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RESEARCH ARTICLE

A Hybrid Optimization Framework for Energy Efficiency and Scalability in Reliable Wireless Sensor Networks

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Abstract – Wireless Sensor Networks (WSNs) play an important role in environmental monitoring and data collection. However, WSNs have several problems, such as energy efficiency, efficient routing for data, and avoidance of energy depletion around the sink. However, these issues have not been resolved by existing clustering and routing schemes. Their main result was that they caused significant energy consumption and network instability. Despite advancements in clustering techniques, the selection of Cluster Heads remains suboptimal, and energy usage is not evenly distributed. This calls for the development of innovative solutions. This study introduces an Adaptive Hierarchical Clustering and Routing Framework (AHCRF) that integrates a multilayered cluster system. In this framework, preprocessing and consolidating data using a subcluster head (sub-CH) minimizes the redundant transmissions. Therefore, the energy consumed by the main CH was reduced. Using the hunting strategies of secretary birds, CH and sub-CH selection may be improved as a result, considering the remaining energy, node concentration, and distance to the sink in the Secretary Bird Optimization Algorithm. Therefore, FTMPR redundancy in communication concerning path creation, which accounts for communication in the routing mechanism, can help reduce the losses associated with data and improve their reliability owing to node failures. In addition, the Dynamic Energy Threshold Adjustment strategy dynamically adjusts the energy consumption of the nodes, avoiding a rapid energy drain near the sink. The experimental results show that the AHCRF outperforms the current protocols with a 94.5% packet delivery ratio, 0.45 J energy, 0.05 s delay, and 3.2 ms jitter. These outcomes illustrate the efficiency, scalability, and reliability of the AHCRF for next-generation WSN.

Index Terms – Wireless Sensor Networks, Adaptive Hierarchical Clustering, Routing Framework, Energy Efficiency, Fault Tolerance, Secretory Bird Optimization Algorithm.

1. INTRODUCTION

Wireless Sensor Networks (WSN) have marked the arrival of an innovative technological approach with applications in agriculture, healthcare, industrial automation, and environmental monitoring. The networks consist of distributed sensor nodes powered by a limited-capacity battery, which together sense, process, and transmit information to enable real-time decisions. Seamless integration with the Internet of Things (IoT) opens new avenues for smart agriculture and urbanization, enhancing productivity and operational efficiency [1].

Despite their immense potential, WSNs face several challenges that impede their performance and scalability. In addition to uneven energy distribution, inefficient data routing and extra communication overhead are the challenges that most critically hinder the development of WSNs. The premature depletion of sink nodes also remained high. Among all the resources available in a WSN, energy is the most constrained; therefore, maximizing energy efficiency is a priority for the sustained operation of the network. To this end, researchers have suggested the use of clustering and routing techniques to spread the communication load among nodes. In this procedure, the Cluster Heads (CHs) play a significant role in intra-cluster aggregation and inter-cluster transmission. However, when it comes to energy consumption, the CHs are often consumed much earlier, thus lowering the entire lifetime of the network. Some optimization methods have been proposed to handle this, such as the Adaptive Remora Optimization Algorithm (AROA), which attempts to enhance CH selection based on parameters such as residual energy, packet delivery ratio (PDR), and throughput to improve the lifetime of the network [2].

The development of Software-Defined Network (SDN) principles in Wireless Sensor Networks (WSNs) has resulted in software-defined Wireless Sensor Networks (SDWSNs). This architecture aims to provide centralized management and higher scalability by separating the control, data, and application planes from one another. Nonetheless, the challenges of routing inefficiencies in SDWSNs, which can lead to congestion and compromise security, stretch for more undisturbed and energy-efficient routing solutions [3]. Recently, hybrid optimization techniques have been implemented in cluster-based approaches. For instance, the Tasmanian Integrated Coot Optimization Algorithm (TICOA) combines Improved Coot Optimization with Tasmanian Devil Optimization for optimized CH selection and routing paths. With respect to energy consumption, delay, and trust, TICOA improves the network lifetime, routing efficiency, and security [4].

There are many emerging applications of IoT-enabled WSNs, such as video surveillance and healthcare; however, they remain challenged by very high energy costs during data transmission. Although multihop routing can reduce energy consumption relative to single-hop approaches, complex optimization leads to restrictions in terms of limited energy and bandwidth. Therefore, bio-inspired and meta-heuristic approaches have been adopted to balance energy consumption, reduce error rates, and preserve scalability under dynamic operating conditions [5][6].

However, traditional protocols for routing, such as the Routing Protocol for Low-Power and Lossy Networks, are not designed for dynamic environments but rather for static topologies. RPL has been measured to have high packet loss, increased power consumption, and degraded quality of service when deployed in IoT scenarios that possess node mobility [7]. New protocols, such as Coalescing QoS Routing and Fault Tolerance (CRAFT), have been designed to address QoS-specific issues, which would manifest as reduced latency, improved robustness, and enhanced reliability against fault-prone conditions. These would greatly improve the performance of WSNs in mission-critical applications by optimizing parameters such as jitter, packet arrival time and delay [8].

The integration of wireless sensor networks (WSNs) with Internet of Things (IoT) applications has shown great progress in diverse domains, such as effective real-time monitoring and obtaining data from a single system. Applications such as precision farming, smart cities, and healthcare have persistently complex operations that require new solutions to problems such as energy inefficiency, unreliable routing, and scalability. The link between WSN technologies and artificial intelligence and optimization techniques has already applied very promising advancements into more energy-efficient, reliable data transfers, and the greater adaptability of networks that dynamically evolve. This study is particularly important because it establishes a bridge between theoretical innovation and its actual application in real systems. Such a bridge will give rise to potent frameworks capable of managing energy consumption and routes efficiently while satisfying specific requirements in dynamic and heterogeneous environments.

As a result, major innovations have influenced the design of clustering and routing protocols for WSNs to provide solutions to multidimensional problems such as energy saving, fault tolerance, and dynamic adaptability. Most clustering algorithms focus on improvements in energy efficiency but do not consider certain important aspects, such as load balancing and seamless data aggregation under node or Cluster Head failures. Likewise, mobility, security threats, and network scalability related to IoT-enabled WSNs have not been well addressed using classic routing models. Although hybrid optimization algorithms and AI-driven techniques have been brought to the fore, these often focus on targeted individual objectives, and thus, present neither a holistic scheme that incorporates energy efficiency and fault tolerance with QoS nor a unified approach through advanced clustering combined with fault-tolerance routing and adaptive optimization, as envisaged in future prospects for WSNs.

The core objective of this study is to develop an energy-efficient and fault-tolerant clustering and routing framework for Wireless Sensor Networks (WSNs). The specific objectives are as follows:

- To develop an Adaptive Hierarchical Clustering and Routing Framework (AHCRF): a two-layer clustering mechanism with sub-cluster heads is introduced to minimize redundant transmissions and balance energy consumption among nodes.
- To optimize cluster head selection: apply the Secretary Bird Optimization Algorithm (SBOA) by considering residual energy, node density, and sink proximity, ensuring balanced and stable cluster formation.
- To enhance routing reliability, a fault-tolerant multipath routing (FTMPR) strategy that guarantees successful data delivery even in the presence of node or link failures is integrated.
- To implement dynamic energy management, a Dynamic Energy Threshold Adjustment (DETA) mechanism is introduced to prevent energy holes near the sink and extend the overall network lifetime.
- To validate performance improvements, comparative simulations were conducted against existing protocols, such as LEACH, MMRA, CHFHIM-EEFR, and DBLOCK-RLB, analyzing key metrics, including energy

RESEARCH ARTICLE

efficiency, packet delivery ratio (PDR), bit error rate (BER), throughput, jitter, and delay.

Through these objectives, the proposed research addresses the limitations of existing clustering and routing techniques while providing a scalable and adaptive solution for energy-constrained WSN environments.

The remainder of this paper is organized as follows. Section 2 describes related works that highlight the improvements and challenges faced by WSNs in terms of energy efficiency, reliability, and fault tolerance. Section 3 discusses the method, concentrating on the Adaptive Hierarchical Clustering and Routing Framework (AHCRF), its strategies for clustering and routing, and energy management. Section 4 describes the experimental setup and performance evaluation of the proposed AHCRF against the benchmark models. Finally, Section 5 concludes the paper with the major findings and future work.

2. RELATED WORK

Several studies have been conducted to improve the energy efficiency, fault tolerance, and security of Wireless Sensor Networks (WSNs), particularly in IoT and precision agriculture applications. These contributions differ in terms of methodologies, algorithms, and optimization techniques, each providing a different contribution and limitation.

This study describes a fault-tolerant architecture proposed for Wireless Sensor Networks (WSNs) constituting precision agriculture, which requires reliability owing to the wide field deployment of sensor nodes and the harsh factors of the outdoor environment. The authors proposed the use of a hierarchical topology, where nodes are grouped in clusters, with each cluster being managed by a Cluster Head (CH), which transmits the aggregated data to a Base Station (BS). The system implements a heartbeat strategy for continuous fault detection to enable the immediate detection of component failure owing to node degradation. Furthermore, hardware redundancy is introduced at both the CH and BS levels to allow backup components to take over in the case of failure without data loss or communication breakdown. The use of sleep mode technology on sensor nodes conserves energy, thus prolonging the operational lifetime of the network. Simulation and formal verification using the UPPAAL model checker demonstrated the system's capability to ensure safety and liveness properties in fault scenarios. This solution is reliable but limited by increased hardware costs because of redundancy and possibly high complexity in large deployments [9].

This is a hybrid energy-efficient routing strategy that integrates two advanced meta-heuristic algorithms: Sailfish Optimization (SFO) and Spotted Hyena Optimization (SHO). SFO selects optimal CHs very quickly, whereas SHO refines routing paths through effective exploitation. The dual-phase model successfully integrates exploration and exploitation to make optimal CH election and effective route discovery for a routing solution. Dynamic speed adjustment, memory-based refinement, and feedback-based optimization render the approach truly adaptable to dynamic WSN conditions and scalable for real-time use, and the augmentation of performance is clearly visible. The overall strength of this approach is that it greatly increases the network lifetime with an excellent Packet Delivery Ratio (PDR), whereas the weakness may include the increased computational overhead of operation using two meta-heuristic algorithms, which may be disruptive to low-power nodes in resource-constrained environments [10].

The Cluster-based Hybrid Flamingo Hazelnut Tree with Improved Marine Predators for Energy-Efficient Fault-Tolerant Routing (CHFHIM-EEFR) introduces a layered methodology to address fault tolerance and routing efficiency issues. The proposed framework is divided into three phases: (i) Main CH selection using a novel Hybrid Flamingo Hazelnut Tree Search Algorithm (Hyb-FL-HTSA), optimized based on a fitness function integrating delay, throughput, and residual energy; (ii) Backup CH (BCH) selection for further resilience against CH failure; and (iii) routing optimization using an Improved Marine Predators Algorithm (Im-MPA), which ensures secure communication by link quality, delay, and trust. This design effectively defends against security threats, such as Black Hole, Sinkhole, and Hello Flooding attacks, and guarantees data integrity. From the simulations, less energy was used, and the network had a longer lifespan. However, the major limitation is the complexity involved in combining multiple algorithms, which increases computations and may not cater to ultra-low-power devices [11].

