Enhanced Crow Search Algorithm with Cooperative Island Strategy for Energy-Aware Routing in Wireless Sensor Networks

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***Abstract*—Energy efficiency is a fundamental problem experienced by Wireless Sensor Networks (WSNs), as limited battery power affects network lifespan and reliability. This paper develops a novel energy-efficient routing protocol based on an Enhanced Crow Search Algorithm (ECSA) optimization approach to optimize cluster head selection. The proposed ECSA combines a cooperative island model and an adaptive tournament selection procedure to overcome traditional Crow Search Algorithm (CSA) disadvantages caused by low population diversity, a slow convergence rate, and undesirable exploration-exploitation tradeoffs. A multi-objective fitness function is constructed by analyzing residual energy and remaining battery life, distance to the base station, packet delivery rate, throughput, and path loss to achieve overall network design optimality. Sensor nodes are organized optimally to reduce power consumption and prolong the system's lifespan. The experimental results demonstrate that, for a network of 100 nodes, the proposed ECSA-based routing protocol significantly outperforms recent metaheuristic approaches. Specifically, ECSA achieved 22% lower optimization cost than CSA, 28.2% than Black Widow Optimization (BWO), 26.3% than Grey Wolf Optimizer (GWO), and 30% than Whale Optimization Algorithm (WOA). It further attained 4.8–10.8% higher throughput, 24.4–40.3% lower path loss, 4.5–13.7% higher packet delivery ratio, and 40.1–109.1% more alive nodes compared to these benchmarks. These results confirm that ECSA provides superior energy efficiency, reliability, and robustness for large-scale WSN deployments.**

Keywords*—Wireless sensor networks; energy efficiency; cluster head selection; Crow Search; island model; routing; optimization

I. Introduction

Wireless Sensor Networks (WSNs) encompass various applications, including environmental monitoring, smart farming, military surveillance systems, and industrial process automation [1]. WSN consists of geographically dispersed sensor nodes cooperating to sense, process, and transfer data to a Base Station (BS) [2]. Although WSNs offer excellent benefits and are flexible, energy efficiency is a core issue [3]. Sensor nodes are mostly battery-operated and installed unexpectedly; replacing batteries is almost impossible. Consequently, energy conservation becomes crucial to enhancing network lifespan and ensuring system performance consistency [4]. Direct communication between sensor nodes and the BS leads to high power consumption, a reduced coverage area, and unnecessary node draining [5]. Thus, energy-efficient communication protocols are required to optimize resource exploitation, enhance data transferability, and ensure the long-term functionality of WSNs in real environments [6].

Clustering methods have been used extensively in WSNs to address energy constraints [7]. In cluster-based routing, sensor nodes are organized into groups resembling clusters led by a Cluster Head (CH). CHs collect data from member nodes and send it to the BS in compressed form [8]. Hierarchical communication reduces transmission distances between normal nodes and significantly decreases energy consumption across the network [9]. Effective CH optimizes intra-cluster distance, reduces energy usage, and increases network lifetime. Imbalanced CH distribution or overloaded CHs result in network partitioning and low performance [10]. Therefore, intelligent and dynamic CH designation schemes are vital to achieve energy balancing, increase scalability, and maintain fault tolerance in WSN deployments.

Many metaheuristic methods have been proposed to solve CH selection problems, such as Genetic Algorithm (GA) [11, 12], Particle Swarm Optimization (PSO) [13, 14], and Ant Colony Optimization (ACO) [15]. These methods yield better results than conventional static methods. Nonetheless, they suffer from several shortcomings. One of the main challenges is premature convergence, when the algorithm converges to a local optimum and fails to capture the global optimum space correctly. Some approaches lack a proper exploration-exploitation balance and yield efficient searches and unstable solutions under dynamic conditions [16]. Some methods depend on initialization parameters and perform differently across network topologies and node densities. Hence, it is desirable to have a more robust optimization methodology that sustains diversity, prevents stagnation, and provides consistent CH selection in WSN scenarios.

The Crow Search Algorithm (CSA) is a metaheuristic algorithm inspired by crows' intelligent behavior in hiding and retrieving food. It has simplicity and robust exploration ability but is restricted by low search precision and early convergence. To resolve these drawbacks, the Enhanced Crow Search Algorithm (ECSA) combines a cooperative island model, adaptive tournament selection, and a transformed movement operator. These features maintain population diversity, increase the convergence rate, and achieve a better exploration-exploitation tradeoff.

