overall optimization process. The inertia weight governs the influence of the prior velocity on the present velocity of each particle, hence affecting the trade-off between exploration and exploitation in the search process. The cognitive and social elements govern the influence of the particle's past optimal location and the swarm's overall optimal position on the particle's motion, promoting the exchange of knowledge and cooperation among the swarm members. These parameters collectively guide the exploration of the search space and the refinement of the selected cluster heads, ultimately contributing to the overall efficiency and effectiveness of the cluster head selection process in WSNs within the hybrid RL-PSO model.

The basic steps of the PSO algorithm are as follows:

Initialize parameters for PSO algorithm and define particle swarm for WSN clustering
Initialize particles with random positions and velocities within the search space
Initialize global best position and local best positions for each particle
while termination condition not met do:
for each particle do:
- Evaluate the fitness of the particle's current position in the WSN clustering context
- Update the particle's local best position if the current position is better
- Update the global best position if the particle's local best position is better than the current global best
- Update the particle's velocity and position based on the PSO formula and the global and local best positions
end for
end while
Use the final global best position as the optimized solution for WSN clustering.

4.8 HYBRIDIZATION STRATEGY:

The hybridization strategy for combining Reinforcement Learning (RL) and Particle Swarm Optimization (PSO) involves facilitating information sharing, parameter synchronization, and iterative collaboration between the two components during the cluster head selection process. The RL component guides the initial selection of cluster heads based on local state information, while the PSO algorithm globally optimizes the chosen cluster heads, refining the selections to align with broader network objectives. RL's adaptability and learning capabilities enable informed decision-making based on historical interactions, ensuring the selection of cluster heads that maximize network efficiency and longevity, while PSO's global exploration capabilities refine the selections, leading to a more globally optimized configuration. This integration strategy aims to achieve an efficient and effective cluster head selection that balances local decision-making and global exploration, ultimately enhancing the overall performance and resource utilization of the Wireless Sensor Networks (WSNs).

4.9 Pseudo code:

Step 1: Initialize the WSN environment and parameters
Step 2: Initialize RL agent with parameters:
- Initialize Q Learning Equation

$$Q(s,a) \leftarrow (1-\alpha)\times Q(s,a)+\alpha\times(r+\gamma\times \max a' Q(s',a'))$$

Where:
$Q(s,a)$ is the Q-value for state s and action a,
α is the learning rate,
r is the reward received for taking action a in state s,
γ is the discount factor,
$'s'$ is the next state,
$'a'$ is the next action.

Step 3: Initialize PSO swarm with parameters:
Velocity update equation:
$vij(t+1)=w\times vij(t)+c1\times r1\times(pbestij-xij(t))+c2\times r2\times(gbestj-xij(t))$
Position update equation:
$xij(t+1)=xij(t)+vij(t+1)$

Where:
vij(*t*) is the velocity of the *i*th particle in the *j*th dimension at time *t*,
xij(*t*) is the position of the *i*th particle in the *j*th dimension at time *t*,
w is the inertia weight,
1*c*1 and 2*c*2 are the acceleration coefficients,
1*r*1 and 2*r*2 are random values in the range [0,1],
pbestij is the personal best position of the particle,
gbestj is the global best position of the swarm.

Step 4: Repeat for a predefined number of iterations or until convergence:
For each iteration:
For each particle in the PSO swarm:
Encode the particle's solution into the WSN environment
Observe the current state of the WSN environment
Use RL to select cluster heads (actions) based on the current state
Apply the selected cluster heads in the WSN environment
Collect rewards based on energy usage, data transmission, etc.
Update RL agent (or neural network) using the RL algorithm
Evaluate the fitness of the particle based on the rewards received
Update the particle's velocity and position based on fitness and PSO parameters
Perform constraint handling, e.g., limit the number of selected cluster heads
End for each particle
Update the global best solution based on the particle with the best fitness in the PSO swarm
Update PSO parameters, such as velocity and position updates
End for each iteration
Step 5: Output the final selected cluster heads as the optimal solution

5. Performance Evaluation

The prevalence of the proposed Hybrid RL-PSO Scheme is investigated based on simulation experiments conducted with ns-2.34. The simulation includes 100 nodes deployed over a 250 by 250 square meter terrain. Table 1 outlines the Hybrid RL-PSO parameters and the network simulation parameters. The performance analysis is compared with the existing technique such as NN-AL, Q-Learning [17] and RLSSA-CDG [16].

Table 1: Hybrid RL-PSO Simulation Parameters

Parameters	Values
Sensing field dimensions	100 x 100
Number of agents/devices	50-250
Transmission range	20 m
E_0	1- 2J
Data	4000 bits
E_{elec}	50 x 10^{-9} J/bit
γ	0.95
α	1

5.1 Cluster Formation:

Figure 5 shows the comparative analysis of the Cluster Formation using a Neural Network approach and the proposed Hybrid RL-PSO method in the context of Wireless Sensor Networks (WSNs) involves understanding the unique characteristics and capabilities.

