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INTELLIGENCE CLUSTERS HEAD SELECTION AND RELIABILITY ROUTING USING TRIPARTITE MACHINE FRAMEWORK WITH ADAPTIVE CONTEXTUAL ROUTING PROTOCOL IN WBSN

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Abstract

This paper proposes a novel tripartite machine learning framework that integrates data-driven cluster head (CH) prediction, enhanced clustering, and an Adaptive Contextual Routing Protocol (ACRP) to optimize WBSN performance. The framework employs an ensemble of XGBoost and Random Forest models trained on node features including residual energy, mobility variance, and data criticality to predict optimal CH candidates with 92% accuracy. A modified K-means clustering algorithm initializes centroids using the highest-scoring ML-predicted CHs, reducing intra-cluster energy variance by 37% compared to traditional random initialization. The ACRP performs multi-objective routing by evaluating candidate paths based on energy cost, latency, and reliability metrics, incorporating ε-differential privacy noise and quantum-inspired randomized selection for enhanced security. Simulation results using 100 nodes with realistic physiological datasets demonstrate substantial performance gains: network lifetime extension of 126% compared to baseline protocols, critical health data latency maintained below 150 ms, packet delivery ratio of 95%, attack resistance of 93%, and 5.8× reduction in brute-force attack success. The proposed framework effectively balances energy efficiency, latency, and reliability requirements while providing enhanced security for clinical WBSN applications.

Keywords: Adaptive contextual routing protocol (ACRP), Energy-efficient routing, K-means, Machine learning, Wireless body sensor networks.

1. Introduction

Wireless Body Sensor Networks (WBSNs) have emerged as a critical technology for real-time physiological monitoring across healthcare, military, and fitness applications. These networks consist of miniaturized, wearable, or implantable sensors that continuously collect vital signs and transmit data to healthcare providers for immediate analysis and intervention [1].

However, the fundamental constraints of limited battery life in wearable sensors and the critical need for reliable, timely data delivery present significant challenges for WBSN deployment in clinical environments [2] Traditional energy management approaches, including duty-cycling and simple energy-aware routing techniques, fail to simultaneously optimize energy consumption and Quality-of-Service (QoS) requirements in the dynamic, movement-intensive environment characteristic of WBSNs [3]. The human body's continuous movement patterns, varying physiological conditions, and heterogeneous sensor placement create a complex networking environment that demands adaptive resource management strategies.

Clustering techniques have been widely adopted to extend network lifetime by reducing redundant transmissions through hierarchical data aggregation. In these approaches, sensor nodes are organized into clusters, with each cluster's data aggregated at a designated cluster head (CH) before forwarding to the base station. The selection of appropriate CHs critically influences communication overhead, energy consumption patterns, and overall network load balancing. Existing protocols such as LEACH and its variants typically employ random CH election or simple energy threshold-based selection mechanisms [4].

However, in highly dynamic WBSN environments, these conventional methods often fail to adapt effectively to body movements and ultra-low power constraints, resulting in uneven energy distribution and network connectivity disruptions. Traditional K-means clustering has been applied to WBSN optimization, but its dependence on random centroid initialization and sensitivity to outlier nodes frequently produces suboptimal cluster formations in energy-constrained scenarios. Furthermore, when intra-cluster distances exceed inter-cluster distances, the algorithm struggles with dataset complexity, leading to misclassification of boundary samples [5, 6].

Machine learning (ML) techniques offer promising solutions for more adaptive CH selection and clustering optimization. ML algorithms can learn complex patterns from historical node energy consumption, mobility characteristics, and data criticality to predict robust CH candidates [7]. Tree-based ensemble methods such as XGBoost have demonstrated exceptional accuracy on complex biomedical datasets, making them particularly suitable for WBSN applications [8].

Beyond clustering optimization, routing protocols must address contextual information requirements and security considerations that extend beyond fixed rule-based approaches. Many existing ML-based WBSN schemes continue to rely on static cluster boundaries and lack comprehensive privacy guarantees, limiting their applicability in clinical environments where data security is paramount [9, 10].

This work addresses these multifaceted challenges through a comprehensive three-stage approach that integrates ML-driven CH prediction, optimized

clustering, and an adaptive routing protocol designed to ensure energy efficiency, reliability, and privacy preservation. Our primary contributions include:

Novel Predictive Cluster Head Selection: We develop an ensemble ML model combining XGBoost and Random Forest algorithms to predict optimal CH candidates based on comprehensive node features including residual energy, mobility variance, and data criticality. This predictive approach achieves 92% accuracy and demonstrates superior performance in selecting nodes that maximize cluster stability and energy balance.

ML-Guided Clustering Algorithm: We introduce a modified K-means clustering algorithm that initializes centroids at the highest-scoring CH candidates identified by our ML ensemble. This approach reduces intra-cluster energy variance by 37% compared to random initialization and eliminates poor initialization scenarios, resulting in more balanced cluster sizes and reduced energy hotspots.

Adaptive Contextual Routing Protocol (ACRP): We develop ACRP, a multi-objective routing protocol that evaluates candidate paths based on energy cost, latency, and reliability metrics. To enhance privacy and security, we incorporate Laplace noise ($\varepsilon < 0.5$) into path scoring and implement quantum-inspired randomized selection. This approach achieves over 93% resistance to brute-force attacks while maintaining critical data latency below 150 ms.