This study proposes a directed acyclic graph (DAG)-based blockchain routing and load balancing model (DBLOCK-RLB) for Software-Defined WSNs (SDWSNs). The methodology integrates clustering, where CHs are selected using criteria such as connectivity, energy, and distance, with blockchain-based transaction recording for secure routing. This approach uses the Camellia Encryption Algorithm (CEA) for authentication and secure key management, ensuring that IDs, MACs, and locations remain tamper-proof. Intelligent routing is performed using the Dual Agent–Twin Delayed Deep Deterministic Policy Gradient (DA-TD3), which allows the simultaneous optimization of forwarder selection and routing paths. Moreover, a Stackelberg game theory–based trading system balances the load between controllers, enhancing fairness and reducing latency. The simulation results revealed improvements in the throughput, latency, and energy efficiency. A major strength is its high scalability owing to blockchain integration; however, this comes at the cost of increased computational and memory demands, which could challenge low-end WSN hardware [12].

RESEARCH ARTICLE

The architecture of this system focuses on Fog-based WSNs for emergency evacuation plans in buildings. It contains a two-tier structure: the sensing layer has distributed sensors that detect an emergency incident, whereas the fog layer processes data and manages responses. The Improved Layer-wise Clustering Protocol (ILC) optimizes energy consumption and load balancing across the entire building by distributing CHs equally among the different floors of the building. The Non-dominated Sorting Genetic Algorithm III (NSGA-III) was incorporated into this system for real-time evacuation planning, in which it dynamically evaluates the optimum routes for evacuation based on multivoiced objectives such as energy, delay, and throughput. Undoubtedly, the major strength of this architecture is observed in emergency cases because it offers both scalability and real-time decision-making. Centralized fog servers lead to bottlenecks and single points of failure; therefore, they cannot be used in environments without a solid computing infrastructure. [13]

The Capuchin Search Optimization-based Routing Protocol (CSORP) is inspired by the cooperative behaviors of capuchin monkeys. The algorithm uses multipath routing to disperse the network load across several optimal paths, thereby improving the Quality of Service under heavy traffic. It uses stochastic universal sampling to quickly converge on optimal paths with respect to the delay, packet delivery ratio, and energy consumption. The methodology ensures adaptive load balancing and reduces the queuing delay. Its simulation in NS-3 proved its superiority over classical routing protocols, such as AODV, DSDV, I-DSDV, and DSR. The major advantage of CSORP is that it is robust in dynamic IoT environments; however, the stochastic approach incurs a heavier routing load and computational demand, making it less suitable for very large networks with constrained processing capacity [14].

The activity of energy harvesting in solar-powered WSNs is achieved using two major components: the Plus-Profile Energy Prediction (PP-Energy) algorithm and the Adaptive Energy Management (AEM) scheme. The PP-Energy algorithm has an impressive prediction capability owing to the combination of historical solar data with real-time weather updates. This affords a dynamic adaptation to changing conditions. The AEM scheme utilizes these prediction outcomes to dynamically schedule tasks that guarantee energy neutrality within a given 24-hour cycle. This minimizes energy wastage and promotes node longevity. The strength of the proposed method lies in balancing consumption against available energy resource input values, while its weakness is the reliance of the method on accurate solar irradiance data, which may be questioned and compromised under erratic climatic variations [15].

The Modified Sandpiper Optimization Algorithm (MSOA) architecture primarily achieves fault tolerance and security improvements in WSNs with two basic techniques: Energy Level Checker (ELC) and Routing Manager (RM). The ELC continuously monitors the node energy in the communication stage and alerts the network when the residual energy reaches defined thresholds for preventive failure management. The RM checks path verification packets, blacklists malicious or faulty nodes, and makes the path available for legitimate communication with acknowledgment. The CH selection process is optimized by the MSOA by solving a multi-objective function that accounts for residual energy, trust, delay, and distance. The hybrid approach enhances fault tolerance, lowers malicious acts, and increases data aggregation. The advantage of this model is its high adaptability to hostile situations with a high fault rate. The downside could be the additional load in communication because of frequent energy monitoring and path validation, which can influence the efficiency of ultra-low-power networks [16].

The Adaptive Ant Colony Distributed Intelligent-Based Clustering (AACDIC) algorithm is an ant-like method based on the principles of ant colony optimization. It focuses on improving clustering performance and energy efficiency in wireless sensor networks (WSNs) and cognitive radio networks (CRNs) using swarm intelligence. The adaptive clustering method is designed to guarantee that the CH is distributed evenly, thereby minimizing the effects of re-clustering that often affect traditional methods. Distributed intelligence provides a significant advantage in terms of a mechanism to vary the frequency of re-electing CHs, thus ensuring that node resources are maximally utilized. The use of real-time spectrum sensing data allows routing and clustering decisions to be adapted to environmental conditions, thereby minimizing false alarms in CRNs. Such a methodology guarantees its scalability and has an increased convergence speed compared to classical clustering algorithms. However, the downside lies in the increased overhead because of the complexity of distributed reclustering and the continuous requirement for environmental data, which, in turn, should increase the overall computation and energy overhead [17].

The Secured Energy-Efficient Opportunistic Routing Scheme (EDSSR) simultaneously addresses energy and security challenges in WSNs. The methodology focuses on opportunistic routing, where neighbor information is continuously updated, and the legitimacy of routing parameters is verified to prevent security breaches, such as Sybil and flooding attacks. Unlike traditional protocols, the EDSSR avoids storing multi-hop routing information, thereby reducing the memory burden and simplifying the protocol design. The introduction of an Assistant Cluster Head (ACH) reduces the workload on primary CHs by storing and forwarding data until an acknowledgment is received from the BS, thereby improving resilience during Sybil attacks.

RESEARCH ARTICLE

Mechanisms such as binary exponential back-off and time-to-live (TTL) adjustment further optimize path discovery and reduce collisions. Although the scheme enhances security and reduces energy consumption, its reliance on continuous neighbor updates introduces an overhead that potentially affects latency in high-traffic scenarios [18].

An Enhanced Cluster Head (CH) selection scheme with an energy-efficient routing algorithm that combines LEACH, Firefly Algorithm (FFA), and Artificial Neural Networks (ANN). Unlike traditional LEACH, which relies on random CH selection, this model utilizes residual energy, distance, and average energy metrics for optimal CH election. FFA refines node property optimization, and ANN classifies nodes into communicating, non-communicating, and malicious categories, thereby enhancing security by isolating the compromised nodes. This hybrid design reduces packet loss, improves reliability, and prolongs the network lifetime. A notable strength of this approach is its ability to simultaneously address security and efficiency, which traditional LEACH variants often overlook. However, ANN-based classification introduces computational complexity, potentially limiting its applicability in resource-constrained sensor networks [19].

The Low Energy and Overhead (LEO) metric for routing in WSNs focuses on reducing retransmissions and conserving energy. Unlike classical metrics such as hop-count, LEO integrates the Packet Reception Rate (PRR) and Signal-to-Noise Ratio (SNR) for a more accurate link quality evaluation. The protocol is supported by an Automatic Transmission Power Control (ATPC) algorithm, which dynamically adjusts the transmission power to maintain reliable communication at a minimal energy cost. The simulation results confirmed that LEO lowers energy consumption and enhances routing reliability, particularly in environments with poor connectivity. The strength of this model lies in its passive operation, which incurs minimal overhead. However, its limitations include its reliance on approximate transmitter energy consumption and the inefficiency of the underlying routing protocol, which still floods the network during path discovery, reducing scalability. [20].

The Capuchin Search Optimization-based Routing Protocol (CSORP) into a multipath routing design for WSNs in IoT applications. The protocol employs the Capuchin Search Optimization (CSO) algorithm to dynamically identify multiple optimal routes that balance node energy and reduce latency. It adopts adaptive multipath routing with efficient scheduling to ensure improved throughput and packet delivery in dense traffic environments. Simulation results using NS-3 show that CSORP achieves an 88% PDR, 35 ms latency, and significant energy savings of up to 26.6% compared to the baselines such as AODV and DSR. Although this scheme enhances reliability and node lifetime, the trade-off is an increased routing load and computational complexity, which may limit its efficiency in extremely large-scale IoT deployments [21].

An energy-efficient adaptive routing framework for heterogeneous WSNs (HWSNs) by combining Improved Particle Swarm Optimization (IPSO) with dynamic clustering and hybrid communication strategies. The IPSO employs a cosine-modulated mechanism for adaptive inertia weights and learning factors, ensuring a balance between exploration and exploitation and avoiding premature convergence. A hybrid single-hop/multihop routing mechanism further optimizes path selection based on real-time energy gradients and node density. To incorporate heterogeneity, the framework embeds node-specific attributes, such as range, residual energy, and role, into a weighted fitness model. Experimental evaluations demonstrated a 32.7% reduction in per-round energy consumption and a 28% increase in network lifetime compared to LEACH. The approach is practical and scalable, particularly for IoT deployments on low-power devices, such as Raspberry Pi. However, the model's dependence on parameter fine-tuning for the IPSO may introduce implementation complexity [22].

The Dual-Energy Harvesting Routing Algorithm for WSNs (DEHRA-WO) integrates solar energy harvesting with radio-frequency (RF) charging. To address the unpredictability of solar power, a Kalman filter was employed for accurate energy prediction, triggering RF charging when required. The methodology includes models for residual energy, communication range (Rayleigh fading), and MAC constraints to ensure realistic node behavior. Routing paths are optimized using the Whale Optimization (WO) algorithm, which balances energy use and packet forwarding. The simulation results show a 30% reduction in packet loss and a 29% improvement in energy utilization compared with QIH and ORDPD. The strength of this hybrid harvesting mechanism lies in its sustainability and adaptability to Green IoT applications. However, reliance on dual hardware (solar + RF) increases the node cost and deployment complexity [23].

A hierarchical WSN routing protocol optimized using the Spider Wasp Optimizer (SWO). The protocol jointly optimizes CH election and inter-cluster routing in a single stage using a fitness function that balances factors such as CH energy, BS distance, cluster size variance, and inter-cluster hop length. After CH selection, K-means clustering groups CHs, mitigating hotspot issues, whereas an equidistant relay strategy reduces long-hop energy drain. The shortest paths between the CHs and BS are determined using Dijkstra's algorithm. MATLAB experiments validated longer network lifetimes and greater data delivery compared with PSO-C, EECHS-ISSADE, and others. Its major advantage is its computational feasibility with O(N) time complexity per

RESEARCH ARTICLE

round. However, the layered use of SWO, K-means, and Dijkstra increases algorithmic complexity, which could pose difficulties in real-time large-scale deployments [24].

