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MULTI-MOBILE SINK-BASED CLUSTERING AND ROUTING IN HETEROGENEOUS WIRELESS SENSOR NETWORKS USING THE CROW SEARCH ALGORITHM

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ABSTRACT

Heterogeneous Wireless Sensor Networks (HWSNs) face conspicuous challenges in maximizing network lifetime due to uncurbed power utilization depletion at sensor nodes (SNs) and cluster heads (CHs). This study presents an optimal Multi-Mobile Sink-based Clustering and Routing (MSCR) control strategy using the multi-objective Crow Search Algorithm (CSA) to address resource-constrained node energy-efficiency challenges. The proposed CSA-based MSCR model enhances deployed node's performance by intelligently coordinating SNs, CHs, and mobile sink (MS) to optimize the data acquisition process while reducing energy consumption. The CSA strategy is deployed for two crucial optimization operations: constructing optimal mobile sink trajectories and selecting energy-efficient cluster heads under limited resources and harsh environmental circumstances. Performance analysis compares the CSA-based model against established traditional metaheuristic methods, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Ant Colony Optimization (ACO). Large-scale simulations conducted under various network and harsh environmental conditions demonstrate significant improvements in critical performance metrics. The CSA-based MSCR approach achieves a 36% reduction in power consumption, 49% accelerated cluster formation and cluster head (CH) selection, and 42% improvements in data delivery efficiency compared to conventional approaches. Furthermore, the proposed model extends average network lifetime by 45% while maintaining data accuracy above 97%. The results endorse the usefulness of the CSA optimization strategy in solving composite multi-objective optimization problems in wireless sensor networks. This work contributes a strong and scalable solution for next-generation IoT applications requiring energy-efficient data collection in challenging deployment environments. The outcome highlights the strengths of metaheuristic algorithms like CSA in advancing MSCR control for WSNs, offering a promising alternative to traditional approaches for improving the data delivery and lifetime of the sensor networks.



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I. INTRODUCTION

Wireless Sensor Networks (WSNs) have emerged as a foundation concept for current data acquisition and monitoring systems, consisting of tiny, limited battery-powered sensor nodes deployed across monitoring areas to collectively observe physical parameters and environmental conditions like light, motion, chemical presence, vibration, humidity, and temperature, then wirelessly communicate changes to central processing locations called base station (BS) or sink. Applications span precision farming, environmental monitoring, human health tracking, industrial process observation, and infrastructure surveillance.

These devices collaborate to collect, process, and transmit information to sink, the basic characteristic of these systems lies in their ability to perform independently without strong human coordination while maintaining collaborative data acquisition over extended schedules. The traditional Internet of Things (IoT), wireless networks, and WSNs face common challenges, including acute battery power constraints, limited storage and computational abilities, unreliable wireless links, high density of nodes, and the need for autonomous operations in a monitoring area. These unique characteristics entail specialized approaches, protocols, and algorithms specifically developed to improve network lifetime [1-3]. Clustering is a traditional network configuration approach that divides sensor devices in a monitoring area into hierarchical organizations to achieve energy-efficient communication and scalable network management. In a clustered WSN, devices are configured into clusters, with each cluster having a co-opted cluster head (CH) responsible for coordinating intra-cluster operations, aggregating data from cluster members (CM), and communicating with the BS or other CHs. Clustering-based organization significantly minimizes energy consumption of nodes compared to traditional topologies where all nodes directly coordinate with unique BS, because most communication happens over short distances within clusters rather than long-distance transmissions. The energy savings from clustering arise from three important factors, such as CMs transmitting data over short distances to nearby CHs, CHs performing data aggregation, and clustering enabling efficient sleep scheduling [4], [5]. Clustering protocols for WSNs can be categorized along multiple objectives based on their operational characteristics, like centralized and distributed protocols, static and dynamic clustering, and probabilistic and deterministic approaches.

Centralized protocols have a BS configure optimal cluster organization using global network information, enabling high-efficiency solutions but requiring expensive communication for status collection and a single point of failure [6], [7]. Distributed protocols like Hybrid Energy-Efficient Distributed Clustering (HEED) [8] enable deployed devices to self-organize into clusters using neighbour node communication, achieving efficient scalability and robustness but particularly creating suboptimal organizations due to restricted visibility. Static clustering protocols process cluster organization during network deployment and continue them throughout operation, reducing control overhead but lacking the ability to dynamic network conditions. Dynamic clustering protocols repeatedly organize clusters based on present network status, such as residual energy, topology changes, and other factors to enhance network age but suffering from control overhead for cluster reconfiguration. Probabilistic clustering approaches like Low Energy Adaptive Clustering Hierarchy (LEACH) [9] and Power Efficient Gathering in Sensor Information Systems (PEGASIS) [10] use randomized CH selection with rotation to distribute equal energy consumption but fail to have energy awareness in identifications. Deterministic clustering approaches specifically obtain CHs based on node characteristics like remaining energy, position, density, and connectivity, providing significant energy utilization but with high computational algorithms. Routing approaches create the route that observed packets traverse from source devices to destination BS or Mobile-Sinks. The WSN's routing must prioritize energy efficiency to improve network lifespan while fulfilling network requirements for reliability and latency. The resource constraints of deployed nodes short routing approaches' complexity, intercepting enlightened routing approaches that store expensive routing tables and complex path computations.

WSN routing algorithms face various unique issues, such as energy-constrained routing, which must obtain a route that reduces energy utilization; dynamic topology resulting from node failures, mobility, and duty cycle; data-centric communication, where BS requests data by representing attributes rather than addresses, which needs routing protocols; and broadcast approaches of wireless communication, which configure opportunities for optimization based on overhearing but also issues from collisions and interference. Based on the unique challenges of WSNs, routing protocols are classified as flat, hierarchical, chain-based, tree-based, and geographic-based protocols. The combination of clustering and routing protocols significantly influences comprehensive WSN performance, as decisions in one phase affect efficiency in the other. Sequential techniques perform clustering initially to configure network organization, then develop paths using that configuration, establishing simple implementation but missing optimization opportunities from combined development. Integrated approaches specifically optimize cluster formation and create paths, identifying that optimal clusters depend on routing requirements and optimal paths depend on cluster organization, through increasing computational complexity. Cluster-based routing generally merges the two procedures, with intra-cluster routing transferring data to CHs using simple one-hop or multi-hop forwarding within clusters, and inter-cluster routing communicating aggregated data between CHs towards BS or sinks. Intercluster routing can engage several strategies, such as direct transmission, multi-hop CH routing, and backbone formation. The combined optimization of clustering and routing in WSNs constitutes an NP-hard combinatorial optimization problem called no polynomial time approach.

It is useful to obtain optimal solutions, and excessive search becomes computationally intractable for scalable network sizes [11], [12]. The multi-objective nature of the optimization synthesizes the difficulty, as network operations concurrently pursue to increasing network lifespan, reducing energy utilization, decreasing data delivery latency, enhancing packet delivery ratio, and stabilizing energy utilization across deployed nodes. These objectives generally conflict in that the cluster organization enhancing lifetime may maximize latency, routing paths reducing energy may minimize reliability, and the dynamic topology increasing coverage may accelerate energy depletion of various nodes. The multi-objective characteristic means no single optimal solution exists, but rather a Pareto front of efficient trade-off solutions. Heuristic approaches design issue-specific protocols based on domain knowledge to configure better solutions efficiently, like selecting high-energy and centrally positioned nodes as CHs, then routing using nearest neighbour chains. While heuristics find fast solutions required for real-time implementation, they provide no optimality guarantees and may perform inefficiently on problem instances violating their fundamental assumptions. The lack of adaptability means designing new heuristics for specific variants of the clustering and routing problem. Metaheuristics employ an impactful alternative mechanism, providing general-purpose optimization frameworks applicable to diverse problem formulations without requiring problem-specific algorithm implementation. Those nature-inspired algorithms, such as Genetic Algorithms (GA) [13], Particle Swarm Optimization (PSO) [14], Ant Colony Optimization (ACO) [15], and Crow Search Algorithms (CSA) [16], provide population-based search approaches that repeatedly enhance candidate solutions through strategies inspired by physical and biological phenomena. Metaheuristics consistently deliver high-quality optimal solutions to complex problems that surpass traditional optimization strategies.

This research paper employs a simulation-based experimental design to evaluate the proposed multi-objective CSA-based MSCR system for heterogeneous wireless sensor networks. The proposed paper is structured to contribute to the following research objectives.