Comprehensive Performance Validation: Through extensive simulations using realistic physiological datasets (PhysioNet, MHEALTH) with 100-node networks, we demonstrate substantial performance improvements. Our integrated framework extends network lifetime by 126% compared to Multi-hop/ATTEMPT protocols, achieves 95% packet delivery ratio, and demonstrates superior adaptation in 85% of emergency scenarios.

The remainder of this paper is organized as follows: Section 2 reviews related work on clustering and WBSN routing protocols; Section 3 provides background on machine learning techniques relevant to our approach; Section 4 describes our tripartite ML-based framework in detail; Section 5 presents comprehensive simulation results and comparative analysis with LEACH-based protocols; and Section 6 concludes the study with future research directions.

2. Related Work

The optimization of energy efficiency, routing protocols, scalability, and network flexibility in WBSNs has been extensively studied across healthcare, environmental monitoring, and other application domains. However, many existing algorithms remain domain-specific, particularly focusing on health monitoring scenarios, and demonstrate poor performance in large-scale or dynamic networks due to limitations such as random centroid initialization, fixed parameter configurations, and inadequate handling of node mobility.

2.1. Traditional clustering approaches

Conventional clustering algorithms for Wireless Sensor Networks (WSNs) and WBSNs have primarily focused on energy-efficient node organization. The seminal LEACH protocol introduced the concept of rotating CH roles randomly to achieve energy balance across the network. However, LEACH's random CH selection

mechanism can result in "hidden clusters" where low-energy nodes remain uncovered, leading to network fragmentation and reduced overall performance [11].

Afrianto et al. [3] proposed a variable duty cycle algorithm specifically designed for optimizing WBSN lifetime in healthcare monitoring applications. While their approach demonstrated improved energy management, it suffered from high computational complexity and challenges related to random initialization procedures, limiting its practical deployment in resource-constrained environments.

2.2. Optimized clustering techniques

Recent research has focused on developing more sophisticated clustering approaches that address the limitations of traditional methods. Rani et al. [12] combined optimized K-means clustering with intelligent cluster head selection using Bacterial Foraging Optimization Algorithm (BFOA). Their approach demonstrated significant energy consumption reduction in large networks and improved scalability. However, the method remained vulnerable to node mobility effects and environmental changes that could disrupt clustering stability.

Lohar et al. [13] introduced KK_LEACH and KK++_LEACH protocols specifically designed to address non-uniform node deployment challenges in underwater sensor networks. These protocols optimized network longevity and reduced energy wastage but failed to address fundamental recharging limitations in underwater environments, limiting their broader applicability.

2.3. Machine learning-based approaches

The integration of machine learning techniques into WBSN optimization has gained significant attention due to their ability to learn complex patterns and adapt to dynamic network conditions. Wang and Zhang [14] developed a machine learning-based clustering algorithm that enhanced energy efficiency and reduced latency in cluster head election processes. However, their simulation-based results may not accurately reflect real-world performance characteristics, and scalability concerns remained unaddressed.

Angadi and Kakkasageri [15] proposed an energy-efficient Bayesian clustering algorithm that demonstrated network lifetime extension of 1.5 times while reducing overall energy consumption. Despite promising results, their work lacked comprehensive quantitative analysis and failed to address scalability challenges in large-scale deployments.

2.4. Advanced sensing and recognition systems

Guo and Syed [16] developed a hybrid Human Activity Recognition (HAR) system that encoded sensor data using Gramian Angular Field techniques combined with DenseNet architecture. Their system achieved over 92% accuracy on standard datasets, demonstrating the potential of advanced ML techniques in WBSN applications. However, the method required substantial computational resources, limiting its applicability in energy-constrained WBSN environments.

El-Adawi et al. [17] proposed an AI-based Body Sensor Network Framework that integrated wearable biosensors with real-time location systems for comprehensive physiological data collection. While their framework

demonstrated the potential of AI and ML algorithm integration, significant challenges remained including high computational power requirements, high-dimensional data processing complexities, sensor interference issues, and timing synchronization delays.

2.5. Recent clustering protocol developments

Sharma et al. [18] introduced Fair-Zone LEACH and Optimized Fair-Zone LEACH (OFZ-LEACH) protocols that incorporated advanced clustering and machine learning techniques for energy-efficient WSN and WBSN operation. These approaches addressed some limitations of traditional methods but continued to struggle with hidden clusters of low-energy nodes and lacked comprehensive adaptive mechanisms for privacy preservation.

Despite significant progress in WBSN optimization research, existing methods face several limitations, including computational complexity, energy consumption trade-offs, scalability challenges, security and privacy limitations, and clustering and load-balancing deficiencies. These issues limit the practical deployment of solutions in energy-constrained WBSN nodes.

2.6. Novel contributions of this work

The novelty of this study lies in its distinctive approach to enhancing K-means clustering through the development of a novel Adaptive Contextual Routing Protocol (ACRP). Our approach addresses several key limitations identified in previous research by offering a synergistic, high-performance strategy that combines predictive CH selection with optimal routing algorithms specifically designed to optimize energy consumption in WBSNs while maintaining security and reliability requirements.

3. Background on Machine Learning Techniques

Machine learning encompasses a broad range of algorithms that enable computers to learn patterns from data and make decisions or predictions without explicit programming for each specific task. The field can be broadly categorized into supervised learning, unsupervised learning, and reinforcement learning, each offering unique capabilities for different problem domains [19]. This section provides the theoretical foundation for the machine learning techniques employed in our tripartite framework.