Hybrid Memetic Evolutionary Algorithm (HMEA) for clustering and routing in WSNs. Recognizing the shortcomings of PSO and GA, particularly premature convergence and high computational overhead, HMEA combines a global evolutionary search with local memetic refinement. CHs are selected adaptively based on residual energy, node density, and proximity, whereas routing paths are refined to minimize energy usage and balance the load. The simulation results demonstrate improvements in throughput, PDR, and energy efficiency compared with the standalone PSO and GA. The strength of the HMEA lies in its adaptability to dynamic network conditions and scalability for large applications, such as healthcare and smart cities. However, memetic refinements increase the computational load, which may challenge ultra-low-resource sensor nodes [25]. Finally, we propose Threshold LEACH with Sleep–Awake Scheduling (T-LEACHSAS), which enhances hierarchical routing through threshold-based CH selection and a centralized sleep–awake scheduling mechanism. Nodes remain CHs only if their energy exceeds a threshold, whereas member nodes alternate between active and sleep states in synchronized TDMA slots, reducing idle listening. This approach significantly improves the network lifetime and data delivery compared with LEACH and T-LEACH. The benefits are reduced re-election overhead and idle energy waste. However, centralized scheduling introduces additional complexity and delays, making the protocol less suitable for real-time or delay-sensitive applications, such as healthcare monitoring [26]. Addressing these limitations remains a priority for sustainable and reliable WSN deployment, as listed in Table 1.

Table 1 Summary of the Recent Researches in WSN

Author	Methodology	Algorithm	Advantages	Disadvantages
Smara et al. [9]	Fault-tolerant precision agriculture WSN	Heartbeat-based detection with redundant CH/BS	Seamless failover maintains data flow; energy saving via sleep mode	Added hardware redundancy raises cost
M. K. Roberts et al. [10]	Hybrid cluster-based routing	Sailfish & Spotted Hyena Optimization	Balanced exploration/exploitation; boosts PDR and energy savings	Increased design complexity; requires fine tuning
Vijay Nandal et al. [11]	Fault-tolerant hybrid cluster routing	CHFHIM-EEFR (Hyb-FL-HTSA + Im-MPA)	Combines CH and backup CHs for resilience; secure routing resists attacks	High computational load; intricate design
Vaggu et al. [12]	Secure SDWSN routing with load balancing	DBLOCK-RLB (DAG + DA-TD3 + Blockchain)	Enhances throughput, latency, and energy efficiency; secure key handling	Heavy reliance on encryption and blockchain adds overhead
Loveleen Kaur et al. [13]	Fog-based WSN for building safety	Improved Layer-wise Clustering (ILC) + NSGA-III	Improves evacuation route planning; balances CHs across layers	Fog computing layer increases complexity
Karthikeyan et al. [14]	Multipath routing for IoT WSN	Capuchin Search Optimization (CSORP)	Optimizes energy, PDR, and latency under dynamic traffic	May increase routing load; heavier computation
Wang et al. [15]	Energy prediction for solar WSNs	PP-Energy + Adaptive Energy Management (AEM)	Accurate prediction improves scheduling and neutrality	Dependent on accurate irradiance trends
Nirmala et al. [16]	Malicious node detection & fault tolerance	Modified Sandpiper Optimization Algorithm (MSOA)	Identifies faulty/malicious nodes; boosts trust in routing	Threshold calibration may affect accuracy
Sharada et	Adaptive clustering for	AACDIC (Ant Colony–	Dynamically balances CH re-election; saves node	Performance sensitive

RESEARCH ARTICLE

al. [17]	WSN/CRN	inspired)	energy	to parameter settings
Yang et al., et al. [18]	Secure energy-efficient routing	EDSSR	Resists Sybil/flooding attacks; ACH improves fault tolerance	Extra complexity in routing maintenance
Aarti et al. [19]	Hybrid energy-efficient routing with security	Firefly Algorithm (FFA) + ANN	Balances CH election; excludes malicious nodes	Training ANN adds complexity and overhead
Matej et al. [20]	Energy metric for routing reliability	LEO metric + ATPC	Cuts retransmissions; improves reliability with low overhead	Relies on approximate transmitter energy; flooding during discovery
Karthikeyan et al. [21]	Multipath IoT WSN routing	CSORP (Capuchin Search Optimization)	High PDR (88%), reduced latency, extended lifetime	Higher routing load; scalability challenges
Zhang et al. [22]	Adaptive routing for heterogeneous WSNs	Improved Particle Swarm Optimization (IPSO)	Cuts energy use by 32.7%; prolongs lifetime by 28%	Extra complexity may slow responsiveness
Hao Sheng et al. [23]	Dual energy harvesting routing	DEHRA-WO (Whale Optimization + Solar & RF switching)	Reduces packet loss >30%; enhances energy utilization by 29%	Complexity in managing hybrid harvesting
Wang et al. [24]	Joint CH election & multihop routing	Spider Wasp Optimizer (SWO)	Balances CH energy/distance; boosts lifetime by 32%	Needs K-means grouping; higher computational effort
Vimalarani et al. [25]	Evolutionary hybrid clustering & routing	Hybrid Memetic Evolutionary Algorithm (HMEA)	Avoids premature convergence; improves throughput and stability	Algorithm complexity; higher resource demand
Siamantas et al. [26]	Enhanced hierarchical routing	T-LEACHSAS (Threshold LEACH + Sleep–Awake Scheduling)	Reduces idle listening; extends lifetime	Centralized scheduling unsuitable for delay-sensitive cases

2.1. Problem Statement

Wireless Sensor Networks (WSNs) are increasingly deployed in critical domains such as healthcare, agriculture, industrial automation, and smart cities. However, their performance and sustainability are severely limited by the constrained energy resources of the sensor nodes. Cluster-based routing protocols have been widely adopted to improve energy efficiency; however, they introduce new challenges, such as rapid energy depletion of cluster heads (CHs), unbalanced energy consumption across the network, and reduced reliability in dynamic environments. Traditional clustering protocols, such as LEACH and its variants, lack adaptability in large-scale and heterogeneous deployments, leading to uneven load distribution and early node failures. Similarly, optimization-based models have improved cluster head selection but often neglect fault tolerance, scalability, and multipath routing considerations. Consequently, issues such as increased delay, packet loss, and limited network lifetime persist.

Therefore, the key problem addressed in this study is the design of an adaptive, energy-efficient, and fault-tolerant clustering and routing framework that can overcome the limitations of existing methods. The solution must balance energy consumption, ensure reliable data delivery, reduce delay and jitter, and extend the overall operational lifetime of the network while maintaining scalability in dynamic IoT-driven environments.

2.2. Need for the Proposed Model

From the survey of existing clustering and routing strategies, it is evident that while algorithms such as PSO, GA, and their hybrid variants improve energy efficiency to some extent, they often face challenges such as premature convergence, high computational burden, and limited adaptability in dynamic environments. Moreover, although fuzzy- or swarm-based methods are flexible, they are highly sensitive to parameter configurations and fail to maintain stability under large-scale deployments. These limitations highlight the gap between theoretical optimization and the practical requirements of WSNs, where adaptability, balanced energy consumption, and long-term sustainability are critical factors. Therefore, there is a clear need for an advanced model that integrates the strengths of local refinement and global search while minimizing the computational cost. The proposed Adaptive Hierarchical Clustering and Routing Framework (AHCRF) is motivated by this requirement, and aims to provide energy-efficient, scalable, and robust clustering and routing mechanisms that address the shortcomings of existing methods and ensure reliable performance in heterogeneous WSN environments.

3. PORPOSED METHODOLOGY

The proposed AHCRF model improves the energy efficiency through three key mechanisms. First, the adaptive cluster head (CH) selection ensures that nodes with higher residual energy and favorable positions are chosen as CHs, thereby reducing the frequency of re-clustering and preventing premature energy depletion in weaker nodes. Second, the framework employs a dynamic energy threshold adjustment that continuously evaluates both the individual and average residual energy levels in the network. This mechanism balances the energy consumption across nodes and prevents the overburdening of specific CHs. Third, the model incorporates a multipath routing strategy in which data packets are transmitted through alternate optimal paths based on real-time network conditions. This not only reduces congestion but also distributes the communication load more evenly, thereby minimizing the transmission energy costs. By integrating these strategies, the proposed AHCRF reduces redundant transmissions, balances the workload among nodes, and extends the overall network lifetime.

The Adaptive Hierarchical Clustering and Routing Framework attempts to initiate an advanced mechanism for overcoming persistent WSN issues, such as energy efficiency, reliability, and fault tolerance. This system established a high-level strategy for an optimized routing process that enhances energy utilization. A layered hierarchical approach to the clustering architecture was used. The sensor nodes autonomously form groups that form CHs and sub-CHs. This hierarchical formation enables efficient task distribution while minimizing overall energy consumption. The Secretary Bird Optimization Algorithm (SBOA) algorithm identifies three key determining factors for the selection of CHs and sub-CHs: the remaining energy levels, proximity to the sink node, and node density in the neighbouring nodes. To enhance the formation of multiple routes and reduce data loss owing to transmission errors, the proposed framework implements an FTMPR mechanism. Moreover, the Dynamic Energy Threshold Adjustment (DETA) uses dynamic threshold adjustments to ensure that the energy is distributed evenly across nodes, thereby preventing depletion close to the sink. This ensured that the network lasted longer than before the training.

3.1. Energy Management in WSN

The adaptive Hierarchical Clustering and Routing Framework is considered one of the most advanced solutions to major WSN issues. It efficiently addresses the optimization of energy usage, streamlines data routing processes, and enhances network communication reliability. In WSN configurations, the nodes are often battery-powered, which means that their source of power is a battery. Extending the lifetime of a network requires several strategies to reduce energy usage while maintaining strong performance. Effective data routing ensures that the information gathered by the sensor nodes is efficiently transmitted to the sink, minimizing delays and maintaining data accuracy. It also needs to address the problem of data loss owing to node failure to make the overall network more reliable.

The system model of the AHCRF is constructed based on certain premises regarding the environment of the network and some characteristics of the nodes, as they are sensors. A fixed sink node is strategically placed at the recommended location to optimize data collection and aggregation. Sensor nodes are spread evenly across the coverage area, and each node has a finite amount of energy reserves that demises sensing, communication, and computational activities.

These nodes also have a defined communication range, allowing them to connect with other nodes and to form clusters. Sensor nodes are provided with environmental monitoring, data transmission, and basic computation functionalities; however, their performance is limited by energy constraints; therefore, they require efficient energy management solutions.