- Design an integrated multi-objective CSA approach that simultaneously optimizes cluster head selection and multi-mobile sink trajectory discovery.
- Develop coordination approaches for multiple mobile sinks to avoid duplicate data and enhance coverage efficiency.
- Validate energy efficiency enhancements through optimized simulation under varying network settings.
- Benchmark performance over traditional metaheuristic algorithms such as PSO, GA, and ACO using various capable metrics.

II. LITERATURE SURVEY

The Crow Search Algorithm (CSA) is a nature-inspired metaheuristic optimization schema introduced by Askarzadesh et al. [16] that is inspired by the intelligent behaviour of crows, basically their outstanding storage capacity, neighbour learning capabilities, and retrieval approaches. Unlike many other bioinspired techniques that were established earlier, like Genetic Algorithms (GA) [13], Particle Swarm Optimization (PSO) [14], Ant Colony Optimization [15], and many others, the CSA brings a unique perspective to optimization by implementing the memory using foraging behaviour and social learning capabilities adopted in corvid species. The application of the CSA to WSNs, gives us a specifically compelling similarity between the algorithm's characteristics and the inherent challenges of network optimization. The WSNs represent a complex optimization landscape characterized by multiple conflicting objectives, dynamic constraints, and resource limitations. The limited battery power of sensor nodes, combined with the need for efficient environmental monitoring, reliable communication, and enhanced network lifetime, creates an optimization problem that basic deterministic techniques struggle to solve effectively. The CSA addresses these challenges through its population using a search approach, which maintains a balance between global exploration of the solution space and local exploitation of promising areas. The memory strategy inherent in the CSA proves specifically crucial in the optimization of WSN operations, like maintaining consistency across multiple rounds of operations while adapting to changing network conditions.

The crow's storage allows the system to retain information about previously successful cluster head (CH) configurations or mobile sink (MS) routes based on the historical information to inform future decisions. This characteristic becomes critical when handling dynamic network topologies where full re-optimization from the beginning would be computationally expensive and a waste of node battery power. The social learning capabilities of the CSA mimic the distributed nature of WSNs themselves. The way crows learn from monitoring their peers, the algorithm's population of candidate solutions communicates data about promising regions of the search space, leading to faster convergence toward optimal solutions. The major strengths and limitations of the CSA require detailed comparison with alternative metaheuristic techniques that have been adapted to WSN optimization. Each approach provides distinct characteristics that make it appropriate for practical problem types, network configurations, and objective optimization. The parallel research comparative analysis provides not just which algorithm performs well overall, but also under what conditions each mechanism excels and combined approaches might prove significant over any one optimization algorithm. Particle Swarm Optimization (PSO) represents perhaps the basic comparison way for CSA, as both algorithms use population-based search with position updates routed by social data sharing. According to [17] establishes critical performance metrics and problem configuration for energy-efficient cluster formation and CH selection as a multi-objective optimization problem using remaining energy, node location and density, distance to BS, and coverage as optimization criteria.

For authors [18] implement a hybrid optimization model by merging the Harmony Search Algorithm (HAS) and Particle Swarm Optimization (PSO) for CH selection; that hybrid metaheuristic model is more efficient than single-algorithm implementations. The research establishes that metaheuristic optimization can significantly outperform traditional probabilistic techniques for clustering. Genetic Algorithms (GA) consider a basically different model of optimization, mirroring biological evolution using selection, crossover, and mutation functions on a population of candidate solutions. For unique problems in WSNs such as cluster formation and CH selection, GAs handle binary specifications primarily without requiring transfer functions, providing them a basic advantage in simulating efficiency. Ant Colony Optimization (ACO) is implemented in graph-based combinatorial problems and is particularly well-structured to routing optimization in WSNs. ACO's pheromone approach configures efficient shortest routes across collective points, where artificial ants deploy pheromone on promising edges that attract future ants. For basic routing problems without mobile sinks, ACO often outperforms CSA due to its native graph-based and incremental solution construction. However, ACO is inefficient with continuous optimization problems such as trajectory planning, requires considerable memory to maintain the pheromone collection, and converges slowly. The Artificial Bee Colony Optimization (ABCO) approach has objectives inherited from Honey Bee Foraging (HBF) behaviour, partitioning the population into adopted bees, onlooker bees, and scout bees that perform unique search jobs.

ABCO represents strong performance on continuous optimization problems and maintains the best population diversity through its multi-step configuration. In [19] implemented WSN clustering using ABCO with modifications specifically designed for the discrete nature of the CH selection problem. This research demonstrates optimization techniques like adaptive parameter adjustment and diversity-based strategy selection. According to [20] provide a comprehensive review on coverage optimization techniques in WSNs, providing context for analysing how metaheuristic approaches adapted to the multiple objectives of WSN optimization. The paper partition the coverage problem into area coverage, point coverage, and endpoint coverage, detailing deterministic, probabilistic, and optimization-based solution techniques for each partition. Grey Wolf Optimization (GWO), a recent development in metaheuristic-based models, represents the hunting behaviour and pack hierarchy of grey wolves. For authors [21] implement modifications to the metaheuristic GWO that enhance the performance of WSNs problems. According to [22] implement mobile-sink based data collection in WSNs through an integrated approach merging load-balanced clustering with optimized mobile-sink route planning. The researchers establish the problem as reducing energy consumption subject to data delivery latency constraints and design a heuristic approach that first divides the network area into optimal clusters and CHs and then creates an approximate trajectory tour visiting CHs. According to [23] focus specifically on mobile-sink trajectory optimization using GA and PSO.

The algorithm configures trajectory planning across the collection points (CPs) to collect data, with the objectives of reducing tour length and enhancing energy efficiency. The analysis of trade-offs between tour length reduction and energy consumption balancing informs multi-objective configurations in hybrid approaches. In [24] implemented an algorithm using CSA with Q-learning reinforcement learning for adaptive optimization in dynamic HWSN. The Q-learning basically learns routing rules that adapt network states to optimal routing operations based on accumulated positives from successful data delivery and negatives for failures. According to [25] provide a detailed comparative analysis of important clustering protocols for WSNs, including traditional algorithms like LEACH and PEGASIS alongside nature-inspired metaheuristic algorithms using PSO, GA, ACO, and ABCO. The comparison adapted standardized simulation scenarios with dynamic node ranges and evaluates critical performance metrics such as network lifespan, throughput, packet delivery ratio, energy consumption, delay, latency, and clustering consistency. The most recent parallel research papers provide that no single algorithm addresses all performance metrics and network configurations, with optimal algorithm identification based on application priorities and network constraints and characteristics. The comprehensive summary of parallel research using CSA and metaheuristics in WSNs is discussed in the following Table 1. Summary of parallel research in WSN using metaheuristic optimization algorithms.

Table 1: Summary of parallel research in WSN using metaheuristic optimization algorithms.