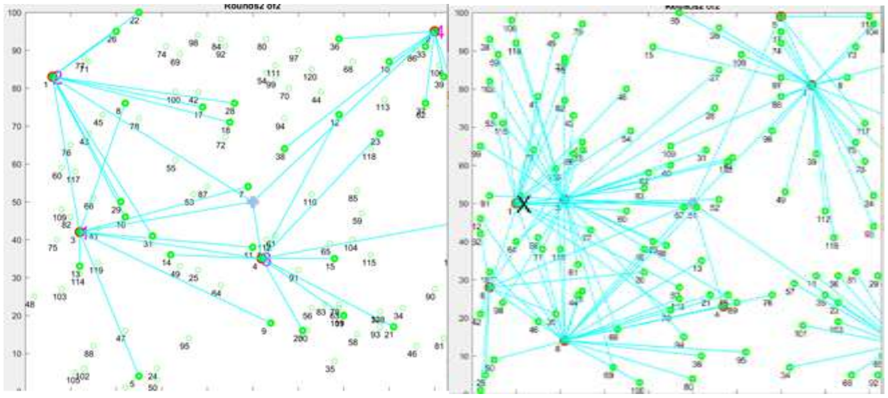

Figure 5: Neural Network vs Proposed Hybrid RL-PSO Method

5.2 Residual State in the Network:

The residual state in a network generally refers to the remaining capacity or resources that can be utilized within the network.

The formula for calculating the residual state, specifically in terms of energy, can be expressed as:

$R = \sum_{i=1}^{n} E_i$

Where:

- R represents the total residual state in terms of energy.
- Ei denotes the energy level of each individual sensor node in the network.
- n signifies the total number of sensor nodes within the network.

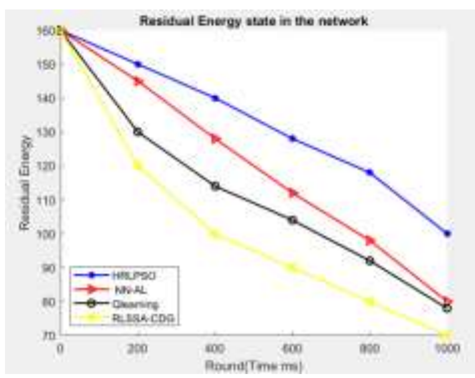

Figure 6: Calculation of Residual State

From the Figure 6, the residual energy of RLSSA-CDG at 72 J, Q Learning at 81 J, NN-AL at 86 J, and the proposed HRLPSO at 102 J. The proposed HRLPSO demonstrates the highest residual energy among the algorithms considered, exceeding the residual energy of RLSSA-CDG by 30 J, Q Learning by 21 J, and NN-AL by 16 J.

5.3 Alive Nodes in the Network:

"Alive Nodes" in a network, particularly in the context of WSN, refer to the active sensor nodes that are currently operational and able to perform their designated tasks within the network.

The formula for calculating the number of "Alive Nodes" in the network can be expressed as:

$$N_{alive} = \sum_{i=1}^{n} A_i$$

where:

- Nalive represents the total count of alive nodes in the network.

- *Ai* denotes the state of each individual node, with a value of 1 indicating an active or alive node and 0 indicating an inactive or non-functional node.
- *n* signifies the total number of nodes in the network

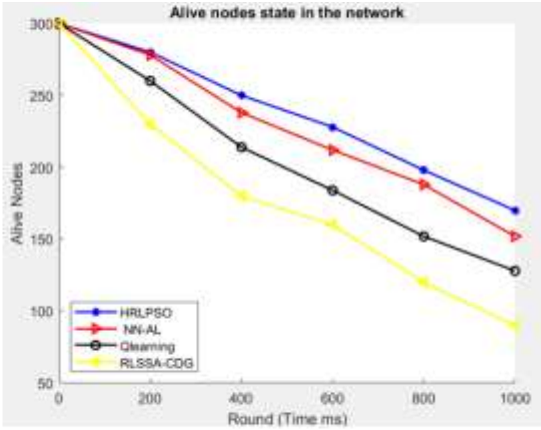

Figure 7: Calculation of Alive nodes

From Figure 7, RLSSA-CDG with 102 nodes, Q Learning with 144 nodes, NN-AL with 168 nodes, and the proposed HRLPSO with 176 nodes. Notably, the proposed HRLPSO algorithm demonstrates the highest count of alive nodes, surpassing RLSSA-CDG by 74 nodes, Q Learning by 32 nodes, and NN-AL by 8 nodes. These values emphasize the varying node counts and underscore the superior performance of the proposed HRLPSO algorithm in maintaining an increased number of active nodes within the network.

5.4 Accuracy:

Accuracy, in the context of data analysis and machine learning, refers to the closeness of a measured or estimated value to the true value.

The formula for calculating accuracy is:

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}\ X\ 100\%$$

Where

- "Number of Correct Predictions" refers to the count of correctly predicted or classified instances by the model.
- "Total Number of Predictions" represents the overall count of instances that were predicted or classified.