The cooperative island model allows parallel subpopulations to develop autonomously by preventing them from being

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influenced by local optima. The adaptive tournament selection facilitates controlled convergence towards optimal solutions. Using ECSA for CH selection, the protocol provided substantially improved energy efficiency, improved network lifetime, and guaranteed data delivery reliability for WSNs. The proposed research contributes to:

- We present the first ECSA-based cooperative model of islands with an adaptive tournament selection for the election of CHs of WSNs that address issues of premature convergence and limited population diversity of metaheuristic-based routing.
- We advance the literature by offering a generalizable framework that integrates hierarchical clustering protocols with swarm intelligence that may be used with other optimization-based network designs.
- We present an end-to-end multi-metric analysis (optimization cost, throughput, path loss, packet delivery ratio, and node survival) across varying network densities while emphasizing the strength and scalability of ECSA over other algorithms.
- Since we provide practical deployment considerations of sustaining network lifetime and reliability at large scales, we bridge the gap between algorithm construction and realistic WSN limitations.

The rest of the paper is structured as follows: Section II presents a review of related work; Section III formulates the problem; Section IV presents the proposed ECSA-based protocol; Section V details the experimental setup and discusses the obtained results; Section VI provides a detailed discussion of the findings and Section VII concludes the paper and outlines directions for future work.

II. Related Work

Nabavi, et al. [17] suggested a combined clustering and routing protocol in WSN using GA and Gravitational Search Algorithm (GSA). The genetic algorithm optimizes intra-cluster distance and energy consumption in selecting CHs, and the gravitational search algorithm supports efficient routing from CH to the sink. The method reduces average energy consumption and enhances delivery rate and transmission efficiency, substantially improving network longevity.

Kathiroli and Selvadurai [18] suggested a hybrid Sparrow Search Algorithm and Differential Evolution (SSA-DE) model for CH selection. SSA provides high exploration efficiency, while DE improves convergence. Using an intelligent energy distribution mechanism to prolong network operation and ensure balanced energy usage among sensor nodes, the hybrid approach enhances node lifetime, residual energy, and throughput.

Janakiraman [19] proposed the IBEABCCR scheme, integrating Improved Bat Optimization (IBOA) and Enhanced Artificial Bee Colony (EABC) algorithms. IBOA conducts CH selection with balanced exploration and exploitation, and EABC facilitates dynamic sink mobility. Their combined strategy, implemented in MATLAB, considerably increases packet delivery, network life, and node survival with more than 25% improvements on several parameters concerning baseline protocols.

The LCPSO-CRP protocol was proposed by Luo, et al. [20] employing chaotic Levy-based Particle Swarm Optimization. The proposed method enhances the convergence speed and the search space exploration to include industrial WSNs. The technique considers CH energy consumption, BS distance, and intra-cluster proximity. It reduces energy consumption by 22.91% and increases the network lifetime by 13.93% compared to traditional schemes such as LEACH and DEEC.

Srivastava and Mishra [21] presented an Innovative Dragonfly Algorithm (IDA) with multi-attribute decision-making for CH selection. The algorithm ranks the nodes based on energy and other parameters to select optimal CHs. Compared to NBA, FLPSOC, and ESO-LEACH, IDA demonstrates better throughput, less energy consumption, and better node life, verifying its efficacy in energy-aware clustering.

Alsuwat and Alsuwat [22] proposed IQ-ABC as an optimized Artificial Bee Colony algorithm integrated with Q-learning to select adaptive CH in WSNs. The technique adopts a fuzzy-weighted multi-objective fitness function accounting for energy consumption, latency, and trust. Simulations indicate that IQ-ABC consumes much less energy than LEACH, HEED, and ACO in high-density or centralized node deployments.

Poonguzhali, et al. [23] proposed a metaheuristic and deep learning-based technique called THDCNN-HCWA, combining the multi-objective CH selection using the Tree Hierarchical Deep CNN and a Hybrid Capuchin-Woodpecker mating algorithm to route data. The method improves alive nodes and detection rates by optimally improving energy, delay, cluster density, and traffic flow under NS2 models.