Ref	Authors	Major Approaches for WSNs	Advancements with Algorithms	Limitations
[26]	Zhang et al. 2024	Deep Reinforcement Learning improved clustering in HWSNs using the DRL-CSA combination for dynamic parameter adaptation.	DQN learns optimal CSA parameter adjustment and adaptation rules. Significant network lifetime (i.e., 35-45%) over standard CSA.	DQN requires high training data across diverse network configurations. DQN training is computationally very expensive.
[27]	Kumar et. al. 2024	Pareto-based multi- objective optimization for joint clustering and mobile-sink trajectory finding with specific trade-off exploration.	Multi-objective optimization like coverage, delay, energy, and load balance. The initial comprehensive Pareto-based cooperative CSA for WSNs includes an archive that maintaining non-dominated solutions.	Archive size management is challenging for large-scale dimensional objectives. Higher execution time (40%) than single-objective CSA due to archive maintenance.
[28]	Martinez et al. 2023	Distributed CSA with consensus algorithms for large-scale WSNs	Asynchronous operations without global synchronization. The network is divided into large-scale areas with parallel local CSA.	The boundary of each local area affects the quality of the solution. Distributed CSA requires 400 – 600 iterations.
[29]	Li, X et al. 2024	LSTM and adaptive CSA-based energy harvesting WSN optimization with solar power prediction.	Significant network lifetime (i.e., over 45%) over standard CSA. Dynamic objective weighting based on harvesting-to -consumption ratio.	LSTM training requires massive historical solar data. Performance degrades significantly in unpredictable weather patterns. Restricted validation on other harvesting sources.
[30]	Ahmed et al. 2023	Federated learning system for privacy-preserving distributed optimization using secure multi-party computation.	Lower communication overhead than centralized techniques. Local CSA at CHs with only aggregated statistics shared. Secure against gradient inversion	Convergence is slower than centralized due to privacy noise injection. Enhanced communication iterations needed for coordination. Limited scalability analysis below 500 nodes.
[31]	Thompson et al., 2024	Quantum-inspired CSA using qubits, superposition, and entanglement for improved exploration in complex optimization landscapes.	Higher solution quality (i.e., 15-25%) than classical CSA. Quantum implementation with probability amplitudes exhibits parallel exploration. Entanglement fixes problem structure.	Limited policies on qubit-to-variable mapping strategies. Not implementable on real quantum hardware. Quantum entanglement design requires domain expertise. Scalability extends to very large problems.
[32]	Wu. T., et al. 2023	Game-based multi-sink coordination with potential game formulation and Nash equilibrium solutions for conflict resolution.	Each mobile sink is designed as a rational player in a potential game framework. Higher lifetime (i.e., 47%) with dual sinks. Load imbalance is very low (i.e., <8%).	Game-theoretic analysis complexity grows with the number of sink nodes. Inter-sink communication overhead for coordination.
[33]	Park et al. 2024	Explainable AI integration using SHAP values for interpretable network configuration with human-algorithm collaboration.	SHAP analysis quantifies feature importance like energy and centrality. The optimization process is interactive and incorporates human preference incorporation.	Higher computational overhead of SHAP value computation. SHAP assumes feature independence, which may not hold.

[34]	Gupta et al. 2024	Edge intelligence with fog computing architecture for real-time optimization in WSNs.	CSA deployed on fog nodes managing some sensor clusters. Faster execution through vectorization and parallelization. Eventual consistency coordination tolerates network divisions.	Energy utilization of fog nodes is not thoroughly analysed. Fog node failures need fast workload redistribution. The deployment costs and complexity of fog infrastructure are significant, and the computational resources of fog nodes are limited.
[35]	Gharaei N et al. 2016	Multi-objective optimization for intra-cluster routing and CH positioning in WSNs	Energy-aware crowding distance prioritizes balanced solutions. Multi-objective, like energy, coverage, and density, with Pareto-based applications across multiple WSN problems. Coverage-specific crossover preserves spatial patterns. Hierarchical routing structure optimization.	No mobile sink consideration. Scalability is limited to 200 – 300 nodes in the monitoring area. Limited to intra-cluster routing, not focusing on inter-cluster. Modified crowding distance appends computational complexity.

Source: Authors, (2026).

The comparative analysis of algorithm performance is summarized in the following Table 2.

Table 2: Comparative analysis of parallel research in WSN using metaheuristic optimization algorithms.

Algorithm	Typical Lifetime Improvement	Convergence Speed	Computational Cost	Application Area
Traditional (LEACH, PEGASIS)	Baseline 100%	Very Fast	Very Low	Small static networks
PSO	115 - 130 % of LEACH	Fast	Low-medium	General clustering and routing
GA	110 – 135 % of LEACH	Slow	Medium-high	Discrete optimization problems
ACO	125 – 135 % of LEACH	Very slow	High	Graph-based routing
CSA	130 – 145 % of LEACH	Fast	Low Medium	Integrated clustering and trajectory planning.
Hybrid CSA and PSO	140 – 155 % of LEACH	Fast	Medium	Complex multi-step optimization.
Advanced DRL with CSA and Quantum CSA	150 – 175 % of LEACH	Very Fast	High	Dynamic adaptive networks

Source: Authors, (2026).

III. METHODOLOGY

Resource-constrained tiny nodes are randomly deployed in a large-scale monitoring area, i.e., $G = (V, E)$, using uniform distribution to ensure unbiased coverage, where G is a monitoring area (called a geographical region), V specifies the collection of resource-constrained tiny 'n' sensor nodes deployed within the G , E transmission lines among nodes, and V_i indicated as i^{th} node of the collection of nodes. There are some assumptions in the development of algorithms; such assumptions include heterogeneity among sensors with unique identification (UID) and varying initial battery capacity and varying node movement. The large-scale monitoring area is divided into grids to form clusters and to elect cluster heads (CHs). Clustering is a widely adopted and proven approach in wireless sensor networks (WSNs) that significantly reduces energy consumption and enhances lifetime of the network.

The multi-sink nodes and one base station is deployed within the monitoring area, and the base station remains static. Base station (BS) can configure the centre of the monitoring area, while mobile sink nodes configure their trajectory to collect data from the cluster heads (CHs). The cluster nodes monitor phenomenon and transmit directly to the cluster head; this scenario, CHs adjust their transmission power according to the distance to the collection point. The BS is equipped with infinite computation and communication capabilities, similarly dual-mobile-sink devices are configured with sufficient computing and communication capabilities and process and aggregate data before delivery to the base station. Sink nodes are mobile devices with some level of power constraints, but can be rechargeable. All sensor nodes can map between sleep and active states to save continuous energy consumption.

III.1.1 Basic Energy Consumption Model

Energy consumption - the mathematical framework for representation of energy consumption of nodes to transfer 'k' bits within a transmission range 'r' of a node can be expressed as:

$$TE_i(k, r) = \{(E_{el}^i * k + k * E_{fs} * r^2); r \leq \partial_t\}$$

E_{el} is represented by the electronic energy of the node per bit of information. Energy consumption of CH to send data to the mobile sink node is

$$TE_c = \begin{cases} (E_{el}^c * k + k * E_{fs} * r^2); r < \partial_t \\ (E_{el}^c * k + k * E_{mp} * r^4); r \geq \partial_t \end{cases} \quad (1)$$

Where E_{fs} is used to specify the amplifier energy of tree space and E_{mp} can represent a multi-path forwarding model, respectively, then $\partial_t = \sqrt{E_{fs}/E_{mp}}$

Node (i) and CH (c) to receive 'k' bits of data is expected as

$$RE_i(k) = (E_{el} * k) \quad (2)$$

$$RE_c(k) = (E_{el} * k) \quad (3)$$

The energy utilization by the CH in aggregation of 'm' redundant data, each consisting of 'k' bits, can be evaluated as

$$E_A^c(m, k) = (E_{ag} * m * k) \quad (4)$$

Where E_{ag} used to specifies the aggregates energy of the cluster head (CH) per bit of information aggregated.

The radio energy model of a sensor node evaluates the energy consumption of nodes during data transmission and reception, and CH estimates the power utilization for communication along with the aggregation. The evaluated energy utilization of sensors and CHs in processing various operations in the monitoring area can be obtained based on equations 1, 2, and 3. Equation 1 indicates the expected power loss of a node in forwarding information over a distance. The calculated power consumption is directly proportional to the distance over which information is forwarded. The cluster head power utilization maximizes with the square of the transmission range for shorter ranges and with r^4 for the longer distance. This includes that cluster heads have faster power consumption in longer transmission ranges than shorter transmission ranges. The transmission range up to which communication is energy efficient is called the threshold transmission range of the node radio system. The value of threshold distance is constructed by using equation 3. By restricting the cluster head to forward data to multi-mobile sink nodes within the distance, the overall power utilization is reduced, enhancing the lifetime of CHs and improving the life of the overall monitoring area. Multi-mobile sink-based data acquisition is an efficient process and enhance the lifespan of the sensor network. Two mobile sink nodes have been used to traverse over a predetermined a trajectory to get monitored data from cluster heads. The mobile sink can construct trajectory near to cluster heads so that cluster heads can use less energy for data transmission. These multi-mobile sink nodes can configure different and opposite directions to get monitored data from CHs.