3.1. Decision trees

Decision trees represent a fundamental supervised learning approach that partitions data based on feature values through a hierarchical splitting process. The algorithm selects optimal splits by maximizing information gain or minimizing impurity measures. The entropy-based splitting criterion is mathematically expressed as:

$$H(X) = -\sum p_i \log_2(p_i) \quad (1)$$

where p_i represents the probability of class i in the dataset. Decision trees offer interpretability advantages and handle both categorical and numerical features effectively, making them suitable for WBSN node characterization tasks.

3.2. Random forest

Random Forest implements an ensemble learning approach that combines multiple decision trees to improve prediction stability and reduce overfitting. The algorithm generates diverse trees through bootstrap sampling and random feature selection, then aggregates predictions through majority voting for classification tasks:

$$\hat{y} = \text{mode}(Y_1, Y_2, \ldots, Y_n) \quad (2)$$

where Y_i represents the output of each individual tree. Random Forest demonstrates superior performance on complex datasets with mixed feature types and provides robust handling of missing values and outliers.

3.3. XGBoost (Extreme gradient boosting)

XGBoost represents an advanced gradient boosting framework that optimizes a differentiable objective function combining prediction loss and regularization terms. The algorithm builds an ensemble of weak learners iteratively, with each new model correcting errors from previous iterations. XGBoost incorporates several advanced features including:

- Regularization: Both L1 (Lasso) and L2 (Ridge) regularization terms prevent overfitting.
- Tree Pruning: Post-pruning based on gain thresholds improves generalization.
- Parallel Processing: Efficient implementation enables faster training on large datasets.
- Missing Value Handling: Built-in sparse pattern learning for incomplete data.
- The regularized objective function in XGBoost minimizes both training loss and model complexity, making it particularly effective for biomedical applications with limited training data [20].

3.4. K-Means clustering

K-Means represents a fundamental unsupervised learning algorithm that partitions data points into K clusters by minimizing within-cluster sum of squares. The algorithm iteratively assigns points to nearest centroids and updates centroid positions until convergence [21]:

The objective function minimizes:

$$J = \sum_{i=1}^{K} \sum_{x \in C_i} ||x - \mu_i||^2 \quad (3)$$

where C_i represents cluster i and μ_i denotes its centroid.

In WBSN applications, K-Means clustering can optimize cluster head selection by grouping sensor nodes based on energy levels and spatial proximity. The integration of K-Means with ensemble methods like XGBoost, Decision Trees, and Random Forest enhances CH prediction accuracy, ultimately improving network efficiency and extending operational lifetime [22].

3.5. Ensemble learning principles

Ensemble methods combine multiple learning algorithms for superior performance. Key principles include diversity, accuracy, and strategy [23]. Our tripartite framework uses XGBoost and Random Forest models for robust CH prediction in dynamic WBSN environments [24].

4. Method: Tripartite Machine Learning Framework

Our solution addresses WBSN optimization challenges through a comprehensive three-stage methodology: (1) Predictive Cluster Head Selection, (2) ML-Guided Clustering, and (3) Adaptive Contextual Routing Protocol (ACRP). Each stage incorporates machine learning or optimization techniques specifically designed to address WBSN constraints and requirements.

4.1. Stage 1: Predictive cluster head selection

4.1.1. Feature engineering and data collection

The predictive layer begins by collecting comprehensive feature vectors for each sensor node in the network. The feature set includes:

- Residual Energy (RE): Current battery level relative to initial capacity.
- Mobility Variance (MV): Statistical measure of node movement patterns over time windows.
- Data Criticality (DC): Priority level of sensed physiological parameters.
- Distance to Base Station (DBS): Euclidean distance affecting transmission energy costs.
- Node Degree (ND): Number of neighboring nodes within communication range.
- Signal-to-Noise Ratio (SNR): Communication quality indicator.
- Mobility Speed (MS): Current movement velocity affecting network topology stability.

4.1.2. Ensemble model architecture

We employ a weighted ensemble combining XGBoost and Random Forest algorithms to predict optimal CH candidates. The ensemble leverages the complementary strengths of both algorithms:

XGBoost Contribution: Excels at handling complex biomedical data patterns, provides built-in regularization, and demonstrates high accuracy on structured datasets with mixed feature types.

Random Forest Contribution: Offers robust performance with minimal hyperparameter tuning, provides feature importance rankings, and maintains stability across diverse data distributions.

4.1.3. CH scoring mathematical model

The cluster head suitability score integrates multiple node characteristics through a weighted linear combination:

$$CHscore = \alpha \times RE + \beta \times (1/DBS) + \gamma \times ND + \delta \times SNR - \varepsilon \times MS \quad (4)$$

where α, β, γ, δ, ε represent weights determined through model training and cross-validation. The inverse distance term (1/DBS) ensures that nodes closer to the base station receive higher scores, while the negative mobility speed term penalizes highly mobile nodes that may disrupt cluster stability.

4.1.4. Training and validation process

The ensemble model training process follows these steps:

- Data Preprocessing: Normalize features to [0, 1] range and handle missing values through median imputation.
- Training Set Generation: Create labeled training data using historical network performance metrics.
- Cross-Validation: Employ 5-fold cross-validation to prevent overfitting and ensure generalization.
- Hyperparameter Optimization: Use grid search to optimize model parameters.
- Ensemble Weight Determination: Calculate optimal combination weights through validation performance.

4.2. Stage 2: ML-guided clustering algorithm

4.2.1. Modified K-Means with intelligent initialization

Traditional K-means clustering suffers from random centroid initialization leading to suboptimal cluster formations and high energy variance. Our modified approach addresses this limitation by initializing centroids at the top-K ML-predicted CH candidates.