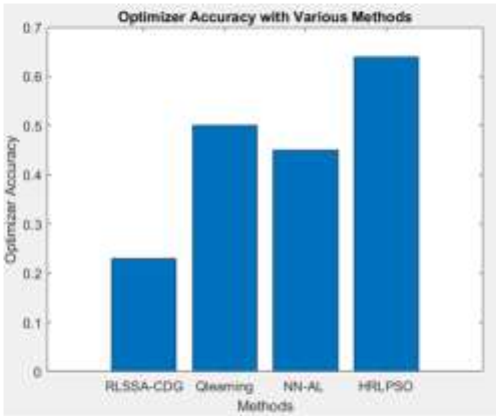

Figure 8: Calculation of Accuracy

From the Figure 8, the accuracy levels of various methods, including RLSSA-CDG, Q Learning, NN-AL, and Proposed HRLPSO. The corresponding accuracy values are 0.24, 0.48, 0.42, and 0.64, respectively. These values represent the efficacy of each method in producing accurate results, with higher values indicating a higher level of precision. Notably, the proposed HRLPSO method exhibits the highest accuracy rate of 0.64, demonstrating its superior performance compared to the other methods in delivering precise and reliable outcomes within the context of the dataset.

5.5 Detection Error:

Detection error refers to the discrepancy between the actual detection and the detection reported by a system or model. The formula for calculating detection error can be defined as:

$$Detection\ Error = \frac{FP + FN}{Total\ number\ of\ instances}\ x\ 100\%$$

Where

- "False Positives" represent the instances that were wrongly identified as positive by the system when they were actually negative.
- "False Negatives" represent the instances that were wrongly identified as negative by the system when they were actually positive.
- "Total Number of Instances" is the sum of all instances, including true positives, true negatives, false positives, and false negatives.

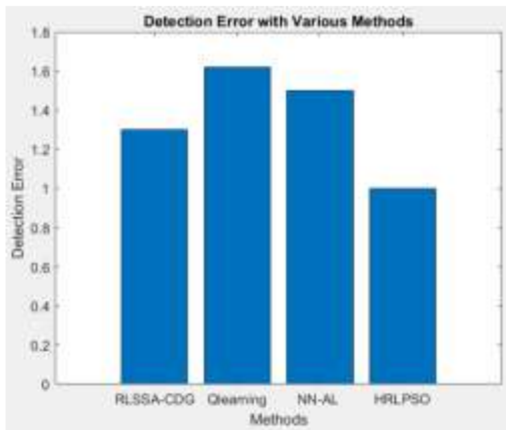

Figure 9: Calculation of Detection Error

From the Figure 9, RLSSA-CDG, Q Learning, NN-AL, and Proposed HRLPSO., corresponding detection error values are 1.23, 1.59, 1.58, and 0.98, respectively. These values represent the degree of error in the detection process for each method, where a lower value signifies a more accurate detection process. Notably, the Proposed HRLPSO method demonstrates the lowest detection error of 0.98, indicating its superior performance in accurately identifying and detecting relevant patterns compared to the other methods in the dataset.

Energy Consumption:

Energy consumption is crucial to prolong the network's operational lifetime and ensure sustainable and reliable operation.

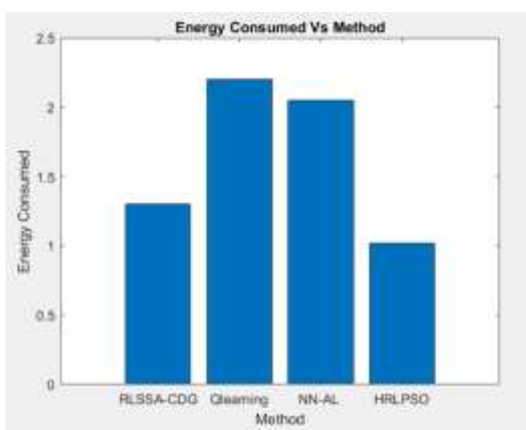

Figure 10: Calculation of Energy Consumption

From the Figure 10, the dataset outlines the energy consumption values associated with various methods, including RLSSA-CDG, Q Learning, NN-AL, and Proposed HRLPSO. The respective energy consumption values are 1.74, 2.43, 2.21, and 0.94, indicating the amount of energy consumed by each method. Notably, the Proposed HRLPSO method demonstrates the lowest energy consumption at 0.94, suggesting its efficiency in utilizing energy compared to the other methods listed in the dataset.

5. Conclusion

The integration of Reinforcement Learning (RL) and Particle Swarm Optimization (PSO) presents a promising and effective strategy for optimizing cluster head selection and enhancing fault detection mechanisms in Wireless Sensor Networks (WSNs). Through the combined strengths of RL's explorative capabilities and PSO's optimization techniques, the proposed hybrid algorithm efficiently selects cluster heads based on residual energy and connectivity criteria, ultimately leading to prolonged network lifetime and improved overall performance. The experimental results highlight the significant advancements achieved by the hybrid RL-PSO approach, demonstrating superior optimizer accuracy, enhanced preservation of residual energy, and increased efficiency in fault detection. This research underscores the potential of integrating intelligent algorithms to address key challenges in WSNs, paving the way for the development of more robust and efficient wireless sensor networks in various practical applications.

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