While prior literature has proposed novel hybrid algorithms to solve CH selection and energy-aware routing problems, certain drawbacks still exist. As summarized in Table I, most methods cannot achieve an appropriate tradeoff between exploration and exploitation, converge prematurely, or perform inefficient searches in sophisticated environments. Furthermore, Q-learning and CNN-based routing yield better decisions but involve high computation overheads.

Most algorithms rely on static scenarios or a single set of parameters, ignoring scalability, convergence rate, diversity, or robustness to changes in network densities. The current research addresses these shortcomings by suggesting a new protocol employing ECSA with cooperative island modeling and adaptive tournament selection to diversify the population, increase the convergence rate, and holistically optimize multi-objective energy parameters.

TABLE I. COMPARATIVE SUMMARY OF RELATED WORKS

Study	Contribution	Improvements	Shortcomings
[17]	Introduced multi-objective clustering and routing using GA for CH selection and GSA for routing	Energy efficiency, delivery rate, and transmission rate	Lacks adaptive mechanisms for dynamic topologies; may suffer from convergence delays
[18]	Proposed a hybrid SSA-DE approach for energy-efficient CH selection	Residual energy, throughput, and node lifetime	Limited diversity preservation; sensitive to parameter tuning
[19]	Developed a dual optimization approach for CH selection and sink mobility	Network lifetime, packet delivery, and alive nodes	High computational complexity; assumes static sink mobility pattern
[20]	Designed a chaotic Levy-enhanced PSO protocol	Energy consumption and network Lifetime	Tailored to industrial settings; less effective in generic WSN deployments
[21]	Used multi-attribute decision-making with dragonfly algorithm for optimal CH selection	Energy consumption, throughput, and node survival	Limited scalability analysis; lacks routing optimization component
[22]	Applied Q-learning to ABC for intelligent CH selection with fuzzy-weighted fitness	Energy usage, network lifetime, and trust-based routing	Increased complexity; performance sensitive to fuzzy rule definition
[23]	Integrated deep learning with hybrid metaheuristics for CH selection and routing	Node survival and detection rate	High computational overhead; less suitable for resource-constrained WSNs

III. PROBLEM FORMULATION

A. Network Architecture

From an Internet of Things (IoT) perspective, WSNs are self-organizing multi-hop networks with spatially dispersed sensor nodes. Sensor nodes independently track environmental parameters and cooperatively transfer collected data to the BS. WSNs integrate embedded computing, distributed information processing, and wireless communication paradigms to support various applications like environmental monitoring, industrial automation, healthcare, and military surveillance.

Every node in the network serves two functions: sensing the environment and forwarding data to other nodes. Each node is typically driven by non-rechargeable batteries and deployed in remote or inaccessible locations; this makes energy efficiency crucial. Low communication overhead is essential since data transmission is much more energy-consuming than sensing and data reception. A common technique is clustering, during which sensor nodes are grouped, and a CH is chosen to collect and transfer data to minimize redundant communication and extend network life.

Let the number of sensor nodes in the network be denoted as N, randomly and uniformly distributed within a field of size $L \times L$. The BS is assumed to be placed at a fixed location, often at the center or outside the sensing field. Nodes can communicate via single-hop or multi-hop links, depending on their distance from the CH or BS.

All nodes are homogeneous hardware-wise, with the same storage, computation power, and initial energy. Every node is assigned a distinct identifier and calculates its local location using localization methods. Nodes are also classified as CHs or regular sensor nodes, with CHs handling inter-cluster communication and data transfer to the BS. Sensor nodes know their intrinsic residual energy and compute the distance between neighboring devices. Nodes can dynamically modify transmission power using available information to save energy. The BS has superior computing power and is the ultimate data sink.

The network data traffic is generally partitioned into three layers: intra-cluster data communication, inter-cluster data communication, and BS communication. Sensor nodes send data to the corresponding CHs. CHs pass data directly to other CHs or the BS if it is in the range. Aggregated data is sent to the BS by CHs via optimized energy-efficient paths.

Communication channels are bidirectional, and nodes can adapt their transmission power depending on the distance to the recipient. Each CH periodically aggregates data from its member nodes and sends it to the BS. The communication model further assumes that all the nodes encounter bursts of data transmission intermittently, as per the sensing rate and events happening in the surrounding area.