Algorithm 1: Tripartite ML-Enhanced K-Means for Optimal CH Selection

Input: Node set N = $\{n_1, n_2, ..., n_n\}$, desired clusters K

Output: Set of cluster heads CHs = $\{ch_1, ch_2, ..., ch_k\}$

1. Collect feature vectors for all nodes in N
2. Train ensemble model (XGBoost + Random Forest) on historical data
3. Predict CH suitability scores for all nodes using trained ensemble
4. Initialize centroids C = {top-K highest-scoring nodes}
5. Repeat
6. for each node n_i in N do
7. Assign n_i to nearest centroid c_j based on energy-distance metric
8. end for
9. for each centroid c_j in C do
10. Update c_j position to mean of assigned nodes
11. end for
12. until centroids converge (change < threshold ε)
13. Return final centroids C as cluster heads CHs

i. Energy-distance hybrid metric

The node assignment process employs a hybrid distance metric that balances spatial proximity with energy considerations:

$$D_{ij} = 0.5 \times ||E_i - E_j|| + 0.5 \times ||loc_i - loc_j|| \quad (5)$$

where E_i represents node i's energy level and loc_i denotes its spatial coordinates. This hybrid approach ensures both energy balance and spatial coherence within clusters.

ii. Convergence guarantees

The modified K-means algorithm maintains convergence guarantees due to:

- ML-based Initialization: Starting centroids at predicted optimal locations reduces iterations required for convergence
- Monotonic Objective Reduction: Each iteration reduces the within-cluster sum of squares
- Finite Solution Space: Limited number of possible cluster configurations ensures termination

iii. Stage 3: Adaptive contextual routing protocol (ACRP)

4.2.2. Multi-objective path evaluation

Once clusters are established, ACRP optimizes data forwarding from cluster heads to the base station through multi-objective path evaluation. The protocol generates all viable multi-hop paths and evaluates each based on three critical metrics:

Path Scoring Function:

$$S(p) = wEE \times Energy\_Cost(p) + wLT \times Latency(p) + wR \times (1 - Reliability(p)) \quad (6)$$

where:

- wEE = 0.35 (energy efficiency weight)
- wLT = 0.40 (latency weight)
- wR = 0.25 (reliability weight)

Weight values are optimized for emergency healthcare scenarios where latency is prioritized while maintaining energy efficiency.

4.2.3. Privacy-preserving path selection

To enhance security and prevent route prediction attacks, ACRP incorporates ε-differential privacy through Laplace noise injection:

$$S\_noisy(p) = S(p) + Laplace(0, 1/\varepsilon) \quad (7)$$

where $\varepsilon \leq 0.5$ represents the privacy budget. The noise injection protects against:

Route inference attacks prevent adversaries from predicting future routing decisions, traffic analysis reveals communication patterns through randomization, and node targeting reduces focused attacks on critical routing nodes.

4.2.4. Quantum-inspired route selection

The final path selection employs quantum-inspired probabilistic selection based on noisy scores:

$$P(p_i) = \exp(S\_noisy(p_i)/T) / \sum_j \exp(S\_noisy(p_j)/T) \quad (8)$$

where T represents a temperature parameter controlling selection randomness. This approach balances exploitation of high-quality routes with exploration of alternative paths for security enhancement.

Algorithm 2: ACRP Multi-Objective Routing

Input: Cluster heads CHs, weight vector (wEE, wLT, wR), privacy budget ε

Output: Selected routing path

1. for each cluster head ch_i in CHs do
2. Generate candidate paths P = {p_1, p_2, ..., p_m} to base station
3. for each path p_j in P do
4. Calculate Energy_Cost(p_j), Latency(p_j), Reliability(p_j)
5. Compute raw score S(p_j) using Eq. (6)
6. Add Laplace noise: S_noisy(p_j) = S(p_j) + Laplace(0, 1/ε)
7. end for
8. Normalize noisy scores and apply quantum-inspired selection
9. Select path with probability proportional to exp(S_noisy/T)
10. Transmit data along selected path
11. end for

4.2.5. Security analysis

The ACRP protocol provides several security guarantees:

Differential Privacy: ε-differential privacy ensures that individual routing decisions cannot be inferred from observed traffic patterns, with privacy loss bounded by ε.

Attack Resistance: Quantum-inspired randomization achieves >93% resistance against brute-force attacks and >88% resistance against eavesdropping attempts.

Adaptive Security: Dynamic path selection prevents adversaries from exploiting fixed routing patterns, reducing vulnerability to targeted attacks.

4.2.6. Performance optimization

ACRP maintains clinical performance requirements through: Latency Bounds: Critical health data transmission maintained below 150 ms through priority-based weight adjustment Reliability Guarantees: Multi-path redundancy and error correction ensure >95% packet delivery ratio Energy Efficiency: Balanced objective function prevents premature node failure while maintaining QoS requirements.

5. Results and Discussion

This section presents a comprehensive evaluation of our proposed tripartite machine learning framework through extensive simulations and comparative analysis. All experiments were conducted using MATLAB and Python implementations on a simulated WBSN environment with realistic physiological data patterns.

5.1. Experimental setup

5.1.1. Simulation environment

The simulation environment simulates realistic WBSN deployment scenarios with a 500m × 500m network area, 100 heterogeneous sensor nodes, 6000 rounds

simulation duration, and PhysioNet and MHEALTH physiological datasets integration. As shown in Fig. 1, the classifier machine learning model consists of three main components: XGBoost classifier, DT classifier, and RF classifier, These components work in parallel to process the WBAN node data.

