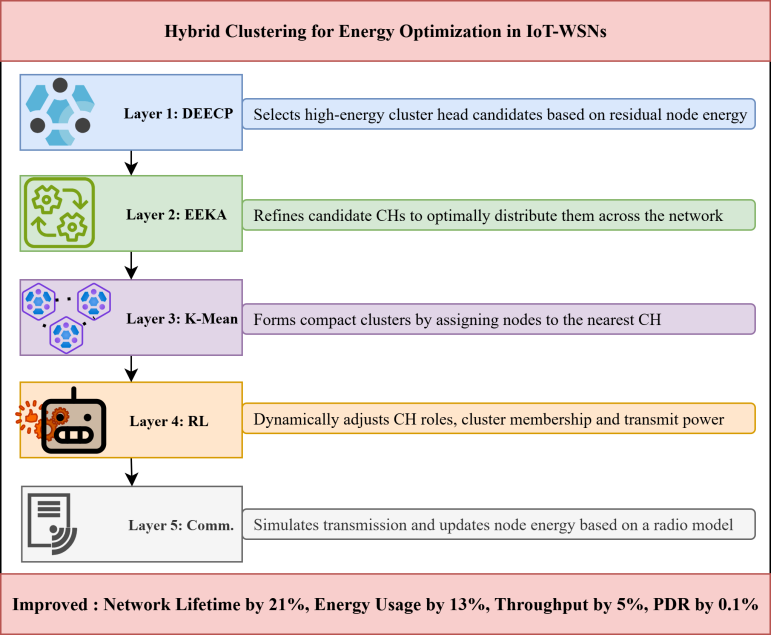
Reinforcement Learning Driven Hybrid Clustering for Energy Optimization in IoT-WSNs

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***Abstract—*In the realm of the Internet of Things (IoT), Wireless Sensor Networks (WSNs) serve as a foundational technology, enabling diverse applications such as urban infrastructure management, industrial automation and environmental monitoring. Despite their widespread adoption, achieving energy efficiency and adaptive clustering remains a major challenge in prolonging the operational lifetime of WSNs. Traditional clustering algorithms such as Low-Energy Adaptive Clustering Hierarchy (LEACH) and Distributed Energy-Efficient Clustering (DEEC) often suffer from uneven energy consumption and static decision-making, limiting their scalability under dynamic network conditions. To address these limitations, this paper proposes a Reinforcement Learning Driven Hybrid Clustering (RLHC) framework that integrates DEEC, the Energy-Efficient Knapsack Algorithm (EEKA) and K-Means with Q-learning based adaptive optimization. In the proposed method, DEEC identifies high energy cluster head (CH) candidates, EEKA ensures energy balanced uniform spatial distribution of CHs, K-Means forms compact clusters to minimize intra-cluster distances and the Q-learning agent dynamically learns optimal adjustment strategies by observing network states defined by residual energy, cluster load and packet delivery ratio (PDR) then executes actions such as CH switching, member reassignment and transmission power tuning. Through continuous interaction with the environment, the agent converges toward energy-optimal configurations. Simulation results demonstrate that the proposed RLHC method significantly enhances network lifetime, PDR and energy balance compared to optimized algorithms built on top of LEACH and DEEC. The improvements include a 21% increase in network lifetime, 13% reduction in energy consumption, 5% higher throughput and 0.1% improvement in PDR. This hybrid intelligence approach provides a scalable and adaptive solution for next-generation IoT-based WSN applications.**

***Keywords*—Reinforcement Learning (RL), Q-learning, Wireless Sensor Networks (WSNs), Distributed energy-efficient clustering (DEEC), Energy Efficient Knapsack Algorithm (EEKA), Energy Optimization, Internet of Things (IoT), K-Means Clustering.**

1. **INTRODUCTION**

Wireless Sensor Networks (WSNs) represent one of the foundational technologies driving the rapid evolution of the Internet of Things (IoT) paradigm. These networks consist of spatially distributed sensor nodes that cooperatively monitor and record environmental conditions and transmit the collected information to a central Base Station (BS) or sink node for further processing and analysis. The ability of WSNs to provide real-time, context-aware data makes them indispensable in modern intelligent systems. They find extensive applications in smart city governance, industrial automation, military surveillance etc [1], [2].

Through efficient data acquisition and communication, WSNs serve as the backbone of IoT ecosystems, enabling data-driven decision-making, predictive analytics and autonomous operations. Despite their vast potential, WSNs face critical constraints in terms of energy efficiency, communication reliability and network longevity. The sensor nodes are typically powered by small, non-rechargeable batteries and deployed in remote or harsh environments, where human intervention for maintenance or battery replacement is highly impractical. Consequently, energy depletion of individual nodes leads to node death, which in turn causes network partitioning, packet loss and degradation in overall system performance. This problem is particularly exist in applications requiring continuous and long-term monitoring such as health diagnostics, disaster prediction and precision agriculture, where uninterrupted operation and consistent data flow are imperative.

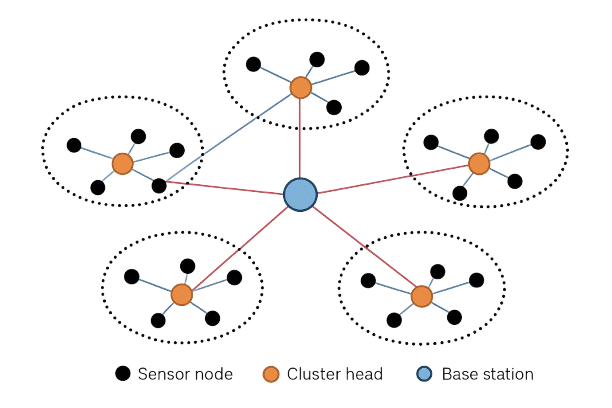
To mitigate such challenges, researchers have proposed numerous energy aware routing and clustering protocols aimed at optimizing energy utilization and balancing power consumption among nodes. Among these, clustering based routing has emerged as one of the most effective strategies for achieving energy efficiency. In this approach, sensor nodes are grouped into clusters, each governed by a Cluster Head (CH) that aggregates data from member nodes and transmits it to the BS. Representative clustering protocols include the Low-Energy Adaptive Clustering Hierarchy (LEACH), Stable Election Protocol (SEP) and Distributed Energy-Efficient Clustering (DEEC) [3]–[5]. These protocols primarily aim to reduce communication overhead and distribute the energy load more evenly across the network. DEEC, in particular, selects CHs based on residual energy and average network energy, thereby extending the network lifetime more effectively than random or static CH selection methods.

Figure 1: Wireless Sensor Network

Figure 1, illustrates a typical communication model of a WSN, where sensor nodes are randomly deployed across the sensing region and relay their sensed data to the base station through CH.

However, traditional clustering protocols still exhibit limitations in adaptability, scalability and dynamic optimization. Most existing schemes assume homogeneous or quasi-static environments, where node energy dissipation, communication distance and network topology remain relatively stable. In real-world IoT deployments, energy dynamics, node heterogeneity and communication interference can vary significantly over time. As a result, static or semi-static CH selection often leads to sub-optimal cluster configurations, premature energy depletion of certain nodes and overall performance degradation. Additionally, existing methods rarely incorporate adaptive learning or feedback mechanisms that can respond to dynamic environmental conditions or operational uncertainties. Thus the design of an intelligent and adaptive clustering mechanism becomes crucial for achieving long-term sustainability.