Fig. 1 shows the overall topology of a clustered WSN. Sensor nodes are divided into groups (clusters), each with a single CH. All local (intra-cluster) and long-distance (inter-cluster or BS) communication is done by the CHs. The BS is a central communication center receiving data from several CHs.

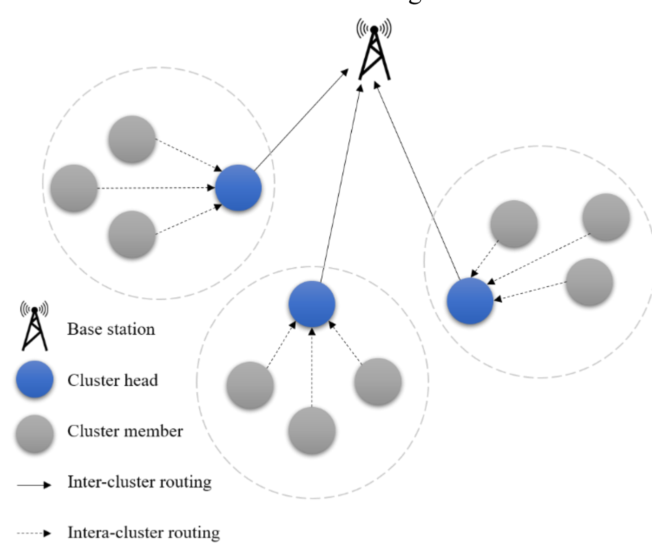

Fig. 1. Network topology of a clustered WSN.

B. Energy Consumption Model

Efficient energy utilization is critical in WSNs, where sensor nodes (motes) are constrained by limited, often non-rechargeable, energy sources. The energy model aims to characterize energy drainage during sensing, data processing, forwarding, and communication tasks. Transmission consumes the most energy compared to sensing or reception, making routing strategies central to prolonging network lifetime. To model energy usage, we consider the energy required to transmit

b bits of data over a distance d using a hybrid transmission model, denoted by Eq. (1).

Efficient energy use is crucial in WSNs, where sensor nodes (motes) are constrained by small, non-rechargeable energy sources. The energy model attempts to model energy drain from sensing, data processing at sensor nodes, data forwarding, and communications. Transmission consumes the most energy compared to sensing or reception, making routing strategies the foremost way to prolong the network lifetime. In modeling energy use, we focus on the energy expended by transmitting b bits of data over a distance d, using a hybrid transmission model represented by Eq. (1).

$$E_{TX}(b,d) = \begin{cases} b.E_{elec} + b.\epsilon_{fs}.d^2, & if\ d \le d_0 \\ b.E_{elec} + b.\epsilon_{mp}.d^4, & if\ d > d_0 \end{cases} \quad (1)$$

The threshold distance d_0 used to switch between free-space and multi-path fading models is calculated using Eq. (2).

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \quad (2)$$

where, E_{elec} stands for energy consumed per bit for processing, ϵ_{fs} denotes amplification energy for the free-space model, and ϵ_{mp} refers to amplification energy for the multi-path model.

The energy required for receiving b bits of data is computed according to Eq. (3).

$$E_{RX}(b) = b.E_{elec} \quad (3)$$

In cluster-based networks, CHs further aggregate the received data. The energy consumed during aggregation is calculated as shown in Eq. (4).

$$E_{AGG}(b) = (E_{elec} + E_{DA}).b \quad (4)$$

where, E_{DA} is the energy cost for data aggregation per bit.

WSN operations are executed in discrete rounds. The remaining energy of a sensor node s in round r is calculated according to Eq. (5).

$$RE_s(r) = RE_s(r-1) - \left(E_{TX}^s(r) + E_{RX}^s(r)\right) \quad (5)$$

The energy for transmission and reception per round is determined by Eq. (6) and Eq. (7), respectively.

$$E_{TX}^s(r) = T_s(r).\left[E_{elec} + \epsilon_{fs}.d^2\right] \quad (6)$$

$$E_{RX}^s(r) = R_s(r).E_{elec} \quad (7)$$

where, $T_s(r)$ and $R_s(r)$ denote the number of bits transmitted and received by node s in round r.