Electing CHs in the monitoring area and constructing a path for a mobile sink is important in the proposed model to enhance the lifetime of the entire network. The crow is an intelligent bird that can remember faces and warn species in danger. One of the most important pieces of evidence of cleverness is hiding food and remembering its location. The Crow Search Algorithm is inspired by the intelligent foraging behaviour of crows, basically their ability to store food in hidden places and use it when essential. The CSA can simulate the behaviour of storing excess food and retrieving it when needed, the behaviour is mathematically approached through a location-updating strategy that balances exploration and exploitation. In the WSN optimization theory, the monitoring area is a search space, and randomly recognizing the location of CH is a feasible solution. Among all cluster nodes, the node where the most energy is available is elected as a CH_i , and the objective function is the amount of node energy. Major phases in clustering and routing using CSA can be defined as follows: Initializing – deploying resource-constrained tiny nodes (crow swarms) in a monitoring area randomly. Dividing the entire network into grids to configure clusters in the monitoring area. A fitness function is used to evaluate each node (crow), and its value is placed as an initial node storage. Each node stores its schedule and energy in its memory variable ' m_i '. Each node updates its residual energy and neighbour node position by selecting another random node, i.e., n_j and generating a random value. If the value is greater than awareness probability (AP), then the node n_i will use x_j to construct a cluster head. Each node updates its locations by selecting a random other node, i.e., n_j and following into know CH_j then n_j is calculated.

III.1.2 Proposed Multi-Objective CSA-Based MSCR Algorithm

The multi-objective CSA-based MSCR optimization algorithm performs in five unique phases computed orderly within each network round. Each round begins with an initialization phase; CSA-based cluster head (CH) election and formation will be done in the next phase, followed by a phase implemented for CSA-based multi-mobile sink trajectory formation and optimization, and the final phase represents data collection and transmission. Network Setup State: The initialization phase in the proposed model establishes the fundamental infrastructure for HWSN with multi-mobile sink nodes that represent deployment of 'n' nodes and the discovery of the nodes in the monitoring area G and the heterogeneity ratio of 'n' nodes. The placement of multi-mobile-sink nodes and base stations is defined. And finally, CSA parameters and weight parameters are configured for a CH selection and mobile sink trajectory optimization. The CH formation and selection in WSNs operates as an NP-Hard combinatorial optimization problem. For a network of 'n' nodes, the primary objective is to divide the monitoring into a specific number of clusters and to elect a subset $S \subseteq 'n'$ as cluster heads where a dual-objective function is optimized by satisfying implementation constraints. The problem can be represented in the equation.

$$\max_{S \subseteq n} F(S) = \sum_{j=1}^k w_j f_j(S) \quad \begin{cases} 0.10n \leq |S| \leq 0.20n \\ E_{res}(m) > 0.4 E_{in} \exists m \in S \\ A_{CH \in S} cov(CH) = N \end{cases} \quad (5)$$

The search space cardinality is $\binom{n}{k}$ for identifying 'k' CHs from 'n' deployed nodes in the monitoring area, which increases exponentially. Traditional deterministic systems are less accurate for this issue class due to combinatorial explosion, multi-objective nature, dynamic constraints, and non-convexity. Nature-inspired Swarm intelligence approaches, particularly the Crow Search Optimization, extend and adopt polynomial-time random similar solutions with validated convergence assurances. The CSO gained attention from ethological observations of corvid maintaining behaviour, where crows hide food in locations and use it later, while concurrently attempting to obtain caches hidden by other crows. This configures a dynamic interchange between exploitation and exploration. An unaware and aware target crow position update approach is defined in the following equations (4) and (5).

$$l_i^{k+1} = l_i^k + rn_i * fl * (s_j^k - l_i^k) \quad \{unware \ traget \ (rn < AP)\} \quad (6)$$

Where

l_i^k – location of crow i at iteration k

s_j^k – Storage position of randomly selected crow i

fl – flight length parameter controlling step size

rn_i – random number in [1, 0]

$$l_i^{k+1} = \text{Random location in search space} \quad \{aware \ target \ crow \ (r < AP)\} \quad (7)$$

The cluster head (CH) identification of the issue inherently represents two binary decision variables such as $l_i \in \{1, 0\}$, where $i = 1, 2, 3, \dots, n$, whether it offers some important representational advantages like semantic clarity, constraint verification, and Hamming distance interpretation. Since crow search optimization performs in continuous space, the sigmoid transformation bridges the implementation gap and decision rule in the following equations (8) and (9).

$$\sigma(l) = \frac{1}{1 + e^{-l}} \quad (8)$$

$$l_i^{binary} = \begin{cases} 0 & \text{otherwise} \\ 1 & \text{if } \sigma(x_j) > 0.5 \end{cases} \quad (9)$$

The proposed crow search optimization employs scalarization to change multiple objectives into a single fitness value represented in the following equation (10) with the help of equation 5. For wireless sensor networks CH identification and formation, the objectives extend enough convexity for weighted aggregation.

$$F = \sum_{k=0}^4 w_k * f_k, \text{ where } \sum_{k=1}^4 w_i = 1 \quad (10)$$

The CHs consume unequal energy due to receiving data from all associated CMs, aggregating and processing data, and long-distance transmission to mobile sinks. Identifying high-battery power nodes as CHs expands the first node death, enhancing the stable period of network performance. The optimization assures scale invariance around networks based on different initial energy configurations, and energy and distance functions are represented in equations (11), (12), and (13); it represents the node battery power utilization model for wireless transmission.

$$f_e = \frac{En_{ch}}{E_{mx}} = \frac{\frac{1}{|S|} \sum_{CH \in S} E_{res(CH)}}{E_{in}^{mx}} \quad (11)$$

$$f_d = \frac{1}{1 + \frac{di}{100}}, \text{ where } di = \frac{1}{n - |S|} \sum_{z \in S} \min_{ch \in S} d(z, ch) \quad (12)$$

$$E_i(k, d) = \{(E_{el}^i * k + k * Ef_s * d^2); d \leq \partial_t\} \quad (13)$$

The deployed member node assignment automatically configures a weighted Voronoi tessellation of the network monitoring area. In traditional Voronoi representations, each point belongs to the position of its nearby location. The optimization algorithm adapts weighted distance for static CHs and reduces total communication cost; each member node should map to exactly one cluster, and nearby nodes probably collaborate in the same cluster. The following equation (14) specifies the weighted distance.

$$d_w(v, CH) = 0.8 * d_e(v, CH) + 0.3 * E_t(v, CH) \quad (14)$$

The Time Division Multiple Access (TDMA) schedule implementation uses graph coloring features adopted to temporal domains. It assigns time slots $\{1, 2, 3, \dots, t\}$ to CMs in a cluster; each node configures exactly only one slot per round. Where no two CMs within the cluster neighbour discovery range share a slot and the total schedule length is minimized.

The adapted schedule length obtains data collection latency, directly impacting network overall performance. Another important aspect for cluster formation and cluster head selection is lower and upper bounds, which indicate the minimum and maximum CHs in the deployed area. For example, the cardinality bounds are $0.10 \leq |S| \leq 0.20$. Where minimum CHs are necessary for coverage, and below this threshold, intra-cluster distances become inefficient. If above the threshold, increased inter-CH communication becomes high CH energy consumption. The high energy utilization of some CMs becomes network division. This phase of the proposed model establishes the CSOA-based cluster formation and cluster selection algorithm as a determined system for combinatorial optimization in WSNs. The multi-objective fitness procedure gathers the important trade-offs in cluster formation and head selection, while the adaptive CSO model provides efficient representation of the exponentially large solution space. In the next phase of implementation, focus on optimizing the routes of multiple mobile sinks to efficiently collect data from CHs while reducing energy utilization, collection delay, and route distance. This phase transforms the route discovery problem into a type of the multiple Traveling Salesman Problem (mTSP) and configures it using the Crow Search Optimization Algorithm (CSOA).