To overcome the aforementioned limitations, this paper introduces a Reinforcement Learning-Driven Hybrid Clustering (RLHC) approach that fuses intelligent optimization techniques across multiple layers of the clustering process. The proposed RLHC framework integrates DEEC, EEKA, K-Means clustering and RL to form an adaptive and energy-aware communication architecture. DEEC serves as the foundational layer, prioritizing nodes with higher residual energy for CH selection to ensure balanced energy consumption. EEKA filters and ranks candidate CH based on centrality and spatial distribution, determining the optimal number of CHs and selecting the best CHs to improve spatial balance to reduce inter-cluster communication overhead.. The K-Means algorithm refines the cluster formation by minimizing intra-cluster distances and balancing the spatial distribution of nodes, thereby further reducing communication cost. The RL layer introduces a self-learning capability that dynamically adjusts CH selection, transmission parameters and cluster reconfiguration based on real-time feedback such as residual energy, node density, cluster load and communication delay. The final layer models the radio energy consumption during data transmission and reception between nodes, CHs and the BS using the first-order radio model. This includes the free-space (d²) and multipath (d⁴) channel models for short and long distances, respectively.

By integrating these five layers, the RLHC framework achieves adaptive energy balancing, enhanced throughput, improved PDR and prolonged network lifetime. This hybrid intelligent model demonstrates the potential to bridge the gap between traditional deterministic routing methods and modern ML-driven adaptive optimization techniques. It provides a robust, scalable and self-evolving solution for the future of IoT-enabled WSNs, paving the way for more reliable and sustainable sensor network deployments in real-world environments.

Our contributions can be summarized as follows:

1. A five-layer RLHC model integrating DEEC (layer 1), EEKA (layer 2), K-Means (layer 3), RL (layer 4) and Communication layer (layer 5) for intelligent energy management in WSNs.
2. Energy-aware optimal clustering and RL based adaptive cluster refinement mechanism that dynamically optimizes cluster configurations in response to real-time variations in node energy and network conditions.
3. Performance enhancement as compared to the optimized algorithms built on top of traditional clustering protocols in terms of network lifetime, throughput, energy consumption and packet delivery ratio.

The remainder of this paper is organized as follows:

Section II presents a comprehensive literature review of existing clustering protocols and reinforcement learning approaches in WSNs. Section III outlines the theoretical and technical background relevant to energy-efficient communication and clustering mechanisms. Section IV describes the methodology of proposed Reinforcement Learning-Driven Hybrid Clustering (RLHC) framework in detail which highlighting its five-layer architecture. Section V discusses the simulation environment, performance evaluation metrics and comparative analysis of the proposed RLHC against existing protocols. Finally, Section VI concludes the paper and outlines potential directions for future research and real-world implementation.

1. **RELATED WORKS**

WSNs have become an integral component of modern IoT systems, enabling applications ranging from environmental monitoring and industrial automation to smart cities. A critical challenge in WSNs is energy

efficiency, as sensor nodes typically operate on limited battery power and network longevity directly depends on efficient energy utilization. Over the years, researchers have proposed a variety of clustering protocols, optimization algorithms and adaptive learning strategies to address this challenge. This section reviews existing work in clustering and energy-efficient WSNs, highlighting their strengths, limitations and the evolution toward hybrid RL-based approaches.

1. *Classical Clustering Protocols*

Clustering is widely recognized as a foundational approach for energy-efficient WSNs. The LEACH protocol is among the most seminal contributions, introducing randomized rotation of CHs to evenly distribute energy consumption among nodes. It reduces the number of direct transmissions to the base station and organizes nodes into energy-efficient clusters. However, it has several limitations, including uneven CH distribution, lack of consideration for residual energy and poor performance in heterogeneous or large-scale networks. These drawbacks motivated the development of variants that incorporate energy-awareness and residual energy into CH selection. Protocols such as LEACH-RLC and ReLeC enhance LEACH by integrating RL for adaptive CH selection. These methods learn network states and make dynamic decisions about CH election to improve energy efficiency and prolong network lifetime. Despite promising results, RL-based variants can impose computational and communication overhead that may be unsuitable for resource-constrained IoT nodes. Additionally, RL models like ReLeC may face convergence issues in large-scale or highly dynamic WSNs, limiting their practical applicability.

1. *Heterogeneity-Aware Protocols*

Recognizing the limitations of classical homogeneous protocols, researchers have introduced heterogeneity-aware approaches such as SEP (Stable Election Protocol) and DEEC. These protocols consider nodes with different initial energy levels and select CHs based on residual energy and network wide energy distribution. This ensures that higher energy nodes are more likely to assume CH roles, balancing the energy load across the network and preventing premature node failures. DEEC, in particular, extends LEACH by incorporating energy heterogeneity and energy based CH selection, improving network stability and prolonging lifetime. Enhancements such as EEKA further optimize CH selection by considering node centrality and spatial distribution, aiming for a uniform CH spread that reduces intra-cluster communication distances and overall energy consumption. These protocols effectively address energy imbalance but often rely on pre-defined thresholds or heuristic rules, limiting their adaptability to dynamic network topologies or sudden changes in energy states.

1. *Metaheuristic and Optimization-Based Approaches*

To achieve better CH selection and network optimization, metaheuristic algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Genetic Algorithms (GA) have been extensively applied in WSNs. PSO minimizes intra-cluster distances and identifies optimal CH positions by simulating social behavior among particles. ACO leverages pheromone based path selection to optimize cluster formation and routing, while GA evolves a population of CH candidates to optimize energy efficiency and load balancing. These approaches have demonstrated significant improvements in network lifetime and communication efficiency. However, metaheuristic based methods typically operate offline or rely on iterative convergence, which makes them less suitable for networks with dynamic topologies, mobile nodes or rapidly changing energy states.

1. *Fuzzy Logic and Multi-Criteria Clustering*

Fuzzy logic-based clustering introduces multi-criteria decision-making for CH selection, considering parameters such as residual energy, node density, distance to the cluster center and network traffic. Protocols like MRCH (Modified RCH-LEACH) utilize fuzzy rules to determine CH candidacy, improving stability, packet delivery ratio and energy efficiency. Fuzzy-based approaches provide a flexible framework for handling uncertainties in sensor networks, enabling adaptive cluster formation under varying network conditions. Moreover, these methods can involve computationally intensive calculations, limiting their deployment on low-power sensor nodes.

1. *Reinforcement Learning in WSNs*

RL has emerged as a powerful tool for dynamic and adaptive WSN management. RL-based approaches model the network as an environment, where nodes or CHs act as agents that learn optimal actions to maximize long-term rewards, such as energy efficiency or network lifetime. Q-learning, SARSA and Deep RL have been explored to optimize CH selection, cluster reorganization and routing decisions. For example, EER-RL improves energy efficiency and prolongs network lifetime by dynamically adjusting CH roles based on learned energy patterns. Similarly, Q-learning LEACH models enhance adaptability to changing network topologies. Despite their effectiveness, RL-based methods often require centralized training, global knowledge or extensive exploration, which may limit scalability in large or highly dynamic WSN deployments.