The overall data traffic load for a sensor node is composed of two components: $T_{relay}^s(r)$, representing relayed data, and $T_{local}^s(r)$, representing locally generated data. The total number of bits transmitted by node s in round r is given by Eq. (8).

$$T_s(r) = T_{relay}^s(r) + T_{local}^s(r) \quad (8)$$

This total is used in Eq. (6) to evaluate transmission energy consumption.

For CHs, an additional energy term is incurred due to data fusion before transmission. The energy for fusing b bits of data is calculated using Eq. (9).

$$E_{CH}(b) = E_{FD}.b \quad (9)$$

where, E_{FD} is the data fusion energy per bit.

IV. Proposed Methodology

The design of efficient routing protocols in WSNs is a challenging problem due to network operation requirements. These constraints are low computing power, low energy budgets, dynamic topology, node failure susceptibility, and exposure to harsh or unreliable environments. Consequently, conventional routing methods, like short path routing, are hardly sufficient for energy-restricted WSNs.

Reliability and energy-aware data transfer between the BS and sensor nodes are among the most critical goals of WSN routing. As energy consumption is the main WSN operation bottleneck, it is imperative to minimize overhead transmissions, even at the expense of traditional cost-based routes. Excessive neighbor communication, common to most routing schemes, increases energy consumption and adds complexity to neighborhood discovery.

In addition, node failures, commonly due to energy depletion, result in topology instability, broken networks, and high fault rates. Non-deterministic route paths, changing link availability, and dynamic participation of nodes complicate network performance management. These dynamics necessitate routes with adaptive capabilities to respond to environmental uncertainties and maintain low energy consumption and high resilience.

WSN routing protocols are traditionally classified by network structure (flat, hierarchical, location-based), but whatever their structure, the protocols have to deal with fundamental issues like Quality of Service (QoS), scalability, delay, power efficiency, connectivity, and fault tolerance. Network topology inconsistency caused by the addition or removal of motes or transient link failures makes path selection even more difficult. Thus, the routing technique has to account for a broad range of parameters like power management, MAC protocols, traffic load, and channel allocation to develop implementable solutions.

With these theoretical and interdependent variables in mind, heuristic and metaheuristic algorithms have been explored as potential methods for designing a WSN routing protocol. This study introduces an energy-efficient framework developed on a multi-objective problem optimized by the ECSA. The framework is focused on optimal CH selection and energy-efficient data routing to achieve maximum network lifespan while fulfilling performance requirements.

Our proposed scheme uses a layered clustering paradigm. CHs collect intra-cluster data and transfer it to the BS by energy-efficient multi-hop routes. Our ECSA dynamically selects CHs using residual energy, node centrality, and communication distance parameters. The approach optimizes competing objectives like energy consumption and throughput maximization, thus constructing a resilient and dynamic routing protocol designed to work in WSN scenarios.

A. Basic Crow Search Algorithm

CSA, proposed by Askarzadeh [24], is a population-based metaheuristic inspired by the natural foraging and memory behavior of crows. These intelligent birds can follow others to steal hidden food while relocating their food caches if they sense being watched. This dual behavior of tracking and evasion is simulated within CSA to navigate the search space intelligently.

In CSA, each solution is represented as a virtual crow, and a population of N such crows explores the search space. Each crow i is characterized by a position vector in a D-dimensional space, denoted by Eq. (10).

$$x_i^t = \left[x_{i,1}^t, x_{i,2}^t, \dots, x_{i,D}^t\right] \tag{10}$$

Each crow's initial position also serves as its memory since it has no experience. The memory vector of crow i at iteration t is expressed as shown in Eq. (11).

$$m_i^t = \left[m_{i,1}^t, m_{i,2}^t, \dots, m_{i,D}^t\right] \tag{11}$$

The crows update their positions by attempting to follow a randomly selected peer. If the selected crow is unaware of being followed, the follower moves toward the peer's memory. Otherwise, it jumps to a random position. This movement rule is calculated according to Eq. (12).

$$x_i^{t+1} = \begin{cases} x_i^t + r_1 . FL . \left(m_j^t - x_i^t\right), & if\ r_2 \geq AP \\ random\ position\ , & otherwise \end{cases} \tag{12}$$

where, r_1 and r_2 are random values uniformly distributed in [0, 1], FL is the flight length, m_j^t is the memory of randomly selected crow j, and AP is the awareness probability governing evasive behavior. The schematic of this condition and the impact of flight length on searchability are shown in Fig. 2.