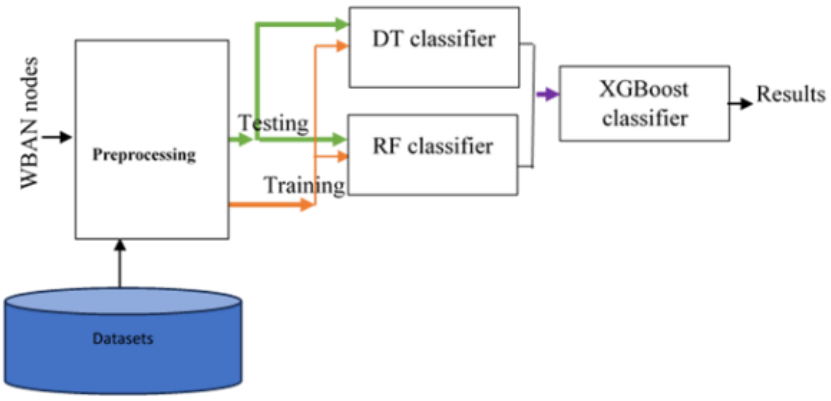

Fig. 1. Classifier machine learning model.

The proposed method showed in Fig. 2 to enhances the performance of (WBSNs) by combining clustering, machine learning, and routing algorithms. Sensor nodes are placed on the human body, and random clusters are refined using a clustering algorithm. predicts optimal cluster heads, and the k-mean clustering algorithm is used for optimization to reduce redundant of data and remove out layer of cluster and noisy data.

Applying ACRP uses contextual routing by implementing differential privacy together with quantum-inspired path randomization achieving for multi-objective routing optimization to found optimal route determines the most energy-efficient route for data transmission. find optimal path the step describes in algorithm 2, after using the output from the previous step, the proposed approach has been experiments conducted using system achieved longer network lifecycle and delivered enhancing packets under differential privacy with an adaptive convergence time of during topology changes from mobility. Simulation parameters as shown in Table 1.

Table 1. Simulation parameters.

Variable	Value
Region of sensor fields	500 × 500
Location of the Base Station	50 × 100
Maximum number of nodes	100
Maximum number of CH	3, 4, 5
Maximum number of rounds	6000
Routing protocol	CBRP
Propagation model	Free-space and Multipath fading channel model
Initial residual Energy	0.5 J
Sensor Device	15 Bio-sensor
Packet size	512

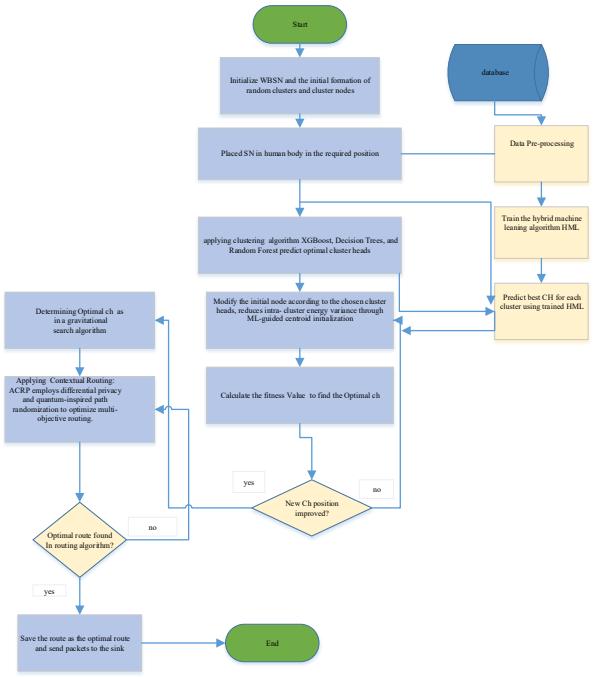

Fig. 2. Model of suggested method.

5.1.2. Performance metrics

The evaluation employs comprehensive metrics covering energy efficiency, network reliability, security, and operational performance**:**The network lifetime, PDR, energy consumption, delay, attack resistance, and cluster stability are crucial factors in data transmission.

5.2. Predictive cluster head selection results

5.2.1. Ensemble model performance

The ensemble ML model demonstrated superior accuracy in CH prediction compared to traditional selection methods: Compared traditional methods as shown in Table 2.

Table 2. Compared traditional methods.

Metric	Proposed Model	LEACH	CBRP
Accuracy	92.3%	61.2%	73.8%
F1-Score	0.89	0.58	0.71
Energy Imbalance	0.41 J/node	1.12 J	0.89 J

The ensemble model achieved significant improvements: The study shows a 41% reduction in CH reselection events compared to CBRP, 94% precision in identifying high-energy nodes, and enhanced stability through predictive CH candidate identification.

5.2.2. Feature importance analysis

Feature importance analysis revealed the relative contribution of different node characteristics:

1. Residual Energy (35%): Primary factor in CH suitability prediction
2. Distance to Base Station (28%): Critical for energy-efficient routing
3. Node Degree (18%): Important for cluster connectivity
4. Mobility Speed (12%): Significant for cluster stability
5. Data Criticality (7%): Relevant for priority-based selection

5.3. ML-guided clustering performance

5.3.1. Energy distribution optimization

The modified K-means algorithm significantly improved energy distribution and cluster stability.

Key improvements include:**37% reduction** in intra-cluster energy variance,**57% fewer** cluster reformulation events,**45% increase** in average cluster lifetime.