1. *Hybrid Clustering Approaches*

Hybrid clustering methods aim to combine the strengths of classical, meta-heuristic, fuzzy and RL approaches. These methods address multiple challenges simultaneously, including CH optimization, energy balancing, spatial uniformity and adaptability. Multi-layered hybrid models often integrate energy-aware CH selection, K-means or fuzzy-based spatial clustering and RL-based adaptive decision-making to maximize network efficiency. Recent work has highlighted the efficacy of such hybrid frameworks. Protocols like EOCGS determine the optimal number of cluster and grid heads to balance energy consumption. These studies show that intelligent hybrid methods can outperform traditional approaches in terms of network lifetime, energy balance and adaptability.

Despite substantial progress in WSN clustering, existing methods continue to face several challenges. RL based and other meta heuristic approaches often introduce significant computational overhead, making them unsuitable for low-power IoT nodes. Many protocols also struggle to maintain efficiency in large-scale or highly heterogeneous networks. Classical methods frequently fail to prevent early node depletion, resulting in network partitioning. Furthermore, most existing solutions rely on static or pre-defined strategies, which are ill-equipped to handle dynamic topologies, node mobility or sudden energy fluctuations. Excessive intra-cluster communication further accelerate energy depletion, limiting overall network lifetime.

**TABLE 1**. Summary of energy efficiency studies in WSN

|  |  |  |  |
| --- | --- | --- | --- |
| **Sl. No.** | **Paper & Year** | **Optimization Technique Used** | **Limitations (Research gap)** |
| 1 | Farahzadi et al. “An Improved Cluster Formation Process in Wireless Sensor Networks to Decrease Energy Consumption” (2021) | Region-based clustering with adaptive CH selection | Assumes ideal energy estimation  Does not consider node location or distance factors |
| 2 | Panchal et al. “EEHCHR: Energy Efficient Hybrid Clustering and Hierarchical Routing for Wireless Sensor Networks” (2021) | Hybrid clustering with hierarchical routing | Increased routing complexity  Static clustering radius |
| 3 | Al-Kaseem et al. “Optimized Energy-Efficient Path Planning with Multiple Mobile Sinks” (2021) | Stable Election Algorithm (SEA)  Residual energy | Scalability issues beyond 100 nodes  Simulation-only |
| 4 | Prajapati et al. “Performance Analysis of LEACH with Deep Learning in Wireless Sensor Networks” (2022) | CNN-based CH selection LEACH | High computational overhead  Limited scalability. |
| 5 | Mohapatra et al. “Mobility Induced Multi-Hop LEACH Protocol in Heterogeneous Mobile Network” (2022) | Residual energy and node mobility factor | Assumes uniform mobility  Limited scalability |
| 6 | Gamal et al. “Enhancing Lifetime of WSNs Using Fuzzy Logic LEACH and PSO” (2022) | Fuzzy rules, residual energy, node centrality, distance to BS | Increased control overhead from fuzzy inference |
| 7 | Bhatia et al. “Cluster Based Energy Efficient Routing Protocol using SA-LEACH to Wireless Sensor Networks” (2023) | Simulated Annealing and LEACH | High computational cost  Limited adaptability |
| 8 | Abose et al. “Improving Wireless Sensor Network Lifespan with Optimized Energy-Conscious Routing” (2024) | Optimized energy-conscious routing | Assumes ideal energy estimation  Does not consider node location or distance factor |
| 9 | El Khediri et al. “Energy-Efficient Cluster Routing Protocol for Wireless Sensor Networks” (2024) | Cluster based routing | High computational cost  Limited adaptability |
| 10 | Zhu et al. “Improved Soft-k-Means Clustering Algorithm for Balancing Energy Consumption in Wireless Sensor Networks” (2024) | Soft-k-means clustering with multi cluster heads | High computational cost  Limited adaptability |
| 11 | Tabatabaei et al. “New Energy Efficient Management Approach for Wireless Sensor Networks” (2025) | Hierarchical clustering model | Assumes ideal energy estimation  Does not consider node location or distance factors. |

1. **TECHNICAL BACKGROUND**
2. *Wireless Sensor Networks and Energy Constraints*

WSNs are composed of spatially distributed sensor nodes that monitor physical or environmental conditions such as temperature, pressure, humidity or vibrations, and transmit the collected data to a central sink. Each sensor node typically has limited energy, computation capability and communication range, making energy-efficient operation critical to prolong network lifetime and ensure reliable data delivery.

The network operates in rounds, each consisting of cluster formation, data aggregation and transmission. Efficient energy management is critical because sensor nodes are battery powered and recharging may be impractical. Key challenges in WSNs include:

1. Limited energy resources.
2. Uneven energy depletion due to repeated CH selection.
3. Scalability for large networks.
4. Adaptability to dynamic conditions such as node failures, mobility and environmental changes.

To overcome these challenges, cluster based routing is commonly employed, complemented by optimization techniques that efficiently manage intra cluster communication and CH selection, thereby enhancing the overall network lifetime.

1. *Particle Swarm Optimization (PSO)*

#### To mitigate the above mentioned limitations various algorithms are developed in which POS is very renowned. It is a population-based optimization algorithm inspired by the social behavior of bird flocking or fish schooling. Each individual in the population called a particle which represents a potential solution. Particles “fly” through the search space, adjusting their positions based on their own best experience and the best experience among all particles. Over iterations, particles converge toward the best solution.

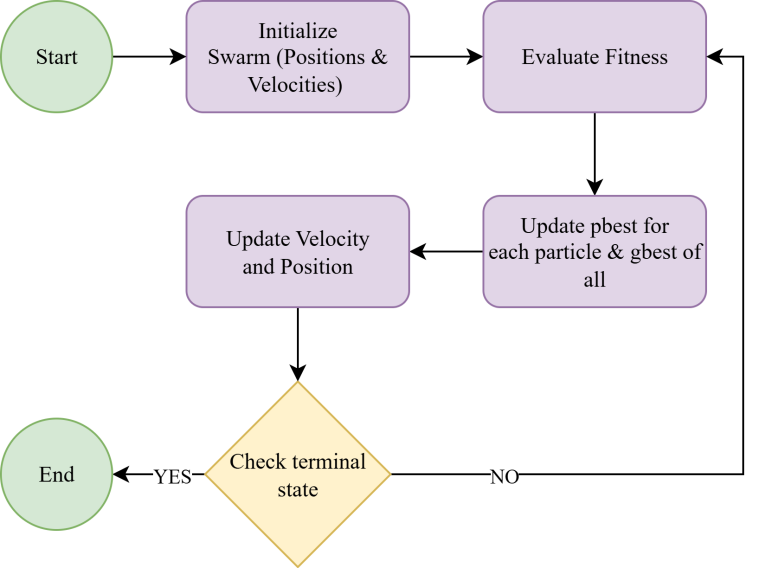
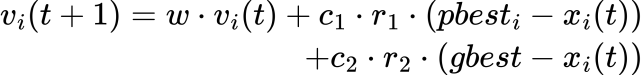


Figure 2: Flow chart of the PSO algorithm

Figure 2 represents the working principle of the Particle Swarm Optimization (PSO) algorithm. The process begins with the initialization of a swarm of particles, each representing a potential solution with random position and velocity. At each iteration, the fitness of all particles is evaluated using the objective function. Each particle then updates its personal best position (pbest) and the global best position (gbest) found by the entire swarm. The velocity and position of each particle are updated according to the Equation 1 and Equation 2 respectively.

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where ‘w’ denotes the inertia weight, ‘c1’ and ‘c2’ are acceleration coefficients and ‘r1’, ‘r2’ belongs to [0,1] are random numbers. These Equations collectively balance the inertia (momentum), cognitive (self-learning) and social (swarm cooperation) components of each particle. The process iteratively continues until the swarm converges toward an optimal or near-optimal solution based on the defined fitness function.