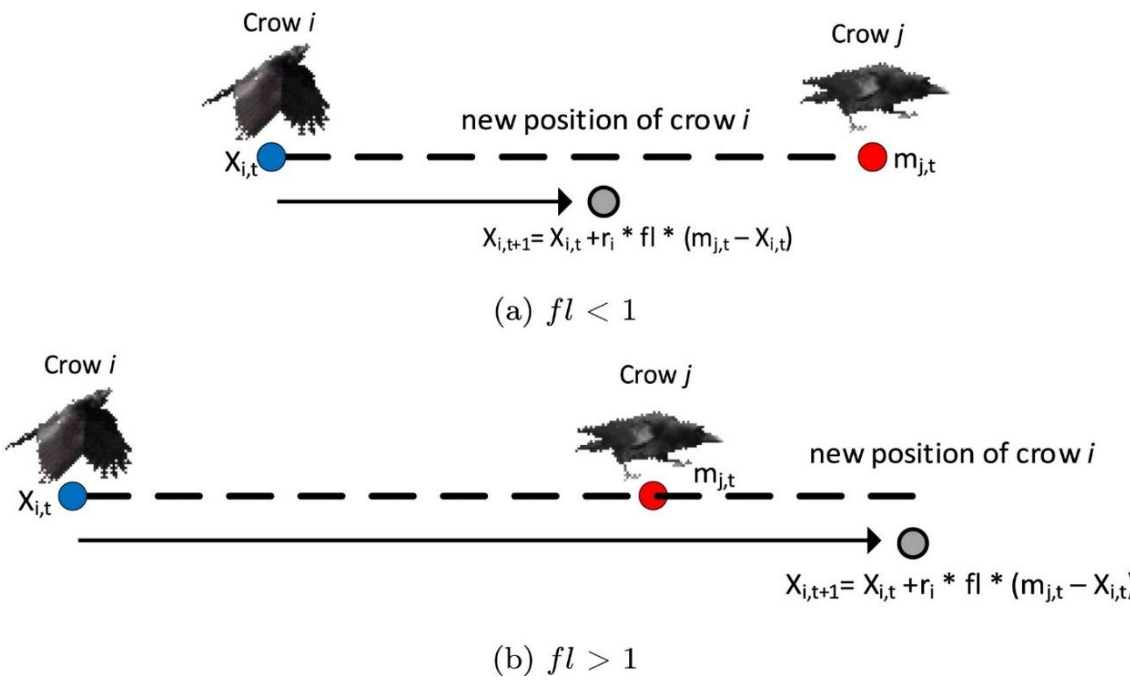

Fig. 2. Illustration of the pursuit mechanism in CSA.

After arriving at new positions, the memory of each crow is updated based on the quality of the new solution. If the new position offers better fitness than the previous memory, it replaces the old one. This memory update mechanism is governed by Eq. (13).

$$m_i^{t+1} = \begin{cases} x_i^{t+1}, & if\ f\left(x_i^{t+1}\right) < f\left(m_i^t\right) \\ m_i^t, & otherwise \end{cases} \tag{13}$$

where, $f(.)$ indicates the objective (fitness) function.

B. Enhanced Crow Search Algorithm

While the original CSA has high exploration capabilities, it has drawbacks like local optima stagnation, lack of diversity, and early-stage convergence. These problems are caused primarily by fixed parameters like Awareness Probability (AP) and Flight Length (FL), using random guidance, and not prioritizing the optimal use of population memory. To overcome all these drawbacks, ECSA incorporates a range of strategies, such as adaptive selection through a tournament and a modified evasion scheme using a random component.

In the basic CSA, each crow i selects another crow j at random to follow toward its memorized position, which could lead to following poorly performing solutions. To improve this, the ECSA framework replaces random selection with a fitness-guided adaptive tournament mechanism. At each iteration t, a crow selects the best guide from a randomly chosen subset of K crows.