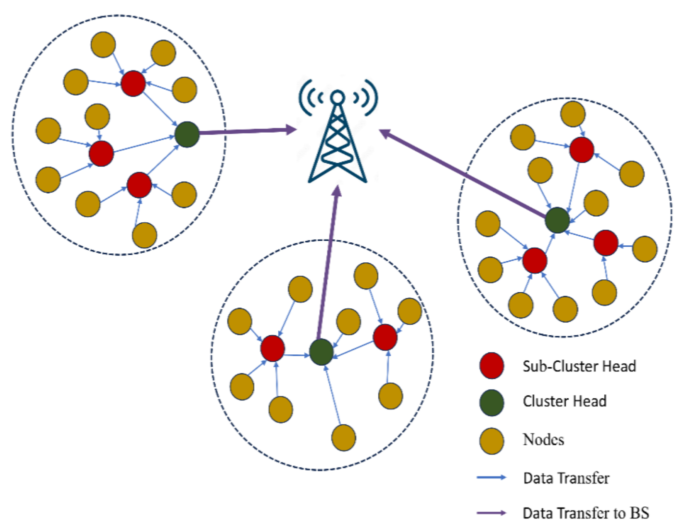

Figure 1 Hierarchical Clustering and Routing Framework for Efficient Energy Management

RESEARCH ARTICLE

The AHCRF clustering mechanism groups the sensor nodes in a local cluster such that the energy usage can be optimized, and the efficiency of routing data can be enhanced. The Euclidean distance is used as a metric to determine the membership in the framework. The distance between two nodes is a key factor in determining the cluster membership. As shown in equation (1), the distance $d_{i,j}$ between two nodes i and j is calculated as

$$d_{i,j} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \quad (1)$$

where (x_i, y_i) and (x_j, y_j) are the coordinates of nodes i and j, respectively. Nodes that fall within the predefined communication range, based on (1), are grouped into clusters to minimize the intra-cluster communication overhead. A hierarchical structure with primary and sub-cluster heads exists in each cluster. The primary CH function as aggregator nodes, and the processed data are transmitted to the sink by the primary CHs. Subcluster preprocessing, together with data aggregation in their own cluster, instead of putting a redundant transmission load across the primary CH. This hierarchical structure facilitates proper load distribution and maximizes energy efficiency in the network, as shown in Figure 1. The selection of CHs and sub-CHs is important for achieving energy efficiency and reliability in the network. The AHCRF employs a fitness function F to dynamically assign roles. The parameters considered are the residual energy of the node, which gives more preference to nodes with higher energy levels (E_r), distance from the node to the sink, where the closer nodes are assigned higher fitness scores to reduce the transmission energy costs (D_s), and node density in the vicinity, encouraging the selection of nodes in well-connected areas to improve the communication efficiency (N_d). As shown in Equation (2), the fitness function is defined as

$$F = \alpha E_r + \beta D_s + \gamma N_d \quad (2)$$

where α, β, and γ are the weight factors that balance the contribution of each parameter and can be dynamically adjusted according to the network conditions. Through the application of a multilayer hierarchical clustering technique, the AHCRF exhibits remarkable gains in terms of energy savings, scalability, and routing effectiveness. The dynamic clustering and routing procedures in the framework ensure the applicability of this robust solution to applications with dependable and energy-efficient sensor networks.

3.2. Secretary Bird Optimization Algorithm (SBOA)

The selection of the cluster heads and sub-cluster heads in the adaptive hierarchical clustering and routing framework is inspired by a nature-based optimization approach called the Secretary Bird Optimization Algorithm (SBOA). The suitability of each node to become a CH or sub-CH is calculated using a fitness function that evaluates parameters such as residual energy, distance from the sink, and node density.

In the exploration phase, the SBOA searches for candidate nodes by exploring their fitness values over a broad range of possibilities. This will make the search more or less similar to that of a secretary bird by not allowing the algorithm to converge to an incorrect solution. Randomly assigned roles to nodes are streamlined by computing their fitness values and updating their positions in the search space. As shown in Equation (3), the new position of a node in this phase is calculated as

$$X_{new} = X_{current} + r \cdot (X_{best} - X_{current}) \quad (3)$$

where X_{new} is the best new position for the node, $X_{current}$ is the current position of the node, X_{best} is the best position for the node found so far, and r is a random variable (0 < r < 1) that introduces randomness, so that the algorithm cannot stagnate to an optimal solution. Therefore, this exploration was conducted to ensure the diversity of the proposed candidate solutions. Once a diverse set of candidate nodes is identified, the exploitation phase narrows the selection of the most suitable nodes for the CH or sub-CH roles. This phase mimics the secretary bird's focused attack on its prey, refining the positions of nodes with the highest fitness values. The adjustment during exploitation is more precise and deterministic, reducing randomness and converging toward the optimal solution. As shown in Equation (4), the position update during this phase incorporates a finer balance of the weighted parameters:

$$X_{new} = X_{current} + c \cdot \left(X_{target} - X_{current}\right) + d \cdot (X_{random} - X_{current}) \quad (4)$$

where X_{target} is the position of the target (optimal node based on fitness), c,d is the control parameters to adjust the influence of the target and randomness, X_{random} is randomly selected position from the population. This phase ensures that the roles of the CH and sub-CH are assigned to nodes that can handle the cluster's workload efficiently, thereby minimizing energy consumption and communication overhead. Fitness evaluation is key to both phases, as it determines how well a node meets the criteria for CH or sub-CH selection. The fitness value of a node is directly proportional to

- Residual Energy (E_r): Nodes with higher energy reserves receive higher fitness scores, reducing the likelihood of failure due to energy depletion.
- Proximity to Sink (D_s): Nodes closer to the sink are preferred to minimize the energy cost of transmitting aggregated data.
- Node Density (N_d): Nodes in densely populated regions are favored to enhance communication efficiency and load balancing.

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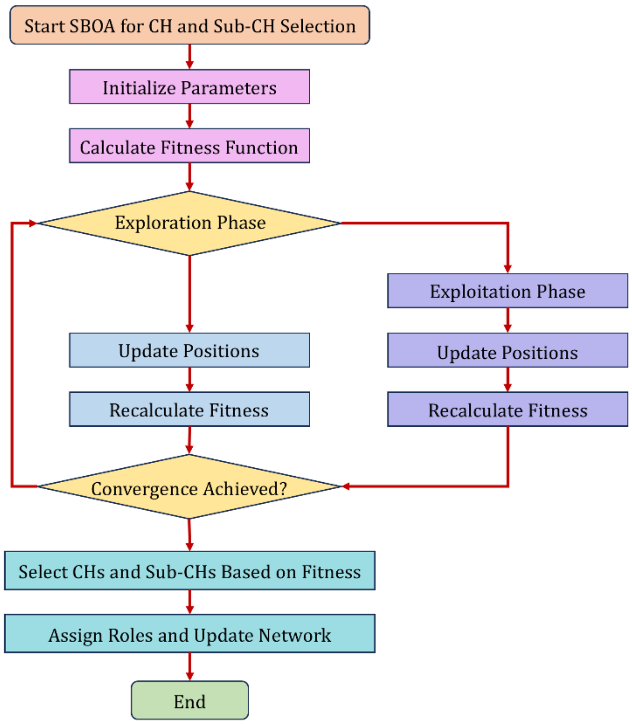

Figure 2 Secretary Bird Optimization Algorithm Flowchart for CH and Sub-CH Selection

The probability P_i of a node i being selected as a CH is determined based on its fitness value. As shown in Equation (5), it is expressed as

$$P_i = \frac{F_i}{\sum_{j=1}^{N} F_j} \quad (5)$$

where F_i is the fitness value of node i and N is the total number of nodes. This probabilistic choice eliminates deterministic biases and allows for dynamic adaptation to varying network conditions. In addition, the combination of the exploration and exploitation phases, along with the fitness function, ensures efficient SBOA energy efficiency and routing reliability. The adaptation of the weighting factors in the algorithm allows the program to adjust dynamically to topology changes to enhance robustness and scalability. The hierarchical clustering mechanism further disperses the energy load across CHs and sub-CHs, thereby extending the lifetime of the network while maintaining reliable data transmission. Thus, SBOA is a critical component in the efficient functioning of the AHCRF for wireless sensors, as illustrated in Figure 2.

3.3. Fault-Tolerant Multi-Path Routing

The AHCRF employs a routing mechanism that guarantees efficient and reliable transfer of data from sensor nodes to the sink with low energy consumption and minimal packet loss. The hierarchical approach is such that data follow a multi-step path, including the sensor node transmitting data to its assigned sub-CH and the sub-CH aggregating the data for forwarding to the Cluster Head (CH). CHs act as the main aggregators and forward the processed data to the sink node. The multilayer approach optimizes routing by spreading the energy load over the nodes and using the shortest and most efficient paths to minimize energy consumption.

To further strengthen its reliability, the AHCRF combines a fault-tolerant, multipath routing mechanism. This creates redundant multipaths among all nodes to the sink, and when a node in the network fails to transmit data to the destination node, this means that multipaths will enable its data to reach its respective destination, while redundancy has an impact on avoiding packet loss; the improvement is observed at the level of network robustness.

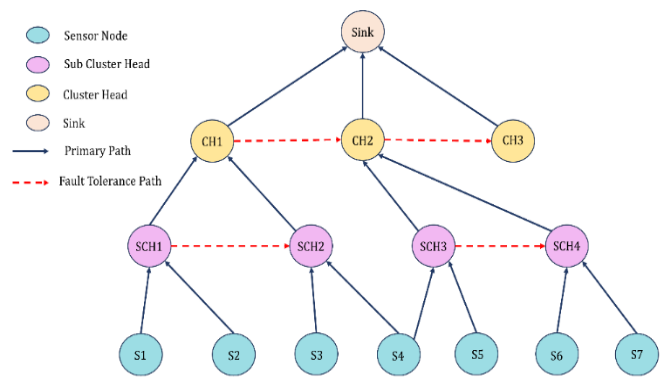

Figure 3 Hierarchical Data Transmission Model with Fault-Tolerant Paths

Data aggregation plays a critical role in routing. Sub-CHs consolidate the data received from individual nodes within their clusters to eliminate redundancy and minimize the volume of data transmitted to the CHs, as shown in Figure 3. This aggregation reduces communication overhead and energy consumption, contributing to the overall efficiency of the network.

The energy consumption for data transmission (E_{tx}) from a node to the Sub-CH, CH, or sink is determined as shown in equation (6):

$$E_{tx} = E_{elec} \cdot k + E_{amp} \cdot k \cdot d^n \quad (6)$$

where E_{elec} is the energy consumed by the electronic circuitry during transmission, k is the size of the data packet, $E_{amp}$is the energy consumed by the transmission amplifier over a distance d, n is the path loss exponent (typically 2 for free space or 4 for multipath environments).

The energy required to receive data (E_{rx}) is calculated as shown in equation (7):

$$E_{rx} = E_{elec} \cdot k \quad (7)$$

RESEARCH ARTICLE

The total energy consumption for a node during one communication cycle is expressed in equation (8):

$$E_{total} = E_{tx} + E_{rx} \quad (8)$$

In FTMPR, the reliability of a path is calculated based on the probability of successful data delivery along the route. For a path P consisting of multiple hops, the reliability R_P is given by Equation (9):

$$R_P = \prod_{i=1}^{H} R_i \quad (9)$$

where H is the number of hops in the path, and R_i is the reliability of the i^{th} hop. A load-balancing factor (LB) is introduced to distribute data across multiple paths, as defined in Equation (10):

$$LB = \frac{\sum_{i=1}^{P} L_i}{P} \quad (10)$$

Here, L_i is the load on the i^{th} path and P is the total number of paths. The FTMPR mechanism minimizes LB to evenly share network traffic through available paths with no congestion or network lifetime extension. By efficiently integrating FTMPR and data aggregation techniques, the AHCRF ensures high reliability, reduces energy consumption, and provides excellent robustness in a Wireless Sensor Network. Thus, it is more suitable for applications that demand the efficient transmission of consistent and reliable data with energy restrictions.