1. *Ant Colony Optimization (ACO)*

Ant Colony Optimization (ACO) is a remarkable metaheuristic algorithm introduced by Marco Dorigo, based on the foraging behavior of real ants. In nature, ants find the shortest path between their colony and a food source by depositing a chemical substance called pheromone on the ground. Other ants sense this pheromone trail and are more likely to follow stronger trails. Over time, shorter paths accumulate more pheromones, leading the colony to converge to the optimal path.

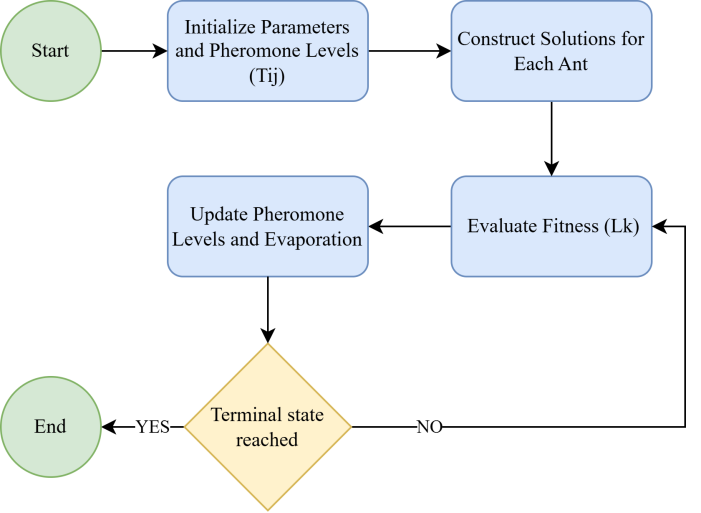
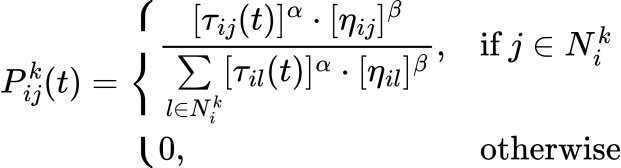
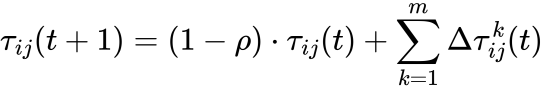
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Figure 3: Flow chart of the ACO algorithm

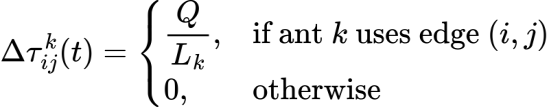
Figure 3 represents the working principle of the Ant Colony Optimization (ACO) algorithm, which simulates artificial ants that iteratively construct solutions using pheromone trails and heuristic information. The process begins with the initialization of parameters and pheromone levels on all paths. During solution construction, each ant builds a solution based on the probability of selecting the next path. After all ants complete their paths, the pheromone update phase reinforces paths used by better solutions while allowing pheromone evaporation to prevent premature convergence. The process continues iteratively until the termination condition such as reaching the maximum number of iterations or convergence is satisfied. The core Equations of ACO are the path selection probability (Equation 3), pheromone update (Equation 4) and pheromone deposition (Equation 5).

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where Pij is probability that ant k moves from node i to node j, Tij is pheromone concentration on edge (i,j) at time t. ηij is equals to 1/dij that is heuristic information (inverse of distance or cost). α, β are control parameters for pheromone and heuristic influence.

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Equation 4 represents pheromone update rule, where ρ represents pheromone evaporation rate (0<ρ<1), m is total number of ants and ΔTij amount of pheromone deposited by ant k on edge (i,j).

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Equation 5 represents pheromone deposition amount, where

Q is pheromone constant and Lk is total cost or path length of the tour constructed by ant k.

1. Fuzzy C-Means (FCM)

The FCM algorithm is a well known clustering technique where each data point belongs to a cluster with a degree of membership rather than belonging entirely to just one cluster. This algorithm is fundamentally an optimization based clustering method which seeks to minimize an objective function that quantifies the total weighted distance between data points and cluster centers. Each data point is assigned a membership degree to all clusters, allowing for soft clustering where points can partially belong to multiple clusters. The optimization process aims to find the optimal cluster centers that minimize the objective function by updating the membership degrees for each data point.

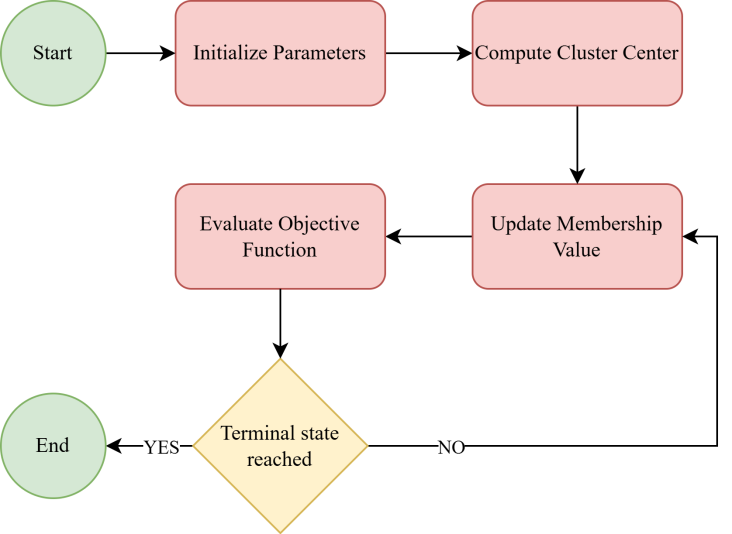
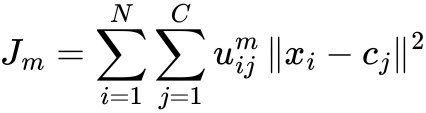
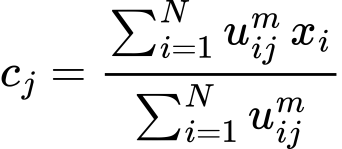
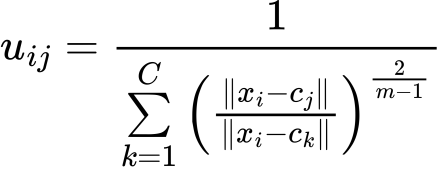


Figure 4: Flow chart of the FCM algorithm

Figure 4 illustrates the working principle of the FCM algorithm. The process begins with the initialization of the membership matrix U, which assigns random membership values to each data point for all clusters. Next, cluster centers are computed based on the current membership values. The algorithm then updates the membership degrees for each data point using the updated cluster centers. Afterward, the objective function is evaluated to measure clustering performance. If the change in membership values or cluster centers between iterations is smaller than a predefined threshold, the process is said to have converged, otherwise, the algorithm repeats the update steps. Once convergence is achieved, the final cluster assignments are generated, representing the optimal fuzzy partition of the dataset.