This algorithm divides the CHs among multiple mobile-sinks for balanced workload, obtains an optimal collection point sequence for each mobile sink, reduces CH transmission energy by locating routes near CHs, minimizes data collection latency through efficient route discovery, and ensures all CHs are covered within the mobile sink communication range with high priority of minimizing sink collisions and data redundancy. The final phase of implementation focuses on the real data collection process, where CMs monitor environmental or surrounding data, transmit to CHs for aggregation, and mobile sinks obtain optimized routes to collect aggregated data from CHs. The mobile-sink route optimization issue specifies a generalization of the TSP with some other complexities that highlight it as a unique problem class. The route optimization extends TSP in several dimensions, such as each CH within communication range of some collection point (CP), continuous CP placement, and multi-objective (energy, time, coverage, and distance). The route fitness function aggregates four important objectives using weighted scalarization that can be defined in the following equation (15).

$$F(R) = \eta * f_{en}(R) + \vartheta * f_{ti}(R) + \iota * f_{cov}(R) + \kappa * f_{len}(R) \quad (15)$$

where

$$R = [(x_1, y_1), (x_2, y_2), (x_3, y_3), \dots, (x_n, y_n)] \text{ specifies the mobile - sink route}$$

The energy (η) of a node is a primary constraint, and CH battery life determines network lifetime. The energy constraint of CH can be analysed with an equation (16).

$$f_{en}(R) = 1 - \frac{E_{tot}^{ch}(R)}{E_{max}^{pos}} \quad (16)$$

Where the total transmission energy of CH configures the first-order radio model also defined in equation (17).

$$E_{tot}^{ch}(R) = \sum_{ch_j \in ch} E_{tr}(ch_j, R) \quad (17)$$

We analysed time component to collect data from CHs and the travel time to reach collection points and defined with the following equation (18).

$$S_{time}(T) = 1 - \frac{S_{tot}(T)}{S_{max}} \quad (18)$$

The total collection time from CH is defined in the following equation (19).

$$N_{tot}(T) = S_{travel}(T) + S_{collected}(T) \quad (19)$$

Mobile sink travel time is defined in equation (20).

$$S_{travel}(T) = \frac{F(T)}{v_{ms}} = \frac{\sum_{i=1}^{n-1} \|\omega_{i+1} - \omega_i\|}{v_{ms}} \quad (20)$$

$$S_{collected}(T) = \sum_{\omega \in T} |N(c)| \cdot t_{tx} \quad (21)$$

Where $N(c) = \{CH \rightarrow |CH - cp| \leq T_{range}\}$ specifies CHs with the communication range of collection points (cps). We also analysed the coverage of the mobile sink that ensures the set cover property; every assigned CH must be within communication (T_{range}) of at least one trajectory collection point (CP), and it can be defined in the following equation (22).

$$f_{coverage}(T) = |\{CH \exists c \in T, \quad \|CH - cp\| < T_{range}\}| / |CH| \quad (22)$$

Some of the other critical WSN constraints are analysed, such as energy, time, coverage, and collection point boundaries; this are defined in the following equations. $E_{route}(MS_i) \leq 0.8 \beta_i$ threshold implements a secure margin ensuring that battery lifetime is capable of being sustained under worst-case scenarios, and that there is an energy reserve for unexpected obstacles.

Time constrains $S_{tot}(T) \leq S_{max}$ bounds staleness. The 0.95% threshold balances complete coverage against computational tractability and can be defined in the following equation (23).

$$\frac{|coverage(T)|}{CH_{assign}} \geq 0.95 \quad (23)$$

Finally, collection points (CPs) and endpoint boundary constraints are common in vehicle routing problems. The MS must return to its charging station to recharge depleted batteries, start the next collection round, and enable predictable scheduling defined in equation (24).

$$CP_1 = CP_m = MS_{pos} \quad (24)$$

For a given 'k' CHs and 'n' MS, partition CHs into 'm' disjoint subsets, reducing total intra-cluster distance.

$$\min\{x_1, x_2, \dots, x_m\} \sum_{i=1}^m \sum_{CH \in x_i} \|CH - \mu_1\|^2 \text{ where } \cup_{i=1}^m x_i = CH \text{ and } x_i \cap x_j = \emptyset \text{ for } i \neq j.$$

Collection point representation and route optimization operate in continuous Euclidean space $T = [(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)] \in R^{2m}$, dimensionality is dynamic, and that m depends on the CH count, dynamic internal collection points, and static end points. Every collection point moves along the line segment connecting its current positions to the corresponding collection points in the target memory. The movement magnitude is controlled by the product of $r.fl$. For intermediate collection points, continuous space update equation (25). Detailed algorithm for representing all the functions to perform heterogeneous wireless sensor networks using crow search optimization.

Algorithm: Crow Search Algorithm (CSA) for Wireless Sensor Network (WSN) Optimization.

Input: Initialization of number of nodes (N_Nodes), monitoring area (A), number of mobile sinks (MS), position of base station (BS), present round (pr), maximum rounds (mr), and clustering interval (ci)

Output: Optimal Algorithm to analysis WSN

```

1. if pr mod ci == 1 then
a. optimalCHs = binaryCSA(N, populationSize, maxIterations, flInitial, APInitial) //Binary CSA for CH selection
b. clusters = formClusters(N, optimalCHs) //Cluster Formation
c. for each cluster in clusters
i. cluster.schedule = createTDMASchedule(cluster.member)
d. CHAssignments = divideCHMSinks(optimalCHs, MS) //Cluster Head division
e. for each sink in MS:
i. sink.route = continuousCSA(CHAssignments[sink.id], locationChargingPoint, populationSize, maxIterations, flInitial, APInitial)
f. MS = avoidCollisions(MS) //Collision avoidance
2. for each cluster in clusters:
a. for each timeSlot in cluster.schedule:
i. member = cluster.schedule[timeSlot]
ii. data = member.senseEnvironment()
iii. distance = euclideanDistance(member, cluster.CH)
iv. energyTx = obtainTxEnergy(data, distance)
v. member.residualEnergy - = energyTx
vi. append(data)
vii. energyRx = obtainRxEnergy(data)
viii. cluster.CH.residualEnergy - = energyRx
b. aggregateData(cluster.CH)
c. energyAg = obtainAggregateEnergy(cluster.CH)
d. cluster.CH.residualEnergy - = energyAg
3. for each sink in MS:
a. sink.position = sink.locationChargingPoint
b. append(sink.collectedData)
c. for each collectionPoint in sink.route
i. distance = euclideanDistance(sink.position, collectionPoint)
ii. energyMove = 0.05 * distance
iii. sink.residualEnergy - = energyMove
iv. sink.position = collectionPoint
v. for each CH in sink.assignedCHs
vi. distanceCH = euclideanDistance(sink.position, CH.position)
vii. if distance <= sink.TRRRange then
viii. energyCHTx = obtainTxEnergy(CH.aggregatedData, distanceCH)
ix. CH.residualEnergy - = energyCHTx
x. energyCHRx = obtainTxEnergy(CH.aggregatedData, distanceCH)
xi. CH.residualEnergy - = energyCHRx
xii. Sink.append(CH.aggregatedData)
d. sink.moveTo(BS)
e. sink.transmitTo(BS, sink.collectedData)
f. sink.recharge()

```

```

4.networkState = obtainNetworkMetrics(network)
5.energyVariance = variance ([node.residualEnergy for node in aliveNodes])
6.deadCHs = count ([CH for CH in optimalCHs if CH.residualEnergy == 0])
7.if energyVariance > threshold || deadCHs > 0 then
a.clusteringInterval = currentRound
8.logRoundStatistics (currentRound, networkState).

```

IV. RESULTS AND DISCUSSIONS

IV.1.1 Simulation Setup and Configuration

The simulation setup for evaluating the performance of the multi-mobile sink-based clustering and routing on HWSN using Crow Search Algorithm (CSA) optimization requires careful focus on simulation configuration, parameter selection, and traditional comparison selection. The performance evaluation of the proposed MSCR-CSA was demonstrated using the NS2 simulation environment on a workstation with fully equipped components and network configuration parameters shown in Table 3. The simulation framework specifies comprehensive energy systems, realistic wireless communication protocols, and a realistic node behaviour system to assure results accurately provide real-world deployment strategies. Each experimental configuration was run 100 cycles with unique random input values to ensure statistical validity.

Table 3: Network configuration parameters.

Simulation Parameters	Values
Monitoring area	500 * 500
Node deployment type	Random uniform distribution
No. of nodes	100 to 500
Network Heterogeneity Ratio	80% normal nodes, 20% advanced nodes
Normal Nodes	
Node Initial Energy	1.0 Joule
Sensing range	15 m
Communication range	30 m
Advanced Nodes	
Node Initial Energy	2.0 Joule
Sensing Range	20 m
Communication Range	40 m
Multi-Mobile Sink Configuration	
No. of mobile sinks	2
Initial position of Mobile-Sink	Opposite corners of the monitoring area
Mobility of Sink	2 m/sec
Communication range of Sink	50 m
CSA Algorithm Parameters	
Population of crows	50
Iteration count	300
Binary CSA, Flight Length	2.0
Continuous CSA, Flight Length	10.0
Binary CSA, Awareness Probability	0.3
Continuous CSA, AP	0.4

Source: Authors, (2026).