To ensure a balanced tradeoff between exploration and exploitation, the value of K is varied linearly throughout the optimization process. It is computed using a self-adaptive formula denoted by Eq. (14).

$$K = round\left(K_{min} + t.\left(\frac{K_{max} - K_{min}}{t_{max}}\right)\right) \tag{14}$$

Where K_{min} and K_{max} are the minimum and maximum tournament sizes, t is the current iteration, and t_{max} is the total number of iterations. This allows the algorithm to perform more exploratory behavior in the early stages (small K) and intensify the search later (large K).

To further combat stagnation, ECSA introduces an evasion operator derived from the Harris Hawks Optimization (HHO) method, which improves population diversity when the awareness probability condition is triggered. The new position of crow i in this phase is calculated according to Eq. (15).

$$X_{i,t+1} = \left(X_{best,t} - X_{avg,t}\right) - r_1 \cdot \left(LB + r_2 \cdot (UB - LB)\right) \tag{15}$$

where, $X_{best,t}$ is the best-known solution at iteration t, $X_{avg,t}$ is the mean position of all individuals in the current generation, LB and UB are the lower and upper bounds of the search space, and $r_1, r_2 \in [0,1]$ are uniformly distributed random numbers. The mean position is calculated as shown in Eq. (16).

$$X_{avg,t} = \frac{1}{N}\sum_{i=1}^{N} X_{i,t} \tag{16}$$

This strategy ensures that evasion is not purely random but guided by the global and average population dynamics.

ECSA begins by initializing N crows in a D-dimensional search space. Each crow's initial position is generated using a uniformly distributed random vector within bounds $\overrightarrow{X_L}$ and $\overrightarrow{X_U}$, as denoted by Eq. (17).

$$\overrightarrow{X_J} = \overrightarrow{X_L} + r \cdot \left(\overrightarrow{X_U} - \overrightarrow{X_L}\right) \tag{17}$$

To further enhance search efficiency and diversity preservation, ECSA incorporates an island model. The population is partitioned into s subgroups (islands), each running its local version of the ECSA. These islands evolve independently but periodically share information through a migration process governed by migration frequency M_f, migration rate M_r, topology (e.g. random ring), and policy (e.g. best–worst exchange) parameters. Each migration phase is triggered every M_f iterations, allowing selected individuals from one island to be exchanged with neighboring islands to prevent premature convergence. The pseudocode and flowchart of the proposed ECSA are presented in Algorithm 1 and Fig. 3, respectively.

Algorithm 1 Pseudocode of ECSA

Inputs:

Problem-specific settings: number of agents N, dimensionality d, upper bound t_{max}

Adaptive parameters: minimum and maximum tournament size (K_{min}, K_{max}), flight length FL, and awareness probability AP

Outputs:

Best solution vector X_{best} and its corresponding fitness score

Initialize all crows' positions X_i randomly across the solution space, for $i = 1 \; to \; N$

Assign each crow's initial memory $M_i = X_i$

Evaluate the fitness value of each crow using the objective function $f(\cdot)$

Determine the initial global best solution X_{best}

Repeat for iteration $t = 1 \; to \; t_{max}$:

  Adjust tournament size K dynamically based on Eq. 14

  Compute the population's average position using Eq. 16

For each crow $i \in \{1, \dots, N\}$:

  Select a candidate crow j to follow via tournament selection

  Generate a random number $r_j \in [0,1]$

  If $r_j \geq AP$:

    Update crow i's position using the pursuit rule (Eq. 12)

  Else:

    Update crow i's position using guided evasion (Eq. 15)