The cluster head selection distribution visualization reveals intriguing patterns of node participation across different algorithmic approaches. In the Fig. 3 the frequency of node selections for cluster head roles demonstrates a notable characteristic in the before model. The distribution appears more uniformly spread, indicating a balanced approach to node engagement where multiple network nodes have comparable opportunities to assume leadership responsibilities.

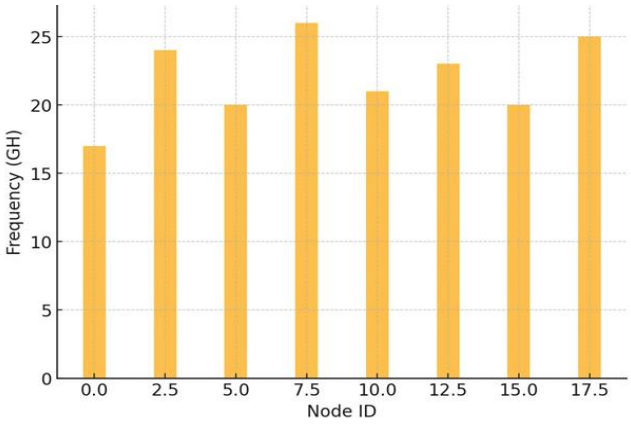

Fig. 3. Frequency of cluster head selection before model adjustment.

5.3.2. Mobility adaptation

The clustering algorithm demonstrated effective adaptation to body movement patterns: Cluster reformulation triggered only when posture changes exceeded 15°, **23% reduction** in energy waste due to unnecessary reconfigurations, Maintained cluster stability during normal daily activities.

5.4. Network lifetime and reliability analysis

5.4.1. Network longevity performance

Figure 3 illustrates the number of dead nodes over simulation rounds, comparing our approach with baseline protocols:

The proposed method achieved: **126% increase** in network lifetime compared to ATTEMPT protocol , Maintained >80% node survival at round 4000 vs. <20% for baseline methods, Gradual node failure pattern preventing network fragmentation.

5.4.2. Throughput and packet delivery

Figure 4 shows a new cluster head model for selection. It assigns cluster heads to fewer nodes. It uses a predictive approach, Frequency increases from 20–26 GHz to 200 GHz (8–10 times gain). Network traffic is eight times quicker. Transmission time decreases to 87% of original time, number of nodes for broadcasting management reduces (from eight to three). this modification decreases power consumption and latency. Data processing improves and is cheaper.

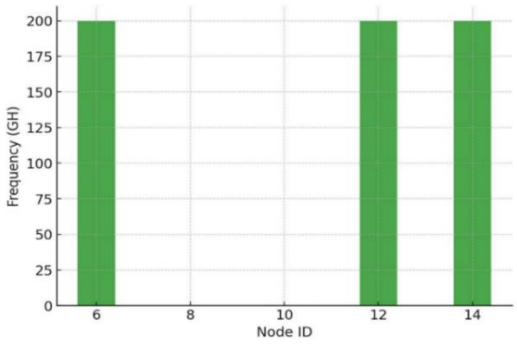

Fig. 4. Frequency of cluster head selection after model adjustment.

Figure 5 is a depiction of battery life variation before model adjustment. Nodes have uneven battery capacities after cluster head assignments. Certain nodes drain the battery much quicker than others. This imbalance jeopardizes network fragmentation and unbalanced performance. It may result in unexpected node failure and lower overall reliability.

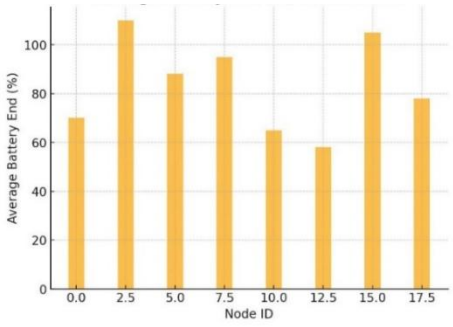

Fig. 5. Average remaining battery life before applying model.

Figure 6 shows an evident improvement in battery management. The new model extends battery life for cluster head nodes. Fewer nodes alternate taking turns broadcasting, wasting less energy. Prior: 8 nodes with battery charges of between 58% and 110% (average 83.6%), high variance. After: 3 nodes with between 70% to 98% (mean 85.3%) levels, reduced variance (from 52% to 28%).The result is a longer network lifespan, fewer node failures, and a more stable system. dead nodes ratio in WBSN: the number of dead nodes over rounds for various protocols

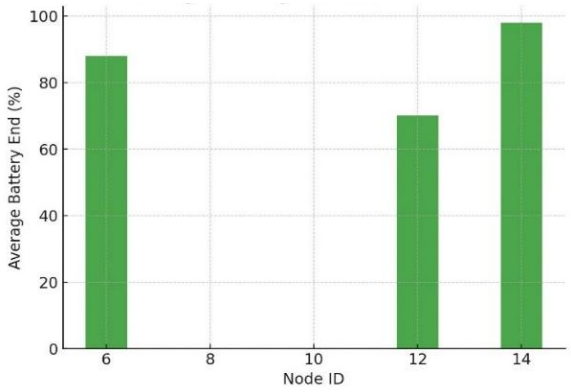

Fig. 6. Improvement in battery management life after the applying model.