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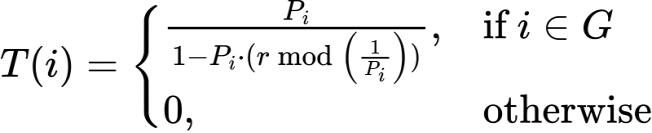
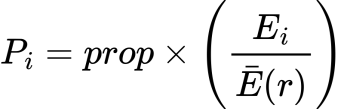
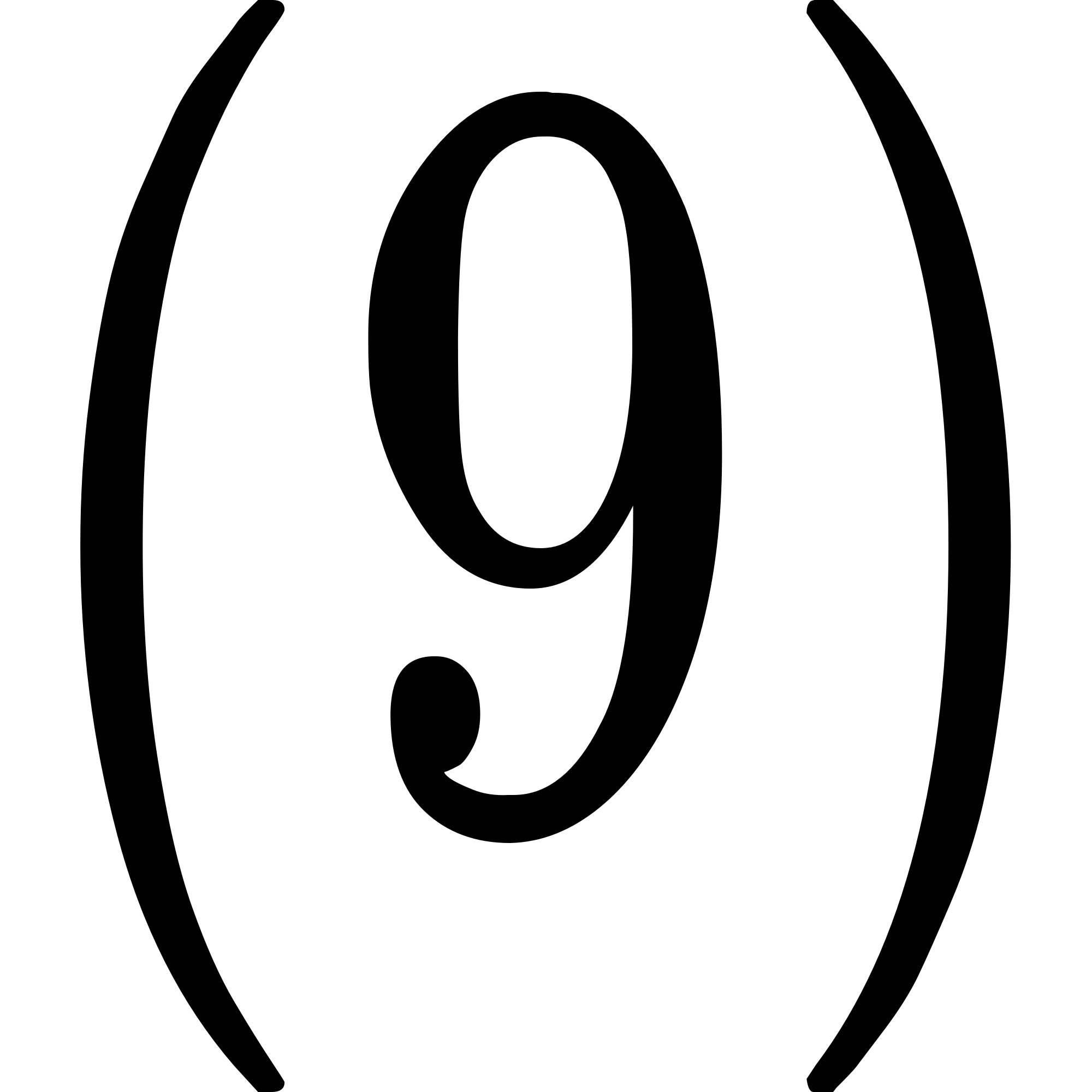
Equation 6 represents the objective function that FCM seeks to minimize. It measures the total weighted distance between all data points xi and the cluster centers cj. The weight is given by the membership value Uij, m which indicates how strongly a data point belongs to a particular cluster. Equation 7 is used to update the cluster center. Each cluster center is calculated as the weighted mean of all data points, where the weights are the membership degrees raised to the power m. Equation 8 defines how the membership value Uij of each data point to each cluster is updated. The membership is inversely related to the distance between the data point and the cluster center meaning closer points have higher membership values. The ratio term ensures that all membership values for a data point sum to 1 across all clusters, maintaining normalization.

1. **THE METHODOLOGY**

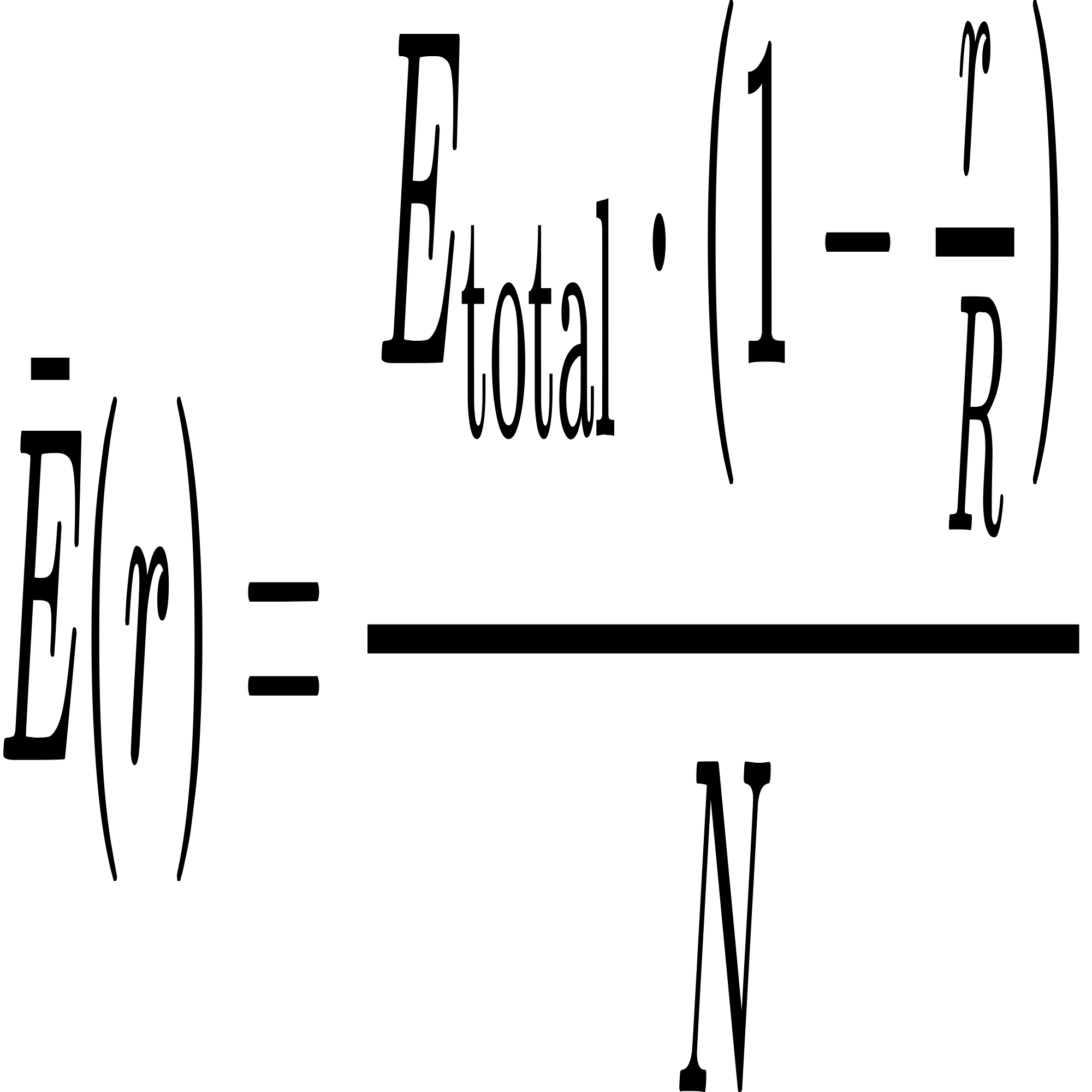
This paper presents a Reinforcement Learning Driven Hybrid Clustering (RLHC) framework to enhance energy efficiency and operational longevity in WSNs. The framework features a five-layer architecture that optimizes CH roles and network management through real-time feedback. The integrated RLHC framework delivers improved throughput, higher packet delivery ratio (PDR), and extended network lifetime by merging deterministic optimization with machine learning driven adaptation, making it robust across diverse IoT enabled WSN scenarios. The RLHC framework comprises five integrated layers designed to enhance energy efficiency and clustering in WSNs.