3.4. Dynamic Energy Threshold Adjustment

Energy management is a critical aspect of AHCRF and is proposed to sustain Wireless Sensor Networks for a more extensive period with the reliability of the network. One such strategy proposed here is called Dynamic Energy Threshold Adjustment, wherein the real-time energy of each node helps determine the regulation of the thresholds at each node for energy management purposes. This mechanism is precisely designed to be fair and well-balanced across the nodes of a network, thereby effectively preventing the existence of "energy holes," areas of the network closer to the sink, and where nodes quickly deplete energy due to multiple data transmissions in those areas. DETA monitors the residual energy of nodes and dynamically alters their operational thresholds. For example, nodes with less residual energy are favored for power-saving techniques that involve reducing the frequency of data transmission from such nodes or even offloading data to adjacent nodes. The load on each node was equally balanced to increase the network lifetime. The $E_{threshold}$ of any node is adapted using E_r and E_{avg}, which is the average of all nodes within the network. The threshold value was obtained using the following formula, as shown in Equation (11):

$$E_{threshold} = \alpha \cdot E_r + \beta \cdot E_{avg} \quad (11)$$

where is E_r the residual energy of the node. E_{avg} is the average residual energy of all nodes in the network. α, β is the weighting factors that determine the relative influence of the node's residual energy and the network's average energy on the threshold. By dynamically updating $E_{threshold}$, the framework adapts to varying energy levels in the network, ensuring a balanced energy distribution.

The total energy consumption E_{total} for a node during a communication cycle, including transmission (E_{tx}) and reception (E_{rx}). The DETA strategy ensures that nodes closer to the sink, which typically bear a higher transmission burden, operate within the adjusted energy thresholds. If the energy of a node falls below a critical value $E_{critical}$, defined as a fraction of its initial energy E_{init}, the node enters a low-power mode to conserve energy. This condition is expressed as equation (12):

$$E_r < \gamma \cdot E_{init} \quad (12)$$

where γ represents the critical-energy fraction. Nodes in low-power mode reduce their communication and processing activities by relying on neighboring nodes to assist with data transmission. In addition to individual adjustments, DETA promotes collaborative energy management by redistributing workloads among neighboring nodes. The workload redistribution factor W_r for a node is calculated as shown in equation (13):

$$W_r = \frac{\sum_{i=1}^{N} L_i}{N} \quad (13)$$

where L_i is the load of the i^{th} neighboring node. N is the number of neighboring nodes in the network.

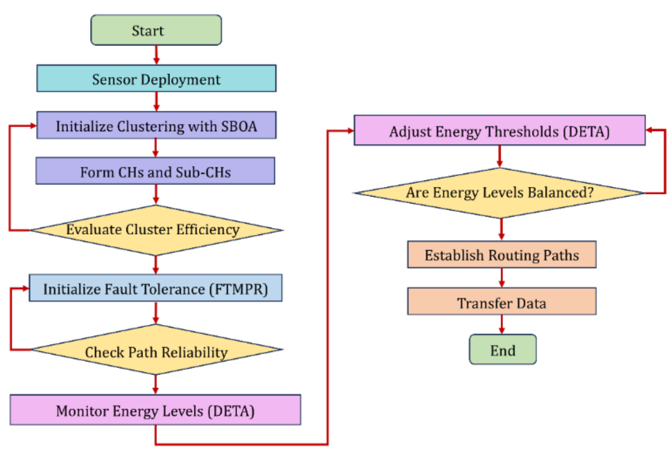

Figure 4 Energy Management and Fault-Tolerant Routing Workflow

This redistribution ensures that nodes with higher residual energy take on an additional workload, thereby balancing the energy consumption across the network. By implementing the DETA strategy, the AHCRF addresses key challenges in

RESEARCH ARTICLE

WSN energy management, such as avoiding energy holes near the sink and maintaining network reliability, as shown in Figure 4. This approach significantly enhances the overall energy efficiency of the network, extends its operational lifetime, and delivers a stable performance even under energy constrained conditions. The effectiveness of these improvements is systematically demonstrated in Algorithm 1, which outlines the step-by-step process of cluster formation, optimized head selection, multipath routing, and dynamic energy adjustment.

Input:

- Sensor nodes N, initial energy E_{init}
- Network parameters: (x_i, y_i) for each node, sink position, communication range (d_0)
- Weight factors (α, β, γ) for fitness evaluation

Output:

- Optimized cluster formation
- Energy-efficient routing paths
- Balanced energy consumption and improved reliability

START

Step 1: Initialization

Deploy N sensor nodes in a 2D area

Set initial energy E_{init} for all nodes

Initialize parameters: d_0 (threshold distance), α, β, γ (fitness weights)

Set up SBOA, FTMPR, and DETA strategies

Step 2: Cluster Formation

FOR each node i in N:

FOR each node j in N:

Compute distance $d_{i,j}$ = sqrt $\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2$

Group nodes into clusters based on communication range

FOR each cluster:

Step 3: CH and Sub-CH Selection

The fitness of each node is calculated.

F = α * Residual Energy + β * Distance to Sink + γ * Node Density

Select Sub-Cluster Head (sub-CH) with high F score

Select Cluster Head (CH) with the highest F score among sub-CHs

Step 4: Data Aggregation and Transmission

FOR each node in the cluster:

Transmit data to assigned sub-CH

Sub-CH preprocesses and aggregates data

Sub-CH forwards data to CH

CH transmits aggregated data to sink

Step 5: Fault-Tolerant Multi-Path Routing (FTMPR)

FOR each CH:

Identify multiple paths to sink

Computation of the reliability of each path

R_P = PRODUCT (R_i for all hops in path)

Distribute traffic using the load-balancing factor

LB = SUM (L_i for all paths) / Total Paths

Step 6: Energy Management via DETA

FOR each node:

Monitor residual energy E_r

Computation of the energy threshold

$E_{threshold}$ = α * E_r + β * Average Energy of Nodes

IF $E_r < \gamma \cdot E_{init}$:

Switch node to low-power mode

Step 7: Cluster Re-evaluation

Periodically update the clusters and reassign CHs/sub-CHs based on

Residual energy

Node density

Distance to sink

Step 8: Termination

IF the number of live nodes < threshold OR total energy depleted.

END simulation

END

Algorithm 1 Adaptive Hierarchical Clustering and Routing Framework (AHCRF)

3.5. Model Development and Demonstration

The Adaptive Hierarchical Clustering and Routing Framework (AHCRF) was designed with three primary objectives: (i) improving energy efficiency, (ii) strengthening reliability against node failures, and (iii) ensuring scalability

RESEARCH ARTICLE

in large-scale wireless sensor networks. To achieve these aims, the framework integrates four key strategies:

- Two-layer clustering structure: Sensor nodes are grouped into local clusters, where sub-cluster heads first preprocess and aggregate data before forwarding them to the main cluster head. This reduces redundant transmission and balances the workload.
- Secretary Bird Optimization Algorithm (SBOA) – A bio-inspired meta-heuristic is applied for the selection of both cluster heads and sub-cluster heads. The decision is guided by the residual energy, proximity to the sink, and local node density, ensuring that high-capacity nodes are dynamically assigned leadership roles.
- Fault-Tolerant Multipath Routing (FTMPR) – Multiple redundant routes are established between cluster heads and the sink. This strategy minimizes packet loss during node or link failures and balances the traffic across the available paths.
- Dynamic Energy Threshold Adjustment (DETA) – Real-time monitoring of residual energy allows nodes to adjust their operational thresholds. This prevents the rapid depletion of nodes located near the sink and distributes energy consumption more evenly across the network.

The framework was implemented in Python and evaluated through simulations for varying network sizes (500–3000 nodes). Comparative studies against benchmark protocols such as LEACH, MMRA, CHFHIM-EEFR, and DBLOCK-RLB consistently showed that AHCRF achieves a lower delay, higher packet delivery ratio, better throughput, and superior energy conservation.

3.5.1. Differences from Previous Models

Although earlier clustering and routing schemes typically emphasized one or two optimization goals, they often overlooked the combined challenges of energy balancing, robustness, and scalability. For example:

- LEACH employs randomized cluster head selection, which often causes uneven energy consumption.
- CHFHIM-EEFR and TICOA enhance cluster head election through hybrid optimization but do not incorporate mechanisms to prevent energy holes near the sink.
- DBLOCK-RLB introduces load balancing in software-defined sensor networks but lacks a preprocessing layer that reduces the communication overhead.

In contrast, the proposed AHCRF offers a unified approach by integrating subcluster pre-aggregation, SBOA-driven adaptive leadership selection, fault-tolerant multipath routing, and dynamic energy thresholding. This holistic combination ensures that energy usage is evenly spread, reliability is preserved even during node failures, and the system remains stable as the network expands. The AHCRF advances beyond prior models by providing a multi-layered, optimization-driven, and fault-tolerant framework that directly addresses the persistent challenges of energy imbalance, unreliable routing, and scalability in wireless sensor networks.

4. RESULTS AND DISCUSSIONS

A comprehensive assessment of the adaptive hierarchical clustering and routing framework (AHCRF) was performed to investigate its performance compared to other existing models, namely LEACH, MMRA, CHFHIM-EEFR, and DBLOCK-RLB. The evaluation accounted for all important metrics across varying network sizes, and some of the key metrics considered were average delay, packet delivery ratio (PDR), hop count to the sink, energy efficiency, throughput, and node survivability. The results show that the AHCRF excels in performance while exhibiting superior scalability, reliability, and energy efficiency compared to all benchmark models. The comparative studies are well supported by graphical and tabular representations and affirm that the AHCRF achieved delay minimization and maximized PDR and throughput under lower energy consumption and larger node retention rates, even under huge network conditions.

4.1. Experimental Configuration

Table 2 Simulation Parameters for Experimental Setup

Parameters	Values
Network area	1000×1000 m²
Number of sensor nodes	500–3000
Initial energy per node	1.0 J
Sink node	Static and centralized
Packet size	1024 bytes
Threshold distance (d_0)	120 m
Energy for receiver/transmitter	45 nJ/bit
Pheromone intensity	2
Heuristic weight value	1.5
Energy for free space amplification	15 pJ/bit/m²
Fitness weight factors (α, β, γ)	0.4, 0.35, 0.25
Energy for multipath amplification	0.001 pJ/bit/m⁴
Residual energy threshold	0.3

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RESEARCH ARTICLE

(γ)	
Detection time interval	30 s
DETA threshold adjustment interval	10 s
Redundant path count (FTMPR)	3

To maintain the accuracy and efficacy of our assessment, we used a state-of-the-art computer hardware and software setup to resolve our research experiments. The testing environment constituted a 64-bit Windows 11 system with an Intel Core i9 processor with 32GB RAM and an NVIDIA GeForce RTX 3090 graphics unit. Such a high-end configuration was warranted to conduct our research trials with the utmost accuracy and computational efficiency. The experimental environment was designed using Python 3.9.

Important libraries, such as NumPy for performing numerical computations, Pandas for data handling, and Matplotlib for graphical visualization, were utilized. For modeling generation and training, deep learning frameworks were used with the help of TensorFlow and PyTorch. Data preprocessing and performance assessment were performed using Scikit-learn. The entire project was implemented in Jupyter Notebook to facilitate the coding and debugging processes. OpenCV was used for image processing. The parameter settings for the experimental setup are listed in Table 2.

4.2. Experimental Results

4.2.1. Average Delay

The average delay is a critical parameter in wireless sensor networks because it directly reflects the responsiveness of data transmission from sensor nodes to the sink. In applications such as real-time monitoring or emergency alerts, minimizing delays ensures the timely delivery of information. Therefore, a protocol that consistently maintains a low delay across different network sizes is considered more efficient and scalable.