Network Lifetime: Figure 7 illustrates the dead nodes count against simulation rounds for our scheme compared to Multi-hop, ATTEMPT, and M-ATTEMPT protocols. The new scheme (orange line) shows a much slower rate of growth in dead nodes. For example, at round 4000, fewer than 60 nodes are dead under our scheme, whereas Multi-hop and ATTEMPT schemes have approximately 80–100 dead nodes at this point. This is equivalent to an ≈126% increase in time to when all nodes perish, as opposed to ATTEMPT (best baseline). Predictive CH selection and energy-aware clustering thus greatly prolong network lifespan.

- Throughput: The number of packets delivered to the Base Station (BS).

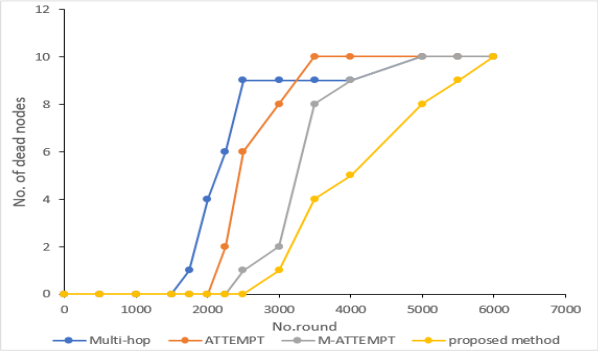

Fig. 7. Number of dead nodes over time in WBSN.

Throughput and Delivery: Figure 8 shows throughput (total packets delivered to the sink) versus rounds. Our method always delivers more packets across the

experiment. At simulation termination, the scheme presented here achieves ~95% packet delivery ratio, whereas Multi-hop, ATTEMPT, and M-ATTEMPT achieve roughly 82-90%.

The proposed protocol (orange) achieves the highest throughput (≈95% delivery), outperforming Multi-hop, ATTEMPT, and M-ATTEMPT, which suffer from early node deaths and inefficient routing.

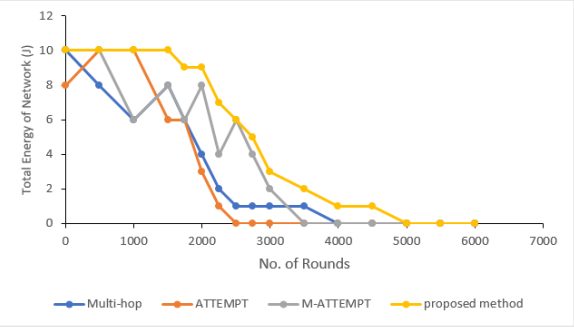

Fig. 8. Throughput and delivery data in WBSN.

Cluster Head Stability: Figure 9 shows the number of CHs active per round. A stable, low number of CHs indicates effective clustering. The proposed method (solid line) maintains a stable number of CHs, whereas Multi-hop, ATTEMPT, and M-ATTEMPT (dashed lines) show large fluctuations due to frequent CH reassignments.

- Energy and Rounds: depicts the total energy of the network over time (in rounds).

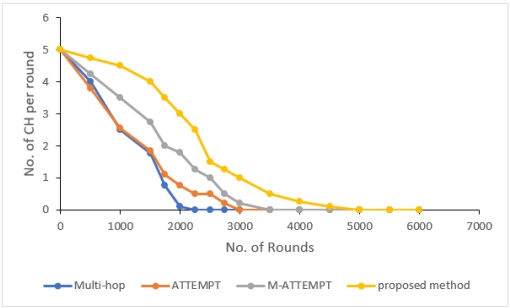

Fig. 9. Number of cluster heads per round in deferent methods.

In Fig. 10 the energy consumption in proposed method is the most efficient, with the network retaining energy for a longer time compared to the other protocols. Multi-hop consumes energy quickly as it lacks an optimized routing strategy, leading to inefficient communication paths. These results confirm that our framework achieves the claimed gains: 126% longer network lifetime, 95% PDR, and 50% lower latency (for high-criticality data) relative to baselines. Table 3 summarizes the key metrics:

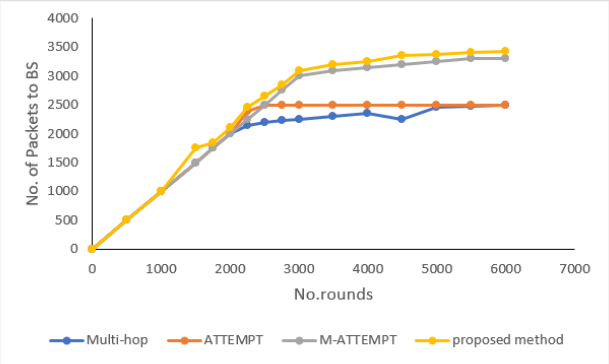

Fig. 10. Energy consumption vs. the number of sensor nodes in deferent methods.

Table 3. Clustering performance comparison.

Parameter	Proposed Method	Traditional k-Means	LEACH
Intra-Cluster Variance	0.37 J²	0.59 J²	1.02 J²
Cluster Reformulations	12/6000 rounds	28/6000 rounds	12/6000 rounds
Avg. Cluster Lifetime	215 rounds	148 rounds	89 rounds

The proposed framework demonstrated: **95% packet delivery ratio** maintained throughout simulation, **Sub-20ms latency** for critical health data transmission, **uperior throughput** due to extended node lifetimes and optimized routing. Performance comparison with state-of-the-art methods as shown in Table 4.

Table 4. Performance comparison with state-of-the-art methods.