1. *Layer 1: Distributed Energy Efficient Clustering Protocol (DEECP)*

DEECP serves as the foundational layer of the proposed RLHC framework. DEECP employs an energy-aware mechanism to identify the most suitable candidates for CH selection by evaluating each node’s residual energy relative to the network’s average energy. This adaptive CH election strategy ensures that nodes with higher remaining energy possess a greater probability of becoming CHs, thereby balancing energy consumption across the network. Through this dynamic mechanism, DEECP effectively mitigates premature node death and enhances network stability by rotating CH roles periodically among eligible nodes. It not only optimizes the initial CH election but also synergizes with higher level adaptive modules to achieve prolonged network lifetime, balanced load distribution and enhanced overall energy efficiency in heterogeneous IoT-enabled WSN environments.



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Equation 9, represents T(n) which is threshold for node n to become CH, Pi is probability of node i becoming a CH, r is current round number and G is set of nodes that have not been CHs in the last 1/Pi rounds.C:/Users/LENOVO WORLD/AppData/Local/Temp/wps.OIWnFywps In Equation 10, the Pi is proportional to the Ei which represents residual energy of node i, E(r) which represent average residual energy of the network at round r, ‘prop’ is optimal CH probability, N represents total numbers of nodes, R represents total numbers of rounds and Etotal represents total energy of the network.

1. *Layer 2: Energy Efficient Knapsack Algorithm (EEKA)*

Following the DEECP layer, the EEKA operates as the second optimization layer within the RLHC framework. While DEECP ensures energy aware CH selection based on residual energy and average network energy, EEKA refines this process by optimizing the spatial distribution and number of CHs using a constrained knapsack formulation. In this layer, each potential CH candidate identified by DEECP is evaluated as an item in the knapsack problem, where parameters such as node centrality, residual energy, and communication distance to the base station act as utility factors. It aims to maximize the overall network utility under the constraint of minimizing total energy consumption. By selecting the most spatially balanced and energy-efficient CH set, it also ensures uniform coverage of the sensing field and reduces excessive intra cluster communication distances. This selection prevents the formation of energy hotspots and promotes equitable energy dissipation across all regions of the network. The integration of EEKA into the RLHC framework enhances both structural balance and energy uniformity, addressing the spatial irregularities often observed in conventional DEECP or LEACH based clustering. The resulting CH configuration not only reduces redundant transmissions but also improves communication reliability and network throughput. Furthermore, the optimal CH distribution established by EEKA serves as an informed input to the subsequent K-Means clustering layer, which further fine-tunes cluster boundaries to minimize intra cluster distances and transmission costs.

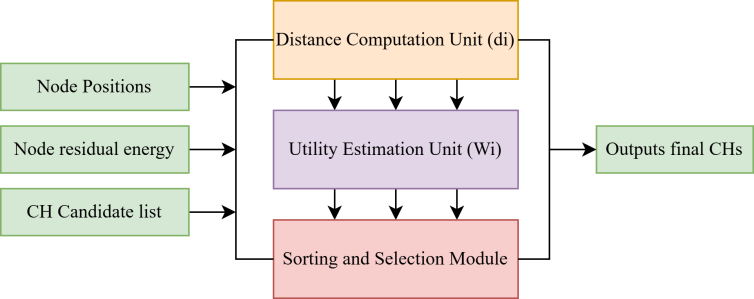
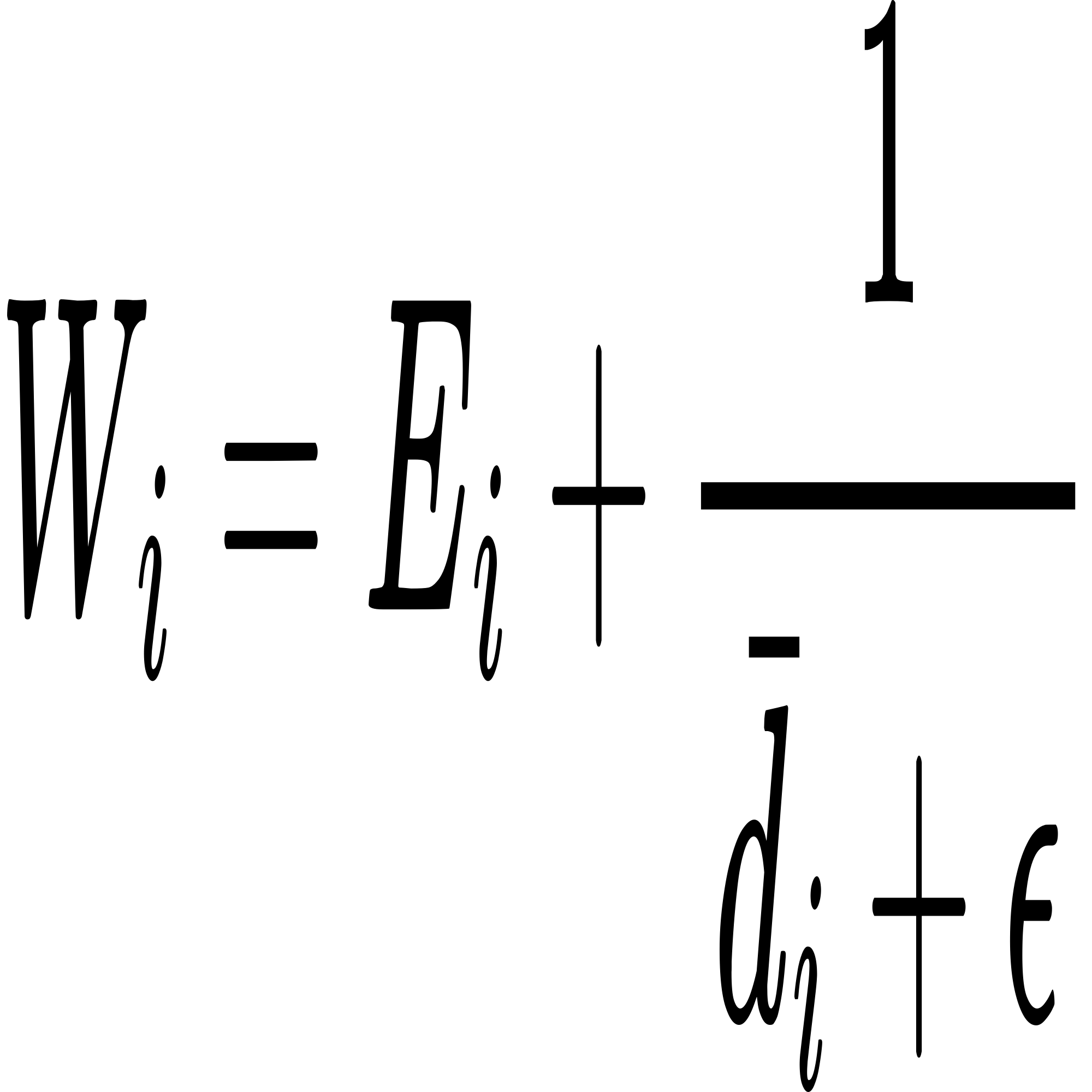