IV.1.2 Important Findings and Performance Achievements

Performance comparisons include five parallel research algorithms representing state-of-the-art strategies: Low Energy Adaptive Clustering Hierarchy (LEACH) as the classical protocol baseline, Particle Swarm Optimization for Multi-Sink Clustering and Routing (PSO-MSCR), Genetic Algorithm for Multi-Sink Clustering and Routing (GA-MSCR), Ant Colony Optimization for Multi-Sink Clustering and Routing (ACO-MSCR), and standard CSA with static parameters. Each baseline is configured with parameters tuned using grid search to ensure better comparison, with a population size of 50 and maximum of 300 loops matching the proposed adaptive CSA configuration. The multi-objective fitness method for CH selection weights remaining energy at 0.4, average CM-CH distance at 0.3, cluster size balance at 0.2, and network coverage at 0.1. For sink trajectory optimization, the fitness function weights CH transmission power at 0.35, total route length at 0.3, data collection time at 0.25, and coverage completeness at 0.1. These weight allocations show priorities established through general sensitivity analysis balancing many performance dimensions.

IV.1.3 Network Lifetime Improvement:

The longer lifespan performance gained from CSA's behaviour to elect CHs with optimal energy saving while simultaneously placing mobile-sink routes to reduce CH transmission distances then leads to balancing energy utilization across the network. Figure 1 and Table 4 represent the First Node Death (FND) results across varying network sizes and mobile-sink configurations.

The results demonstrate that the proposed CSA-based MSCR consistently gains significant network lifetime compared to all parallel research algorithms. The experimental results demonstrated that integrated multi-objective CSA-based MSCR received significant enhancement in network lifespan compared to traditional metaheuristic algorithms such as PSO, GA, and ACO. The proposed CSA-based MSCR achieved a 44% higher network lifespan compared to PSO-based MSCR, a 49% enhancement over GA-based model, 55% efficiency compared to ACO-based algorithms, and 181% longer efficiency over the traditional LEACH algorithm. The performance adjustments remain static across all network scales from 100 to 500 nodes in the simulation.

Table 4: Number of rounds – dual mobile sink configuration.

Nodes	CSA– MSCR	PSO-MSCR	GA–MSCR	ACO–MSCR	CSA	LEACH
100	4387	3421	3156	3587	3912	1523
200	4156	3267	2978	3421	3756	1467
300	3942	3089	2834	3267	3598	1398
400	3734	2867	2645	3089	3445	1334
500	3521	2678	2489	2912	3267	1289
Average enhancement	Baseline	+28.4	+39.6	+21.3	+9.8	+182

Source: Authors, (2026).

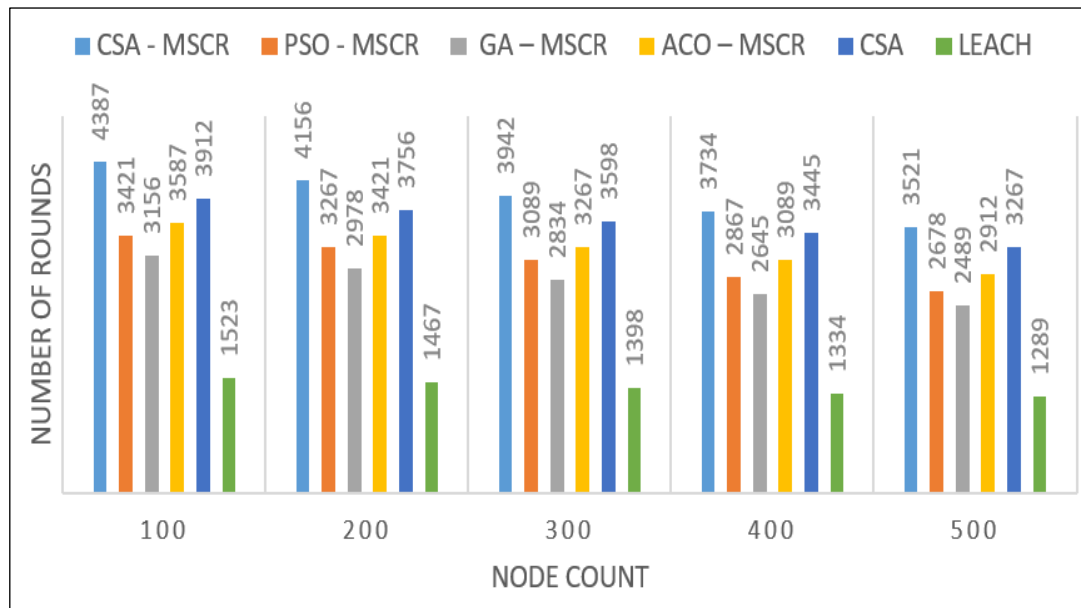


Figure 1: Number of rounds and dual mobile sink configuration.

Source: Authors, (2026).

IV.1.4 Energy Consumption

Figure 2 and Table 5 present detailed power consumption analysis for the 300-node dual-mobile sink evaluation over 3000 functional iterations. The proposed multi-objective CSA-based MSCR energy utilization analysis achieved substantial energy-efficiency that 24% minimization in total network energy consumption over PSO-based MSCR, 29% minimum battery utilization compared to GA-based models, and 33% battery power saving compared to ACO-based algorithms. The dual-mobile sink coordination approach contributed magnificently to these achievements by dividing the network into optimal operational areas, minimizing the average CH – Sink communication distance that leads to the significant power savings using the quadratic relationship between distance and power in the multi-route propagation system.

Table 2: Energy consumption in 3000 rounds with 300 nodes and dual mobile sinks.

Component	CSA-MSCR	PSO-MSCR	GA- MSCR	ACO-MSCR	Reduction vs PSO
Intra-Cluster	389.7	478.3	512.6	534.8	- 18.5%
Inter-Cluster	298.4	412.7	445.3	468.9	-27.7%
Cluster Member	412.8	501.2	534.7	556.3	-17.6%
Cluster Heads	275.3	389.8	423.2	447.4	-29.4%
Mobile-Sink movement	108.6	118.4	125.7	132.1	-8.3%
Mobile-Sink Communication	67.8	74.2	79.3	83.6	-8.6%
Control overhead	52.4	68.9	76.4	81.2	-24.0%
Overall Network	830.7	1088.2	1168.3	1236.8	-23.7%

Source: Authors, (2026).

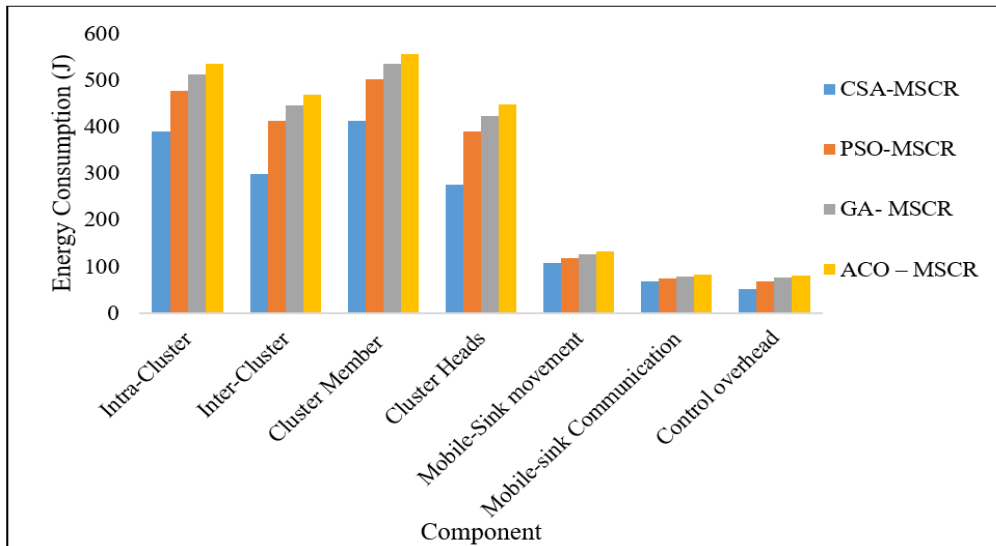


Figure 2: Energy consumption of nodes based on various constraints.
Source: Authors, (2026).