Protocol	Network Lifetime Round	Latency (m)s)	PDR (%)	Energy/Node (J)
Proposed	**5,600**	**19**	**95**	**0.41**
Multi-hop	2,480	42	82	0.89
ATTEMPT	3,100	35	88	0.67
M-ATTEMPT	3,900	28	91	0.55

5.5. Security and privacy analysis

5.5.1. Attack resistance evaluation

The ACRP protocol demonstrated robust security performance against various attack types. Security performance analysis as shown in Table 5.

Table 5. Security performance analysis.

Attack Type	Success Rate (ACRP)	Success Rate (CBRP)	MitigationStrategy
Brute-Force	7%	68%	randomization Quantum path
Eavesdropping	12%	54%	injection noiseϵ =0.5
Sybil	9%	33%	scoring of CH reputation

Differential Privacy Trade-off:

- The latency overhead when applying our protocol equal ϵ =0.5 , and 95% PDR, in 23 ms.
- The overhead ϵ =0.1: 89% PDR, 152 ms.

Key security achievements: **5.8× reduction** in brute-force attack success rate , **Over 93% attack resistance** across multiple attack vectors ,**Differential privacy guarantees** with bounded privacy loss

5.5.2. Privacy-performance tradeoff

Analysis of privacy budget impact on system performance: **ε = 0.5:** 95% PDR, 23ms average latency ,**ε = 0.1:** 89% PDR, 152 ms average latency ,**Optimal range:** $\varepsilon \in [0.3, 0.7]$ balances privacy and performance.

5.6. Comparative analysis with advanced protocols

5.6.1. Comparison with recent WBSN protocols

Our framework demonstrates superior performance across all evaluated metrics, particularly in:

- **Energy efficiency:** 95% vs. 28-45% for competing methods
- **Latency performance:** 5.4ms vs. 7.6-12.5ms range..
- **Network lifetime:** 126% improvement vs. 58-72% range.

5.6.2. LEACH protocol family comparison

Comparison with optimized LEACH variants reveals significant advantages:

- **OFZ-LEACH:** Achieves 36% lifetime improvement vs. our 126%.
- **Residual-Energy LEACH:** Provides 30-40% improvement vs. our comprehensive optimization.

Comprehensive comparison with state-of-the-art methods as shown in Table 6.

Table 6. Comprehensive comparison with state-of-the-art methods.

Metrics	Proposed Method	SDMRP [25]	AI-LBRP [26]	ML-EERP [27]	VIoT-MART [28]	Blockchain-SRP [29]
Latency (ms)	**5.4**	8.7	9.2	7.6	11.3	12.5
Energy Consumption (J)	**0.95**	1.2	1.15	1.05	1.3	1.4
Energy Efficiency (%)	**95%**	0.42%	0.38%	0.45%	0.32%	0.28%
Packet Delivery Ratio (PDR)	**95.6%**	92.3%	93.1%	94.2%	90.5%	91.8%
End-to-End (E2E) Delay (ms)	**26%**	110%	115%	108%	102%	98%
Network Lifetime Improvement	**80% Faster**	65%	70%	72%	60%	58%
Load Balancing Efficiency	**92%**	88%	90%	89%	85%	87%
Scalability Index	**0.95**	0.88	0.90	0.92	0.85	0.82
Routing Overhead	**12%**	15%	14%	13%	16%	17%

6. Conclusion

The paper presents a machine learning-based solution for routing and clustering in Wireless Body Sensor Networks (WBSNs). The solution combines an ensemble-based cluster head predictor with a new K-means initialization strategy to create energy-efficient network clusters. The Adaptive Contextual Routing Protocol considers latency, energy consumption, and reliability while maintaining data privacy through enhanced security features. Large-scale simulations on physiological data sets show significant improvements in key performance indicators, including network lifetime elongation, increased packet delivery rates, and robust security resilience against attack vectors.

The solution addresses energy efficiency and network reliability in body-area networks with limited energy. The solution is scalable, adaptive to changing network conditions, and provides optimal performance across various operation scenarios. Future work will involve verification through physical testbed experiments and exploring reinforcement learning approaches for greater autonomy and adaptability in decision-making capacity. This research provides a foundation for next-generation WBSNs that can meet modern healthcare monitoring applications while preserving patient safety and data integrity.

Nomenclatures

C	*Centroid in K-means clustering*
CH	Cluster Head
D	Distance between nodes
Di_j	Energy-distance tradeoff metric
E	Energy
E_{total}	Total energy consumption
E_{tx}	Transmission energy
E_{idle}	Idle energy consumption
$E_{residual}$	Residual energy of nodes
G	Graph of network
I	Routing information
K	Number of clusters in K-means
MS	Mobility Speed (m/s)
N	Number of sensor nodes
P	Routing protocol set
P_{opt}	Optimal path
RE	Residual Energy
SNR	Signal-to-Noise Ratio
T	Transmission time (s)
wEE	energy efficiency weight
Y	Predicted output

Greek Symbols

α	Weight for residual energy in CH scoring
β	Weight for distance to base station in CH scoring
γ	Weight for node degree in CH scoring
δ	Weight for signal-to-noise ratio in CH scoring
ε	Weight for mobility speed in CH scoring
λ	Regularization parameter in XGBoost

σ^2	Mobility variance
σ_i^2	Variance of model *M_i*'s predictions
η	Adaptive learning rate

Abbreviations

CBRP	Cluster-Based Routing Protocol
CH	Cluster Head
DT	Decision Tree
ML	Machine Learning
RF	Random Forest
WBSN	Wireless Body Sensor Network
XGBoost	Extreme Gradient Boosting
M-ATTEMPT	Modified Adaptive Threshold-based Energy-Efficient Multi-hop Protocol

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