Figure 5 presents the variation in the average delay as the number of sensor nodes increases from 500 to 3000. The results clearly show that the proposed AHCRF model consistently achieves the lowest delay compared with LEACH, MMRA, CHFHIM-EEFR and DBLOCK-RLB. For instance, at 500 nodes, AHCRF records a delay of only 0.05 s, whereas LEACH, MMRA, CHFHIM-EEFR, and DBLOCK-RLB report 0.12, 0.10, 0.08, and 0.07 s, respectively.

As the network size increases to 3000 nodes, the delay in LEACH increases sharply to 0.40 s, whereas AHCRF maintains a much smaller value of 0.20 s. This trend highlights the robustness of the AHCRF in scaling up without significant degradation in latency.

The superior performance of the AHCRF is attributed to architectural and algorithmic innovations. First, sub-cluster heads ensure that data are pre-processed and aggregated locally to reduce redundant transmissions and lower the communication burden on cluster heads. Second, the Secretary Bird Optimization Algorithm was applied to improve the cluster head and sub-cluster head selection in terms of residual energy, sink distance, and node density. An efficient election process helps yield balanced clusters and shorter communication paths, hence decreased latency. Finally, by offering fault-tolerant multipath routing mechanisms to ensure reliable data delivery through alternate routes in the case of failure, it avoids the retransmission delay commonly faced by other protocols. Figure 5 shows that, in terms of average delay, the proposed AHCRF model performs significantly better than the older approaches. This added ability to sustain low latency, even with higher density nodes, adds weight to its scalability and suitability for time-critical applications in wireless sensor networking.

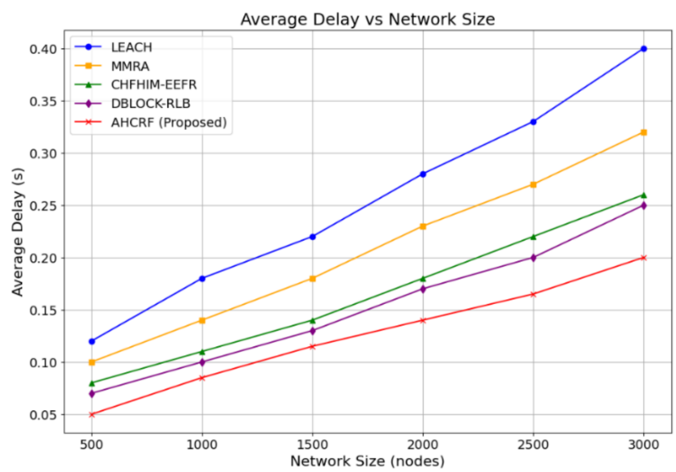

Figure 5 Average Delay vs. Network Size for Different Models

4.2.2. Packet Delivery Ratio (PDR)

The Packet Delivery Ratio (PDR) is the most valued performance metric in wireless sensor networks because it indicates how reliable the data from the sensor nodes are to reach the sink. The higher the PDR, the more stable the network is in delivering packets without loss while routing in an efficient manner, and this is primary in real-time applications where accuracy and data integrity are important. Therefore, the accepted protocol is to sustain high PDR levels for increased network dimensions.

The PDR results of the AHCRF are summarized in comparison with LEACH, MMRA, CHFHIM-EEFR, and DBLOCK-RLB for network scales between 500 and 3000 nodes in Figure 6. The AHCRF outperforms the other approaches in terms of the achieved PDR under all network conditions. PDR at 500 nodes, however, came out as 94.5% for AHCRF whereas 91.2% was established for the alternative protocol, DBLOCK-RLB. CHFHIM-EEFR, MMRA, and LEACH achieved 89%, 87.5%, and 85.2%, respectively. Although the network was scaled up to 3000 nodes, AHCRF still managed to present a 91.5% PDR, with other results showing the percentages drop to 88.8% for DBLOCK-RLB, 86.2% for CHFHIM-EEFR, 83.2% for MMRA, and 80.5% for LEACH.

The primary reason for the superior performance of the AHCRF is its design features. The fault-tolerant multipath routing (FTMPR) mechanism first guarantees multiple alternative routes leading the data packets to the sink, even if some nodes or links fail. With redundancy given in this way, packet loss is minimized, and fortified reliability is achieved. Second, sub-cluster heads reduce congestion through preprocessing and aggregating the data locally before dispatching them to the cluster heads, thereby not straining a line. Finally, the dynamic energy threshold adjustment (DETA) ensures that all energy use balances out at the network level, making all nodes close to a sink fail too early; nowhere is this more common cause of packet drop in traditional protocols than there. From Figure 6, it is clear that compared with the different baseline models, the AHCRF maintains a consistently higher PDR. This is combined with fault-tolerant routing, balanced energy management, and efficient cluster design to help maintain packet delivery above 91%, even when dense. The other models degrade with an increase in the number of nodes. Thus, the AHCRF is set to offer greater levels of reliability and scalability to a large scale wireless sensor network.

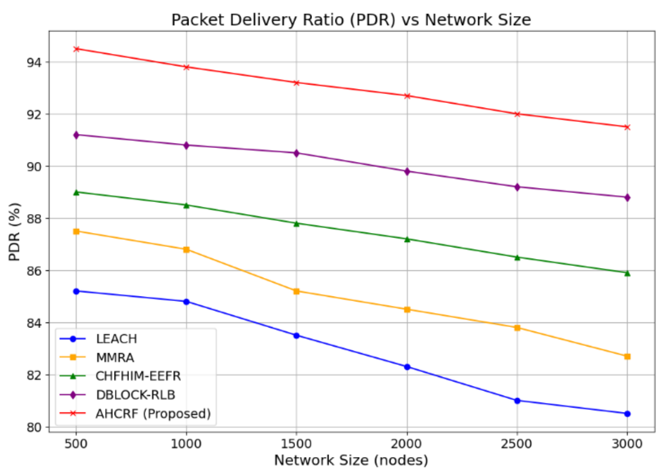

Figure 6 Packet Delivery Ratio (PDR) vs Network Size

4.2.3. Average Number of Hops to Sink

The number of hops between the sensor nodes and the sink plays a significant role in determining the communication efficiency. A lower hop count generally translates to reduced energy consumption, shorter transmission delays, and a lower chance of packet loss. Therefore, protocols that can minimize the average number of hops while scaling to larger networks are considered efficient and reliable.

Figure 7 illustrates how the average hop count changes with network size for the AHCRF and baseline models (LEACH, MMRA, CHFHIM-EEFR, and DBLOCK-RLB). Across all scenarios, the AHCRF consistently demonstrated the lowest hop count. At 500 nodes, AHCRF records an average of 2.9 hops, whereas LEACH, MMRA, CHFHIM-EEFR, and DBLOCK-RLB report 3.5, 3.4, 3.2, and 3.3 hops, respectively. As the network size scales to 3000 nodes, AHCRF maintains 5.4 hops, which is significantly lower than those of LEACH (6.1), MMRA (6.0), CHFHIM-EEFR (5.8), and DBLOCK-RLB (5.6).

The reduction in the hop count achieved by the AHCRF can be attributed to several design choices. First, the introduction of a two-layer clustering structure ensures that sub-cluster heads aggregate data and efficiently forward them to cluster heads, minimizing unnecessary relay transmissions. Second, the Secretary Bird Optimization Algorithm (SBOA) selects cluster heads not only based on residual energy but also their distance to the sink and local density. This careful placement of cluster heads shortens the routing paths, reducing the number of intermediate nodes involved. Finally, the multipath routing strategy distributes traffic intelligently, preventing congestion and avoiding detours caused by overburdened or failed nodes. Together, these mechanisms ensure that the AHCRF provides shorter and more stable communication paths than competing protocols.

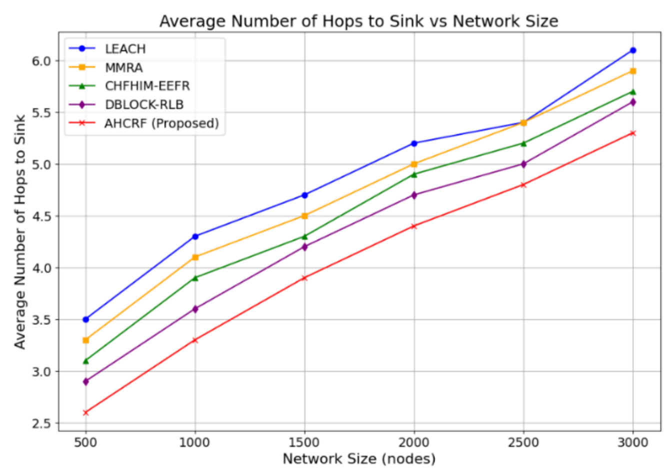

Figure 7 Average Number of Hops to Sink vs. Network Size for Different Models

From Figure 7, it is evident that the proposed AHCRF consistently reduces the number of hops to the sink compared with all the baseline models. By maintaining shorter routes, the AHCRF achieves lower energy expenditure, reduced

RESEARCH ARTICLE

transmission delay, and improved overall network performance, especially as the network scales to thousands of nodes. This highlights the scalability of the protocol and its advantage in designing energy-efficient, low-latency wireless sensor networks.

4.2.4. Average Remaining Energy

The remaining energy is a vital parameter in a wireless sensor network because it directly indicates the sustainability of node operation and overall network lifetime. Protocols that exhibit higher residual energy at network half-life can satisfy the requirements of energy efficiency, fair load distribution, and enhanced stability over a longer duration. Therefore, this parameter must be studied to understand how effectively routing protocols prevent premature depletion of nodes and extend network survival.

Figure 8 compares the average remaining energy of the AHCRF with that of the baseline models (LEACH, MMRA, CHFHIM-EEFR, and DBLOCK-RLB) across different network sizes. The results show that the AHCRF consistently retains the highest residual energy at the network half-life. At 500 nodes, AHCRF recorded approximately 0.45 J of remaining energy, whereas DBLOCK-RLB, CHFHIM-EEFR, MMRA, and LEACH achieved 0.39 J, 0.37 J, 0.34 J, and 0.30 J, respectively. As the network size increases to 3000 nodes, AHCRF maintains 0.32 J, whereas DBLOCK-RLB, CHFHIM-EEFR, MMRA, and LEACH drop to 0.28 J, 0.26 J, 0.23 J, and 0.20 J, respectively.

The superior performance of the AHCRF stems from its integrated mechanisms. The two-layer clustering structure reduces redundant transmissions by preprocessing data at sub-cluster heads, which lowers the communication burden on the cluster heads and conserves energy. The Secretary Bird Optimization Algorithm ensures that nodes with higher residual energy and favorable positioning are selected as cluster heads, thereby distributing energy consumption more evenly across the network. Moreover, the Dynamic Energy Threshold Adjustment (DETA) mechanism actively prevents nodes near the sink from being overburdened, mitigating the "energy hole" problem that typically shortens the network lifetime in other protocols. Finally, the multipath routing strategy avoids excessive retransmissions caused by congestion or failure, which further reduces energy wastage.

From Figure 8, it can be inferred that the AHCRF outperforms all baseline models in most aspects of the average remaining energy. This energy-aware cluster head selection, along with a balance of workloads and fault-tolerant routing, ensures that a greater percentage of energy within the overall network remains even as it grows. Hence, this advantage highlights that the existing protocols have proven the AHCRF to be the most effective in prolonging the operational life of large-scale wireless sensor networks.