IV.1.5 Cluster Quality and Efficiency

Table 6 and Figure 3 examine the organizational characteristics of cluster formation by various approaches for the 300-node and dual-mobile sink configuration. The proposed multi-objective CSA-based MSCR cluster formation demonstrated significantly high-performance characteristics, such as 38% lesser cluster formation time compared to PSO; the load balance index of the proposed model is 0.89, which is better compared to 0.75 for ACO and 0.72 for PSO; and the proposed model coverage efficiency is 98.2% of nodes optimally appended to CHs compared to PSO is 92.4% of node optimality. The significant clustering quality achieved from effective multi-objective CSA-based optimization that simultaneously considered power saving, spatial distribution, load balancing, and coverage efficiency, whereas parallel research algorithms generally prioritized only one or two objectives.

Table 6: Cluster Formation Analysis with 300-nodes, and dual-mobile sinks.

Metric	CSA – MSCR	PSO – MSCR	GA – MSCR	ACO – MSCR
Avg. Cluster Count	23.4	26.7	28.3	25.9
Avg. Cluster Size	12.8	11.2	10.6	11.6
Cluster Size Std Dev	3.8	6.9	7.8	6.4
Max. Cluster Size	21	34	38	31
Min. Cluster Size	7	4	3	5
Avg. CM – to – CH distance (m)	18.7	26.4	29.1	25.3
Load balance index	0.887	0.723	0.681	0.754

Source: Authors, (2026).

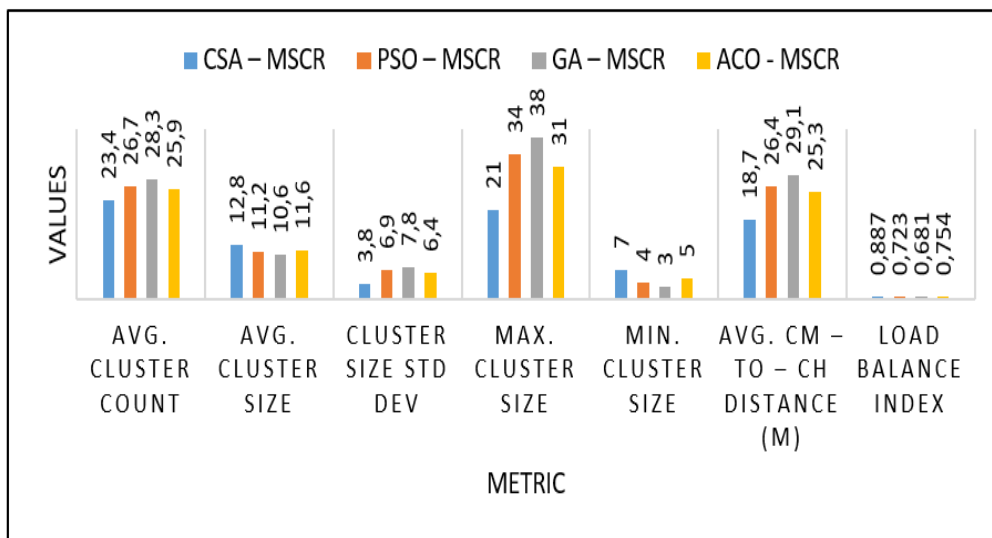


Figure 3: Analysis of Clustering in various Algorithms.
Source: Authors, (2026).

Table 7 and Figure 4 represent the simulation properties of re-clusters formed by various approaches for the 300 nodes and with dual-mobile sink configuration.

Table 7: Re-cluster formation analysis in 4000 rounds – 300 nodes and dual-mobile sinks.

Metric	CSA-MSCR	PSO-MSCR	GA-MSCR	ACO-MSCR	CSA
Total Re-clustering events	62	87	103	94	71
Avg. rounds between	64.5	46.0	38.8	42.6	56.3
Energy per Re-cluster (J)	12.7	15.3	17.8	16.4	13.4
Total Re-cluster Energy (J)	787.4	1331.1	1833.4	1541.6	951.4

Source: Authors, (2026).

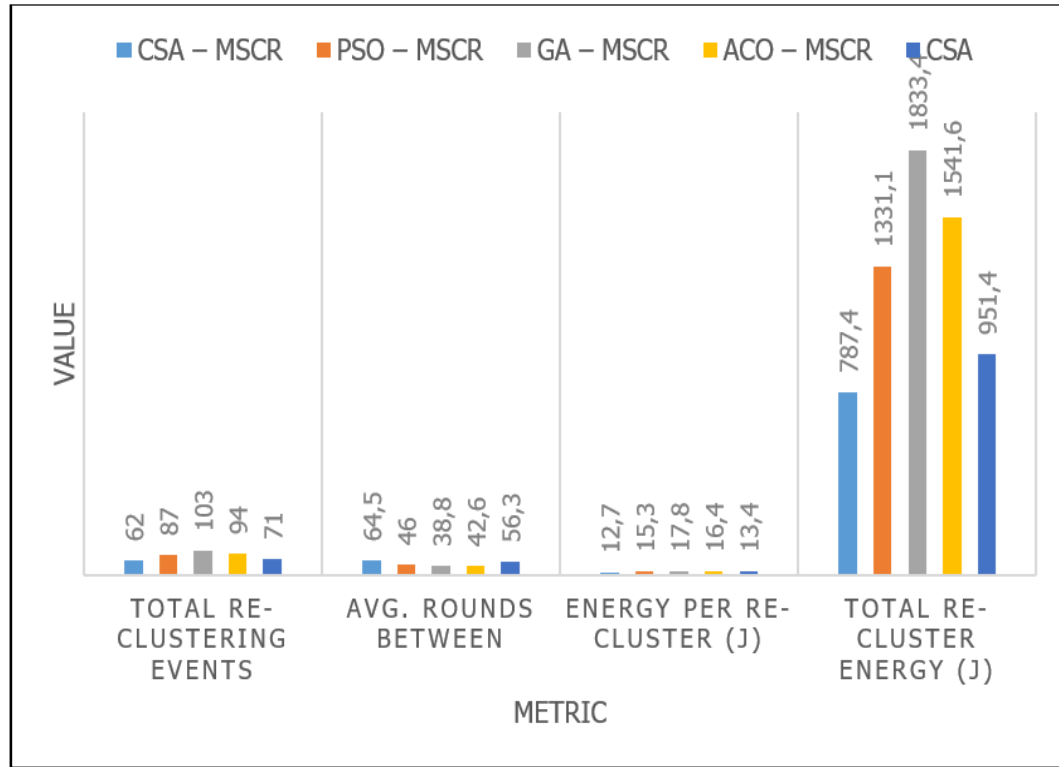


Figure 4: Re-clustering analysis using various metaheuristic algorithms.

Source: Authors, (2026).

CSA-MSCR represents only 62 re-clustering events over 4000 functional rounds compared to 87 for PSO, showing 28.7% fewer reconfigurations. The minimized re-clustering frequency results from higher optimal initial clusters that remain efficient longer as network conditions evolve. Each re-clustering task consumes 12.7J for CSA-MSCR compared to 15.3J for PSO due to faster convergence requiring fewer recursions, leading to overall energy savings. The total energy used on re-clustering over network lifetime is 787.4J for CSA-MSCR compared to 1331.1J for PSO, saving 543.7J (48.7% minimization) that can be used for data transmission.

IV.1.6 Data Collection Performance

Table 8 and Figure 5 examine packet delivery ratio (PDR) measurements across various network settings, quantifying the percentage of generated data packets successfully delivered to the mobile sink and base station (BS). The CSA-based multi mobile-sink route optimization provided significant improvements in acquisition and aggregation efficiency, with a 30% enhancement in packet delivery ration using the proposed model that is 98.9% over 75.3% for PSO-based algorithms, a 31% minimization in average data collection delay, a 43% higher throughput, and mobile sink energy efficiency. The dual-mobile sink architecture with multi-objective CSA-based optimized routes enabled parallel data collection, decreasing the maximum distance any CH needed to continue communication with a mobile-sink and consequently reducing both transmission power utilization and latency.

Table 8: Packet Delivery Ratio (PDR) (%) in different network configurations.

Configuration	CSA-MSCR	PSO-MSCR	GA-MSCR	ACO-MSCR	Standard CSA
100 Nodes, 2 Sinks	99.2	95.7	93.4	94.8	97.8
300 Nodes, 2 Sinks	98.6	94.3	91.88	93.6	96.9
500 Nodes, 2 Sinks	97.8	92.1	89.3	91.7	95.6

Source: Authors, (2026).