Figure 5: Internal block diagram of the EEKA algorithm

The internal architecture of EEKA operates by receiving candidate cluster heads, along with node energy and positional data. It computes average inter-node distances to estimate node centrality, then evaluates a combined utility function (as defined in Equation 12) to rank the candidates. Finally, the top K nodes are selected as cluster heads, ensuring optimal energy balance and uniform cluster distribution across the network.

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where the utility function Wi represents the energy centrality score of each node and determines its suitability to become a CH. It integrates two crucial parameters, residual energy and spatial centrality into a single quantitative metric.

1. *Layer 3: K-Means Algorithm*

The third layer of the RLHC framework employs the K-Means clustering algorithm to refine the cluster formation process based on the CHs selected by the EEKA layer. While DEECP and EEKA collectively determine the most energy efficient and spatially balanced CHs, the K-Means algorithm ensures that the remaining sensor nodes are optimally associated with these CHs to minimize intra cluster communication cost.

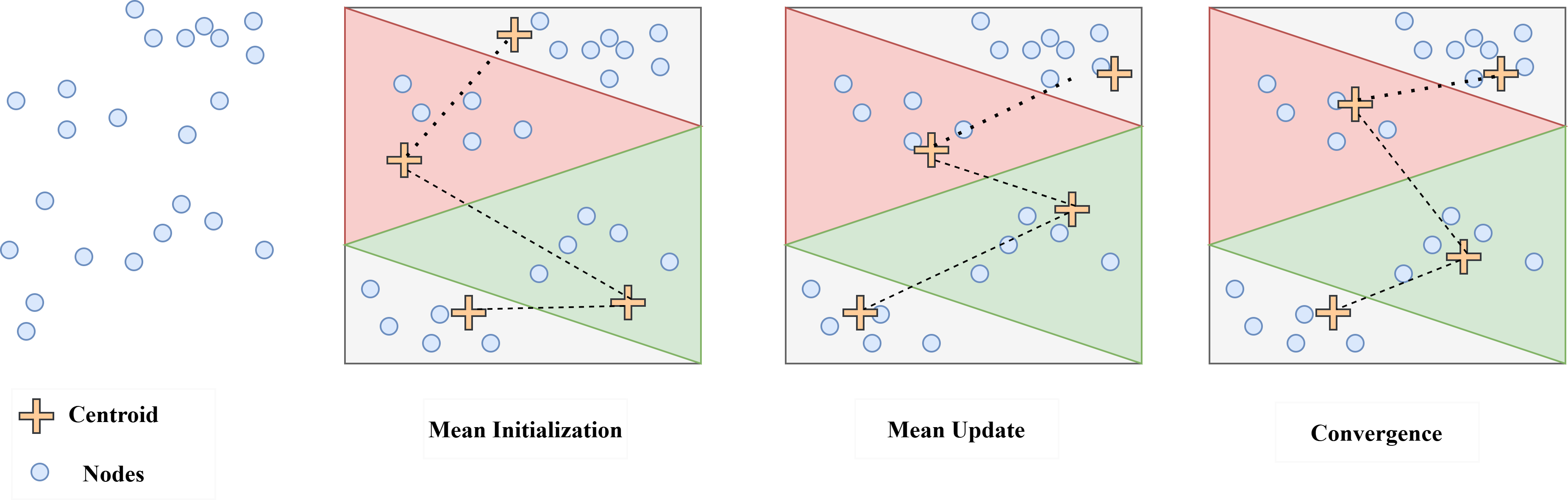
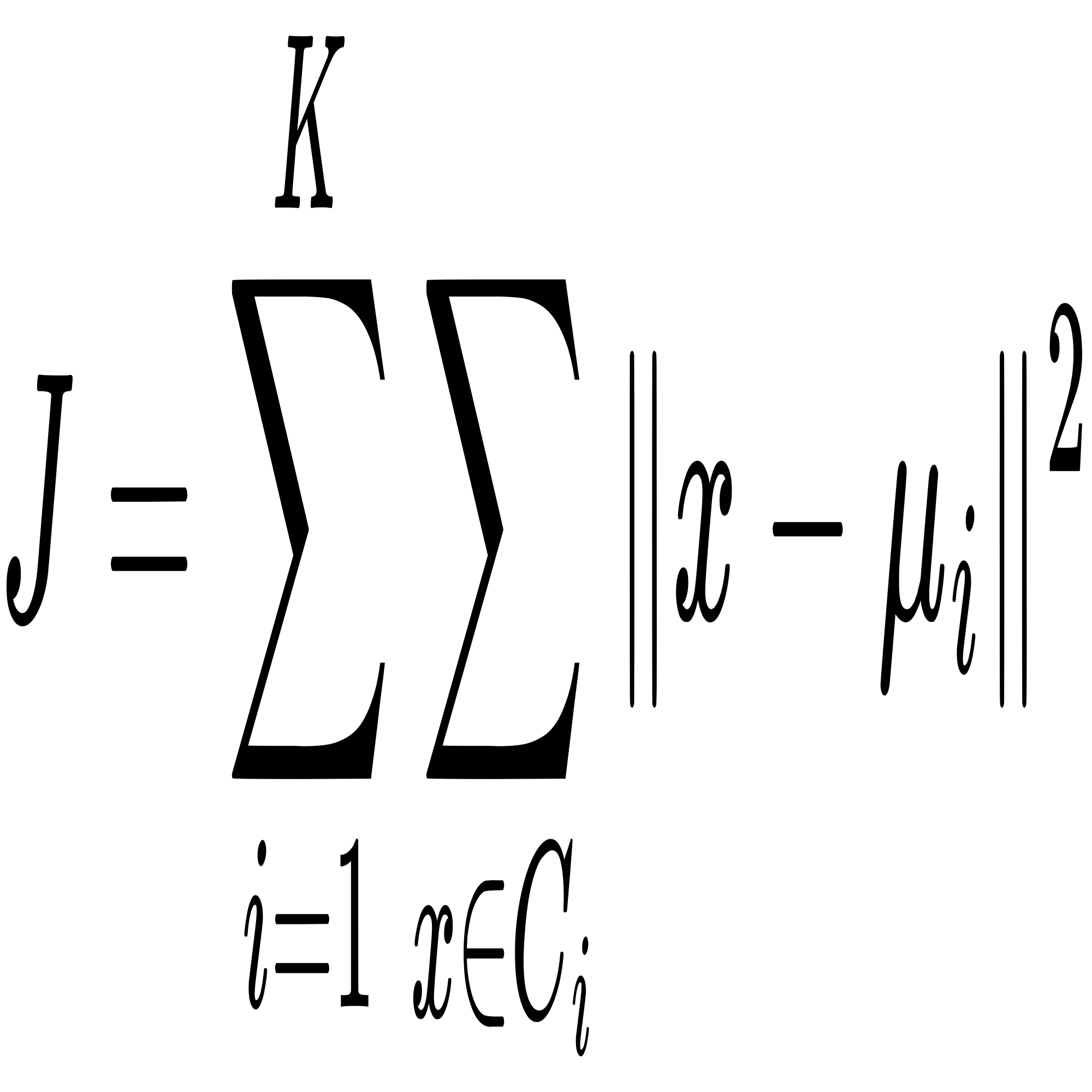