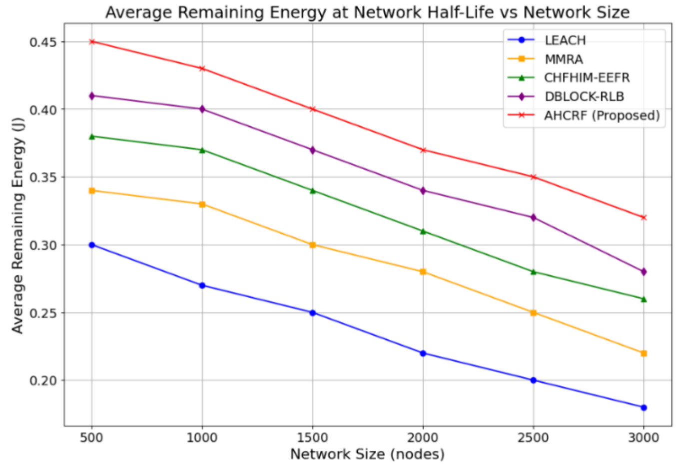

Figure 8 Average Remaining Energy at Network Half-Life vs. Network Size

4.2.5. Throughput

In wireless sensor networks, throughput is a key performance metric that indicates the rate of successful data delivery over time. The higher the throughput, the greater the quantity of data packets that are reliably transmitted, which is a concern in large-scale and real-time interactive applications. Here, the continuity of the data and timeliness are important. Another important aspect of throughput evaluation is the ascertainment of the forwarding-engineering performance of the routing protocol considering the increased node density and communication overhead.

Figure 9 shows a comparison of the throughput performance of the AHCRF and the four baseline protocols, namely LEACH, MMRA, CHFHIM-EEFR, and DBLOCK-RLB, for variable network sizes. The results indicate that AHCRF attains the highest throughput in all scenarios. For example, at 500 nodes, the AHCRF throughput is approximately 105 kbps, whereas those of DBLOCK-RLB, CHFHIM-EEFR, MMRA, and LEACH are approximately 97, 95, 90, and 85 kbps, respectively. At a network size of 3000 nodes, AHCRF still achieves approximately 91 kbps, whereas DBLOCK-RLB and CHFHIM-EEFR drop down to 85 kbps and 83 kbps, MMRA to 79 kbps, and LEACH to 72 kbps.

The superior throughput of the AHCRF can be attributed to its architectural and algorithmic innovations. First, the two-layer clustering mechanism ensures that raw data are preprocessed by sub-cluster heads, thereby reducing communication redundancy and enabling faster transmission. Second, the Secretary Bird Optimization Algorithm dynamically selects optimal cluster heads and sub-cluster heads based on energy reserves, node density, and proximity to the sink, which minimizes congestion and packet collision. Third, the fault-tolerant multipath routing mechanism provides alternative data paths, preventing bottlenecks and reducing packet drops

RESEARCH ARTICLE

during failures or heavy traffic. Finally, the Dynamic Energy Threshold Adjustment (DETA) balances the energy load across nodes, ensuring that nodes closer to the sink do not exhaust prematurely, which often leads to throughput degradation in traditional models.

The AHCRF has shown considerable throughput advantages over other conventional protocols, as shown in Figure 9. The consistent performance advantage across all tested network sizes lends credence to the AHCRF being better equipped to handle capacities in large-scale data-intensive environments. The advantage of AHCRF in delivering more data rates in comparison to efficiency and scalability comes from the unique combination of hierarchical clustering, optimized head selection, energy-aware routing, and multipath reliability.

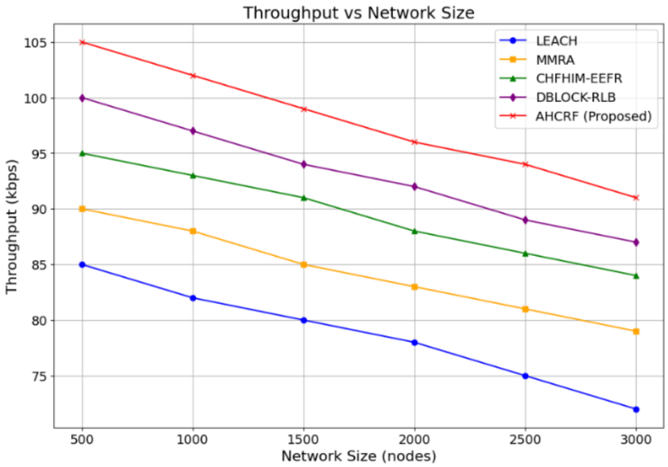

Figure 9 Throughput vs. Network Size for Different Models

4.2.6. Number of Alive Nodes

The number of alive nodes in a wireless sensor network is a direct measure of sustainability and resilience. A higher count of active nodes indicates better energy distribution, effective routing, and reduced probability of early node failure. This metric is essential for evaluating the duration for which a network can remain functional and maintain coverage, particularly in large-scale deployments, where node failures significantly impact data accuracy and reliability. Figure 10 illustrates the number of alive nodes across different network sizes for AHCRF compared with LEACH, MMRA, CHFHIM-EEFR, and DBLOCK-RLB. The results clearly demonstrate that the AHCRF preserves more nodes in the active state throughout all tested network scales. For a 500-node network, AHCRF retains approximately 490 live nodes, whereas DBLOCK-RLB, CHFHIM-EEFR, MMRA, and LEACH maintain approximately 480, 470, 460, and 450 nodes, respectively. At the largest scale of 3000 nodes, AHCRF sustains nearly 350 active nodes, whereas DBLOCK-RLB, CHFHIM-EEFR, MMRA, and LEACH fall to 335, 325, 312, and 295 nodes, respectively.

The superior performance of the AHCRF is attributed to its holistic framework. The two-layer clustering structure distributes communication tasks more effectively by allowing sub-cluster heads to preprocess and aggregate data, thereby reducing the energy burden on the primary cluster heads. The Secretary Bird Optimization Algorithm (SBOA) ensures that nodes with higher residual energy and optimal positioning are selected as cluster heads and sub-cluster heads, balancing energy usage across the network. The Fault-Tolerant Multipath Routing (FTMPR) mechanism reduces packet loss and retransmissions, ensuring that energy is not wasted owing to failed paths. Furthermore, the Dynamic Energy Threshold Adjustment (DETA) actively prevents sink-adjacent nodes from rapid energy exhaustion, a common issue in conventional protocols. Collectively, these mechanisms slow down node death rates, prolonging the survival of a larger proportion of networks.

The illustrations presented in Figure 10 ascertained that the AHCRF surpasses other existing models in maintaining alive nodes. The balanced clustering, optimal routing, and adaptive energy management of AHCRF provide longevity in the network in addition to resiliency even in large-scale and high-density environments. This demonstrates the robustness of the AHCRF for sustaining real applications for reliable functioning of a real-world wireless sensor network.

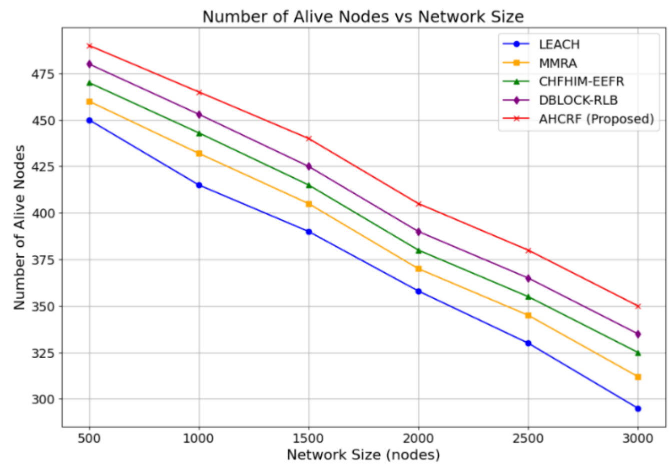

Figure 10 Number of Alive Nodes vs Network Size for Different Models

4.3. Comparative Analysis

Table 3 presents the comparative performance of the proposed AHCRF protocol against the four benchmark approaches of LEACH, MMRA, CHFHIM-EEFR, and DBLOCK-RLB. The evaluation consists of five critical performance metrics: average residual energy, bit error rate (BER), packet delivery ratio (PDR), jitter, and delay. These collectively determine the efficacy, reliability, and stability of the wireless sensor network operations.

- Energy (J): In terms of residual energy, the AHCRF proposed here retains the maximum (0.45 J), whereas LEACH retains only 0.25 J. This means that the AHCRF uses more energy to arrive at this stage with the help of its two-layer clustering structure, energy-aware cluster head selection, and balanced load distribution for higher energy retention, which, in turn, selects a longer network lifetime and slower node depletion in comparison to other models.
- Bit Error Rate (BER): Among the three algorithms, AHCRF achieved a BER of 1.2, which was significantly lower than the BER of LEACH and MMRA at 2.5 and 2.1, respectively. The multipath fault-tolerant routing mechanism is mainly responsible for this, as it allows reliable packet forwarding in the presence of link failures, thereby reducing the number of retransmissions and error probability.
- Packet Delivery Ratio (PDR %): The AHCRF maintained the highest PDR at 94.5%. This was followed by DBLOCK-RLB (91.2%), CHFHIM-EEFR (89%), MMRA (87.5%), and LEACH (85.2%). The gains are attributed to multipath routing redundancy, local data aggregation at sub-cluster heads, and congestion avoidance near sink nodes. All these mechanisms work together to enhance the reliability of packets in scenarios with varying densities.
- Jitter (ms): The value of jitter in the instance of AHCRF minimizes its importance at 3.2 ms compared to 5.5 ms in the case of LEACH and 4.8 ms in the case of MMRA. The ability of a protocol to provide a consistent packet interval is vital for time-sensitive applications, which is highlighted by the reduction in jitter. Load balancing, in combination with efficient routing paths, prevents the change in delivery time from one instance of packet delivery to another.
- Delay (s): The delay achieved by the proposed model was 0.05 s, which was the lowest compared with other methods, with LEACH being the second-worst algorithm at 0.12 s. The benefits arise from the optimized cluster head placement-induced reduction in the hop count and avoidance of congested routes for faster data delivery.

From Table 3, it can be inferred that the AHCRF is far ahead of all other benchmark models in terms of each important metric. Its higher residual energy, lower BER, higher PDR, jitter, and delay all demonstrate the protocol’s strength. This confirms that hierarchical clustering integration, energy-aware optimization, and fault-tolerant multipath routing contribute to reliable scalability and energy-efficient communication for AHCRF in large-scale wireless sensor networks.

Table 3 Comparative Performance Metrics for Different Models

Method	Energy (J)	BER	PDR (%)	Jitter (ms)	Delay (s)
LEACH	0.25	2.5	85.2	5.5	0.12
MMRA	0.3	2.1	87.5	4.8	0.1
CHFHIM-EEFR	0.33	1.9	89	4.1	0.08
DBLOCK-RLB	0.38	1.6	91.2	3.7	0.07
AHCRF (Proposed)	0.45	1.2	94.5	3.2	0.05

4.4. Discussion

The performance evaluation clearly shows that the Adaptive Hierarchical Clustering and Routing Framework (AHCRF) consistently outperforms benchmark protocols such as LEACH, MMRA, CHFHIM-EEFR, and DBLOCK-RLB on several important metrics. Each metric depicts a distinct view of network efficiency and reliability, and the superior performance of the AHCRF can be directly correlated with its overarching design strategies.