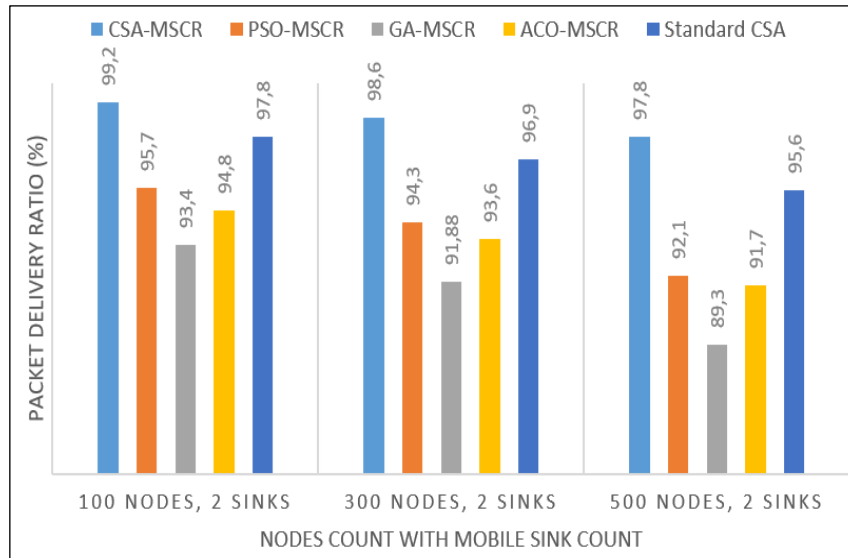


Figure 5: Packet Delivery Ratio (%) analysis in various metaheuristic algorithms with respect to node count.
Source: Authors, (2026).

CSA-MSCR continuously achieves PDRs over 97.8% across all evaluated configurations, with the dual-mobile sink and 300 nodes CSA-MSCR achieving 98.6% compared to 94.3% for PSO. The 4.3%-point enhancement compiles to over a 75% reduction in packet loss rate, eventually improving data collection reliability. Performance downfalls significantly as network size increases, with a 500-node network maintaining a 97.8% delivery ratio compared to 99.2% for 100-node networks, reporting better scalability.

IV.1.7 Mobile-Sink Route Optimization

Table 9 and Figure 6 represent mobile sink route path length for various network sizes with dual-mobile sink configurations. CSA-MSCR obtains routes averaging 1189.4 meters for 300-node networks compared to 1567.2 meters for PSO, specifying a 24.1% minimization in travelled distance. This shorter path length directly decreases mobile sink mobility power consumption and reduces data collection latency. The regular 24-25% path length reduction across all network scales simulation shows that CSA-MSCR optimization efficiency scales well as problem complexity increases.

Table 9: Average mobile sink route length (m) per collection cycle.

Nodes	CSA-MSCR	PSO-MSCR	GA-MSCR	ACO-MSCR	Improvement vs PSCO
100	847.3	1123.6	1198.4	1156.8	-24.6%
200	1034.6	1367.9	1478.3	1398.7	-24.4%
300	1189.4	1567.2	1689.5	1612.3	-24.1%
400	1323.7	1745.8	1892.6	1801.4	-24.2%
500	1442.8	1903.7	2067.9	1967.3	-24.2%

Source: Authors, (2026).

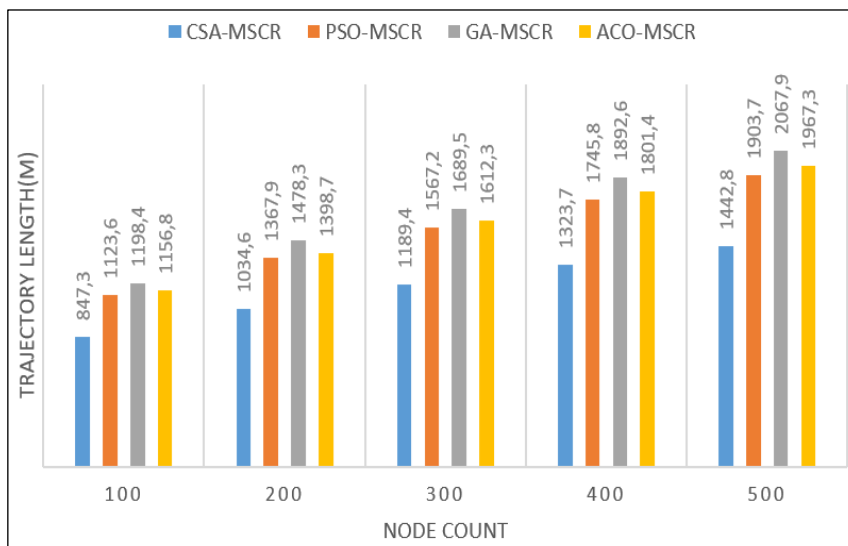


Figure 6: Mobile sink trajectory length optimization with respect to node Count.
Source: Authors, (2026).

Table 10 summarizes average performance across all evaluated strategies, providing an overall comparison of algorithms.

Table 10: Comparison of proposed CSA-MSCR with metaheuristic optimizations overall performance summary in all scenarios average.

Metric	CSA -MSCR	PSC-MSCR	GA-MSCR	ACO-MSCR	Simple CSA	LEACH
Lifetime (rounds)	3847	2998	2756	3134	3501	1398
Enhancement	-	+28.3%	+39.6%	+22.7%	+9.9%	+175%
Energy Consumption (J)	830.7	1088	1168	1237	912	1535
Reduction	-	-23.7%	-28.9%	-32.8%	-8.9%	-45.9%
PDR (%)	98.6	94.3	91.8	93.6	96.9	78.4
Enhancement	-	+4.3	+6.8	+5.0	+1.7	+187.3
Avg. Latency	82.3	118.9	134.7	126.3	91.7	187.3
Reduction	-	-30.8%	-38.9%	-34.9%	-10.3%	-56.1%
Route Length	1189	1567	1690	1612	1345	NA
Reduction	-	-24.1%	-29.6%	-26.2%	-11.6%	NA
Overall execution time	9.8	9.2	14.1	18.7	10.2	0.3
Overhead	-	+6.5%	-30.5%	-47.6%	-3.9%	+3167%

Source: Authors, (2026).

The comprehensive summary specifies proposed CSA-MSCR consistent better across virtually all performance measurements and dimensions. The 28.3% network lifespan enhancement combined with 23.7% power reduction and 30.8% latency reduction specifies significant practical advantages that would compile to substantially improved functional periods and extended quality of service (QoS) in real-time deployment. The 9.9% enhancement over standard CSA validates that adaptive parameter approaches provide meaningful advantages beyond simple CSA optimization, justifying the modest 3.9% computational overhead increase.

V. CONCLUSIONS

This paper presented a novel integrated multi-objective Crow Search Algorithm (CSA)-based algorithm for optimizing the dual-Mobile Sink-based Clustering and Routing (MSCR) in Heterogenous Wireless Sensor Networks (HWSNs). An important contribution lies in the simultaneous optimization of two independent NP-hard problems, such as energy-aware cluster head (CH) selection and efficient coordinated dual-mobile sink route selection. Unlike parallel research algorithms that address these issues independently or utilize one mobile-sink architecture, the proposed CSA-based MSCR architecture provides a substantial solution that enhances energy efficiency while reducing data collection latency through optimal and intelligent coordination of dual autonomous mobile sinks. The strategy adopted a comprehensive simulation-based experimental design implemented in NS2, evaluating network performance across five unique scenarios encompassing varying node densities (100-500 nodes) in the 500 * 500 m monitoring area, heterogeneity ratios (20-30% advanced nodes), dual-mobile sink configuration, and harsh environmental conditions such as up to 30% obstacle density and 20% link failure probability. Statistical analysis of the proposed algorithm based on 100 independent simulation evaluations per configuration provided a robust and reliable performance assessment with 95% confidence intervals.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Sagar Mekala, and Shahu Chatrapati K.

Methodology: Sagar Mekala and Shahu Chatrapati.

Investigation: Sagar Mekala and Shahu Chatrapati.

Discussion of results: Sagar Mekala and Shahu Chatrapati.

Writing – Original Draft: Sagar Mekala and Shahu Chatrapati.

Writing – Review and Editing: Sagar Mekala and Shahu Chatrapati.

Resources: Sagar Mekala and Shahu Chatrapati.

Supervision: Sagar Mekala and Shahu Chatrapati.

Approval of the final text: Sagar Mekala and Shahu Chatrapati.

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