Figure 6: Process flow chart of K-Mean algorithm

The K-Means algorithm partitions a set of N sensor nodes into K clusters by iteratively minimizing the sum of squared Euclidean distances between each node and its assigned cluster head. The process involves three main steps: centroid initialization, mean (centroid) update, and convergence check. The objective function for this clustering process is given in Equation 13.



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where Ci​ represents the set of nodes in cluster i, μi is the centroid (cluster head) of cluster i, and sq(x−μi) denotes the squared Euclidean distance between node x and its cluster centroid.

1. *Layer 4: Reinforcement Learning (RL)*

Layer 4 incorporates a RL agent that provides self-learning, adaptive control for the wireless sensor network. It dynamically optimizes CH selection, transmission parameters, and cluster reconfiguration based on real-time network feedback. By employing the Q-Learning algorithm, this layer improves CH selection and transmission decisions to maximize long-term objectives, such as network lifetime and energy efficiency. The RL agent continuously refines its strategies over time, overcoming the limitations of static, rule-based systems. It synergizes with outputs from preceding layers to enhance overall decision-making, ensuring scalable, efficient, and adaptive clustering. While it introduces minimal computational overhead, this layer is essential for enabling intelligent and resilient operation in IoT-based WSN applications.

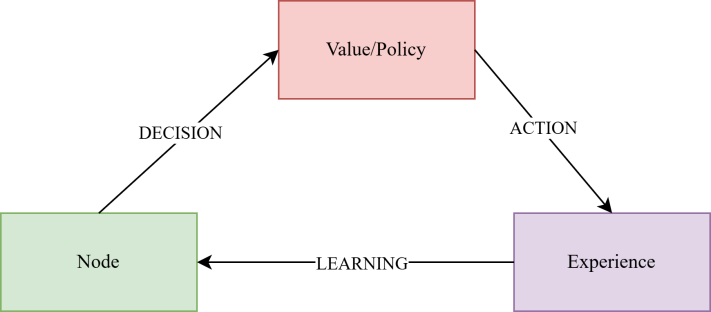
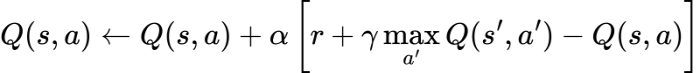


Figure 7. RL based Decision-Making Framework

From the above diagram, it is evident that by incorporating RL, the system can dynamically adapt to changing conditions and make increasingly optimal decisions over time, making it highly suitable for real-time IoT applications.

In Layer 4, a Q-learning agent is deployed whose core function is to observe the current network state, execute actions such as CH reassignment, switching CHs, or adjusting transmission power, and gain experience in the form of rewards. After executing an action, it receives feedback from the environment, including updated node energies, cluster configurations, and network metrics (e.g., PDR, throughput) and computes a reward. This experience is then used to update the Q-table, refining future decision making. By introducing adaptive learning, this layer transforms static cluster management into a self-learning mechanism, enabling the network to optimize long-term objectives such as energy efficiency and network lifetime.

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Equation 14 is used to update the Q-table, where α is the learning rate that determines how much new information overrides old knowledge, γ is the discount factor that defines the importance of future rewards, and ‘a’ represents the action taken by the agent. This update allows the agent to iteratively improve its policy by balancing immediate rewards with long-term benefits, enabling more optimal decision making over time.

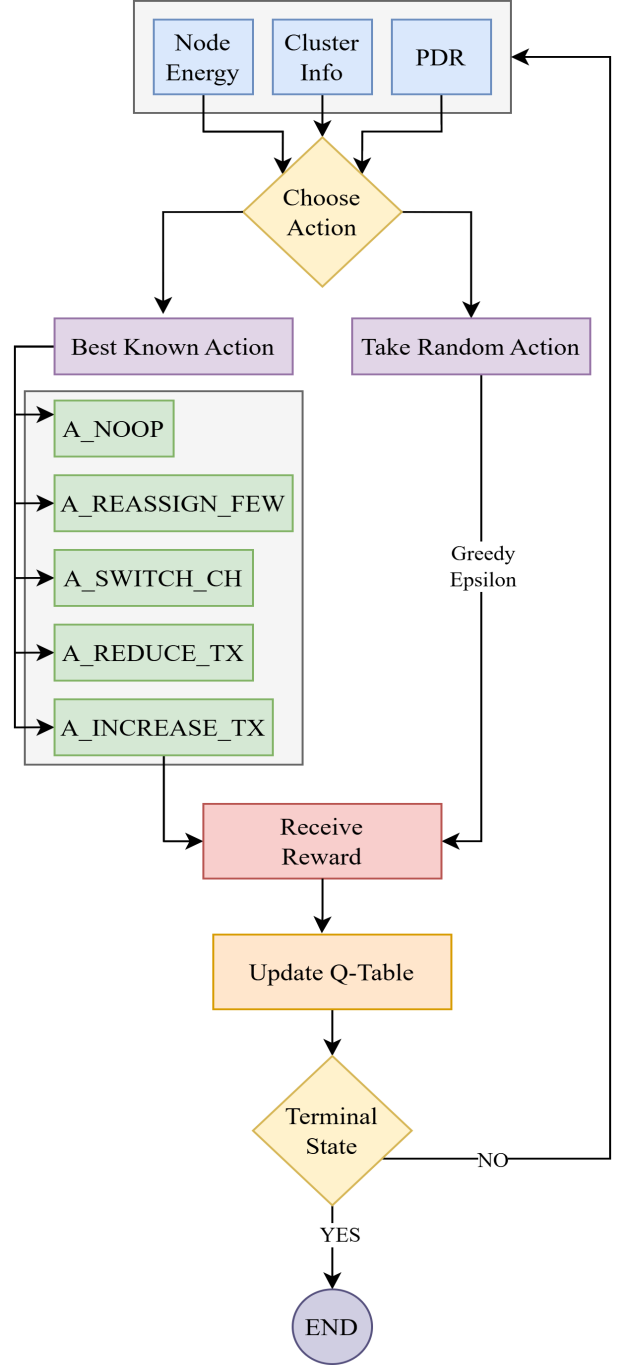


Figure 8. Q-Learning agenrt decision making framework

Page 9: layer 5, combined view and flow chart of the whole process.   
Page 10 : proposed algorithm  
  
Page 11: Simulation result  
Page 12 -13 Conclusion