The average residual energy of the proposed AHCRF is 0.45 J, which is higher than that of LEACH (0.25 J), MMRA (0.30 J), CHFHIM-EEFR (0.33 J), and DBLOCK-RLB (0.38 J).

This improvement is the result of multilayer clustering, with each subcluster head preprocessing data locally before sending them to the main cluster heads. Therefore, the transmissions reduce redundancy and proportionately share energy burdens, thus preventing the formation of energy holes near the sink and prolonging the network lifetime.

RESEARCH ARTICLE

The lowest BER of 1.2 was recorded for AHCRF, followed by LEACH (2.5), MMRA (2.1), CHFHIM-EEFR (1.9), and DBLOCK-RLB (1.6). The reduction in the BER in this case is due to the characterized fault-tolerant multipath routing mechanism (FTMPR). By creating redundant reliable paths with the perspective of ensuring that the data reach the sink even when some nodes die), packet loss and the need for retransmission are extremely minimized.

The AHCRF outperformed the other models (LEACH: 85.2%, MMRA: 87.5%, CHFHIM-EEFR: 89%, and DBLOCK-RLB: 91.2%) with a PDR of 94.5%. The high success rate in delivery is attributed to the Secretary Bird Optimization Algorithm (SBOA), which chooses cluster heads and sub-cluster heads based on factors such as residual energy, distance to the sink, and density of nodes. The optimally selected cluster and sub-cluster heads ensure stable and efficient routing paths with fewer dropped packets, thereby enhancing overall reliability.

The jitter value of the AHCRF is only 3.2 ms, showing reduced variability in packet arrival times compared with those of LEACH (5.5 ms), MMRA (4.8 ms), CHFHIM-EEFR (4.1 ms), and DBLOCK-RLB (3.7 ms). Lower jitter is particularly critical for real-time applications, and in the AHCRF, it is achieved through efficient routing paths and the avoidance of overloaded nodes, which stabilizes the packet flow. The AHCRF recorded the lowest delay of 0.05 s, outperforming LEACH (0.12 s), MMRA (0.10 s), CHFHIM-EEFR (0.08 s), and DBLOCK-RLB (0.07 s). The reduced delay is the result of shorter optimized routes and reduced retransmissions owing to the fault-tolerant routing mechanism. The AHCRF ensures faster data delivery by minimizing hop counts and balancing loads.

Overall, the obtained results confirm that the superior performance of AHCRF is not coincidental but is a direct consequence of its integrated design: (i) a hierarchical two-layer clustering system that minimizes redundant communication, (ii) multi-criteria cluster head selection through optimization, (iii) fault-tolerant multipath routing that enhances delivery reliability, and (iv) adaptive energy threshold adjustment that mitigates sink-neighborhood energy depletion. Together, these innovations explain why the AHCRF achieves higher energy efficiency, lower delay, reduced jitter, better reliability, and improved scalability compared with conventional approaches.

5. CONCLUSION

The main objective is to design innovative and flexible frameworks that would address persistent problems in WSNs, such as power efficiency, dependability, and expandability. The AHCRF has emerged as a transformative solution that can effectively mitigate these issues. The AHCRF utilizes a multilayer clustering architecture with dynamic CH and sub-CH selection that is optimized by the SBOA; this ensures efficient use of energy along with improved performance in routing. FTMPR, which includes fault-tolerant multipath routing for the enhancement of reliability, and DETA, with its dynamic energy threshold adjustment that helps in a well-balanced distribution of energy, also contribute significantly to the efficiency of the proposed approach. A comprehensive analysis shows that the AHCRF considerably outperforms alternative options, with higher results for most metrics. The packet delivery ratio was 94.5%, with a maintained throughput of 2 Mbps. The delay value was very low, that is, 0.05 s. The jitter was minimized to 3.2 ms, and the energy consumption was significantly reduced to 0.25 J. These findings illustrate the ability of the framework to prolong the network lifespan and sustain reliable operations, even in large-scale and complex deployment scenarios. Future improvements in the AHCRF should be directed toward adapting it to changing conditions. Thus, their application can be more viable in dynamic and heterogeneous network environments. Its application in diverse scenarios involving real-time machine learning techniques for optimizing parameters can be further advanced in dynamic environments. The sophistication of security features in addressing possible data protection risks will make the system more applicable to critical sectors, such as health monitoring, emergency response, and urban intelligence systems. These advancements would transform the AHCRF into an adaptable and flexible framework capable of meeting the demands of future generations in wireless sensor networks.

REFERENCES

[1] Padmini, M. S., and S. Kuzhalvaimozhi. "Energy and delay aware routing model for smart crop monitoring application using internet of things." Computers and Electrical Engineering 116 (2024): 109207.

[2] Kaviarasan, Solayan, and Rajkumar Srinivasan. "Developing a novel energy efficient routing protocol in WSN using adaptive remora optimization algorithm." Expert Systems with Applications 244 (2024): 122873.

[3] Liu, Kaiyun, Weibei Fan, Fu Xiao, Haolin Mao, Huipeng Huang, and Yizhou Zhao. "Secure paths based trustworthy fault-tolerant routing in data center networks." Concurrency and Computation: Practice and Experience 36, no. 23 (2024): e8229.

[4] Shinde, Namita K., and Vinod H. Patil. "Secured and energy efficient cluster based routing in WSN via hybrid optimization model, TICOA." Sustainable Computing: Informatics and Systems 44 (2024): 101052.

[5] Singh, Madhav, and Laxmi Shrivastava. "Multi-objective optimized multi-path and multi-hop routing based on hybrid optimization algorithm in wireless sensor networks." Wireless Networks (2024): 1-17.

[6] Priyadarshi, Rahul. "Energy-efficient routing in wireless sensor networks: a meta-heuristic and artificial intelligence-based approach: a comprehensive review." Archives of Computational Methods in Engineering 31, no. 4 (2024): 2109-2137.

[7] Abujassar, Radwan S. "A multi path routing protocol with efficient energy consumption in IoT applications real time traffic." EURASIP Journal on Wireless Communications and Networking 2024, no. 1 (2024): 1-27.

[8] Aruna, R., Virendra Singh Kushwah, S. Phani Praveen, Rahul Pradhan, Amit Jaykumar Chinchawade, Renas Rajab Asaad, and R. Lakshmana Kumar. "Coalescing novel QoS routing with fault tolerance for

RESEARCH ARTICLE

improving QoS parameters in wireless Ad-Hoc network using craft protocol." Wireless Networks 30, no. 2 (2024): 711-735.

[9] Smara, Mounya, and Al-Sakib Khan Pathan. "An Enhanced Mechanism for Fault Tolerance in Agricultural Wireless Sensor Networks." Network 4, no. 2 (2024): 150-174.

[10] Roberts, Michaelraj Kingston, Jayapratha Thangavel, and Hamad Aldawsari. "An improved dual-phased meta-heuristic optimization-based framework for energy efficient cluster-based routing in wireless sensor networks." Alexandria Engineering Journal 101 (2024): 306-317.

[11] Nandal, Vijay, and Sunita Dahiya. "Cluster based hybrid flamingo hazelnut tree with improved marine predators for fault tolerant energy efficient routing in wireless sensor network." Peer-to-Peer Networking and Applications (2024): 1-27.

[12] Vaggu, Nagesh Mallaiah, and Ravi Sankar Barpanda. "DBlock-RLB: An energy efficient framework for intelligent routing and trading based load balancing in SDWSN environment." Ad Hoc Networks 159 (2024): 103475.

[13] Kaur, Loveleen, and Rajbir Kaur. "Energy-efficient smart architecture for fog-based WSN using NSGA-III and improved layer-wise clustering for enhanced building evacuation safety." Annals of Operations Research (2024): 1-24.

[14] Karthikeyan, M., D. Manimegalai, and Karthikeyan Rajagopal. "Optimizing energy efficiency in wireless sensor networks: dynamic routing with capuchin search algorithm." Multimedia Tools and Applications (2024): 1-25.

[15] Wang, Yuanxiang, Zhen Xu, and Lei Yang. "Plus-profile energy harvested prediction and adaptive energy management for solar-powered wireless sensor networks." The Journal of Supercomputing 80, no. 6 (2024): 7585-7603.

[16] Nirmala, B. Vijaya, and K. Selvaraj. "Malicious node detection in wireless sensor network using modified sandpiper optimization algorithm." Wireless Networks (2024): 1-22.

[17] Sharada, K. A., T. R. Mahesh, Saravanan Chandrasekaran, R. Shashikumar, V. Vinoth Kumar, and Jonnakuti Rajkumar Annand. "Improved energy efficiency using adaptive ant colony distributed intelligent based clustering in wireless sensor networks." Scientific Reports 14, no. 1 (2024): 4391.

[18] Yang, Ruili, Manoj A. Patil, Potu Narayana, D. Jayaram, K. Keerthi, N. SudhakarYadav, Premkumar Chithaluru, Sunil Kumar, Diaa Salama Abd Elminaam, and Deema Mohammed Alsekait. "EDSSR: a secure and power-aware opportunistic routing scheme for WSNs." Scientific Reports 14, no. 1 (2024): 28625.

[19] Sharma, Aarti, and Ankush Kansal. "Enhanced CH selection and energy efficient routing algorithm for WSN." Microsystem Technologies 31, no. 3 (2025): 735-747.

[20] Fitoš, Matej, Juraj Ďuďák, Gabriel Gašpar, Juraj Machaj, and Peter Brida. "LEO: An innovative metric for energy-efficient routing in wireless sensor networks." Internet of Things 29 (2025): 101472.

[21] Karthikeyan, M., D. Manimegalai, and Karthikeyan Rajagopal. "Optimizing energy efficiency in wireless sensor networks: dynamic routing with capuchin search algorithm." Multimedia Tools and Applications 84, no. 15 (2025): 15453-15477.

[22] Zhang, Yang, Ling Yang, and Yan Tan. "Energy-efficient adaptive routing in heterogeneous wireless sensor networks via hybrid PSO and dynamic clustering." Journal of Cloud Computing 14, no. 1 (2025): 46.

[23] Sheng, Hao, Chen Jun, Cui Jianqun, Fan Xiying, and Li Zhen. "An energy-efficient routing algorithm for dual-energy harvesting-assisted wireless sensor networks based on whale optimization strategy." The Journal of Supercomputing 81, no. 1 (2025): 8.

[24] Wang, Zhendong, Yaozhong Yang, Xiao Luo, Daojing He, and Chan Sammy. "Energy efficient clustering and routing for wireless sensor networks by applying a spider wasp optimizer." Ad Hoc Networks 174 (2025): 103841.

[25] Vimalarani, C., CP Thamil Selvi, B. Gopinathan, and T. Kalaivani. "Improving energy efficiency in WSN through adaptive memetic-based clustering and routing for resource management." Sustainable Computing: Informatics and Systems 45 (2025): 101073.

[26] Siamantas, Georgios, Dimitris Rountos, and Dionisis Kandris. "Energy Saving in Wireless Sensor Networks via LEACH-Based, Energy-Efficient Routing Protocols." Journal of Low Power Electronics and Applications 15, no. 2 (2025): 19.

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