  Check feasibility of the new position

Evaluate the updated positions X_i^{t+1} and compute their fitness

If $f\left(X_i^{t+1}\right) < f(M_i)$, then update the memory $M_i = X_i^{t+1}$

Update X_{best} if any crow achieves a superior fitness

Until stopping criteria ($t = t_{max}$) is met

Return the best-obtained solution X_{best}

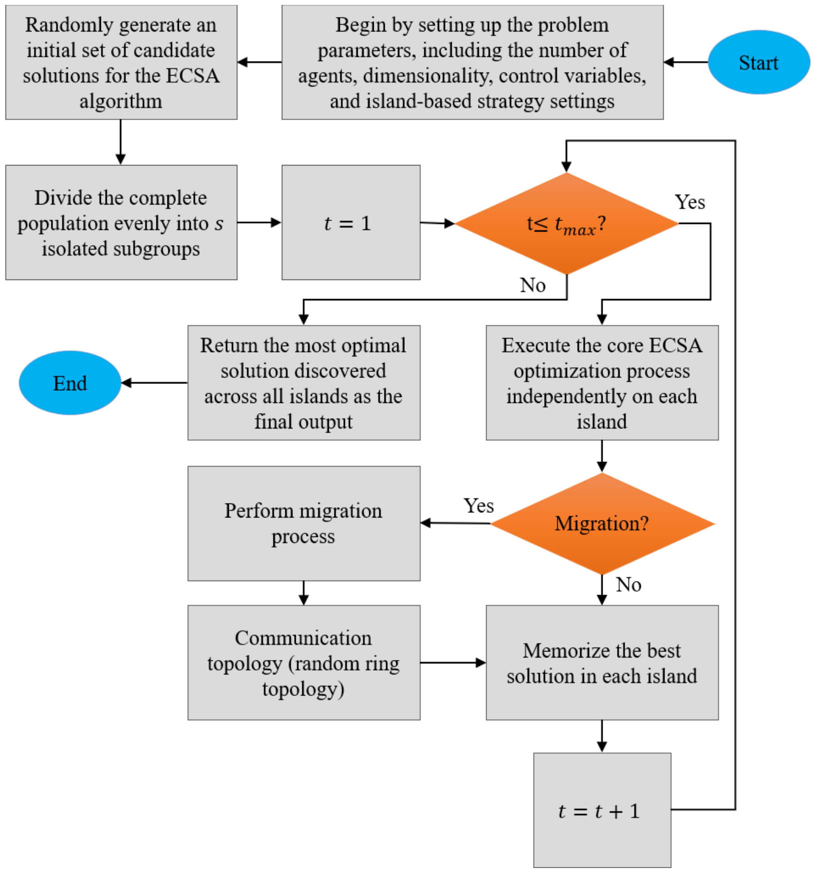

Fig. 3. Flowchart of CSA.

V. Results

A comprehensive simulation in MATLAB 2020a was performed to assess the effectiveness of the proposed ECSA for energy-saving routing within WSNs. Performance was measured using a range of vital metrics, including convergence behavior, path loss, PDR, throughput, and energy usage. For extensive investigation, ECSA was compared with four metaheuristic algorithms: CSA, Grey Wolf Optimizer (GWO) [25], Black Widow Optimization (BWO) [26], and Whale Optimization Algorithm (WOA) [27]. These algorithms were chosen because of their suitability for WSN routing and clustering purposes. Simulations were performed on three distinct network configurations with varying sensor nodes deployed: Experiment 1 with 50 nodes, Experiment 2 with 100 nodes, and Experiment 3 with 150 nodes. Table II lists simulation parameters.

As illustrated in Fig. 4, ECSA consistently achieves a high convergence score across all node arrangement scenarios. In particular, in Scenario 1, ECSA surpasses the comparative methods by 55.2%, 51.4%, 48.4%, and 41.3%. This indicates the algorithm's stability in reaching optimal or near-optimal solutions rapidly. The increased convergence comes from ECSA's adaptive exploration-exploitation tradeoff to avoid premature convergence inherent in conventional methods.

TABLE II. Simulation Setup Parameters Applied in Evaluating the Proposed Routing Framework for WSN

Parameter	Configured value
Maximum simulation rounds	2000
Initial node energy	0.3 J
Energy dissipation for signal transmission	$50 \times 10^{-9} J$
Energy dissipation for signal reception	$50 \times 10^{-9} J$
Power amplifier (free-space model)	$10 \times 10^{-12} J$
Power amplifier (multi-path model)	$0.0013 \times 10^{-12} J$
Energy cost for data aggregation	$5 \times 10^{-9} J$
Energy consumption in idle state	0.05 W
Node displacement rate	0.05 meters/min
Channel model	Physical/wireless physical
Communication radius	40 meters
Underlying routing baseline	LEACH protocol
Simulation area size	$100\ m \times 100\ m$
Sensor node counts across scenarios	50, 100, 150
Control message size	80 bits
Data packet size	512 bytes
Cluster head election likelihood	0.1%
Optimization iterations per run	10
Sub-populations for the metaheuristic algorithm	10

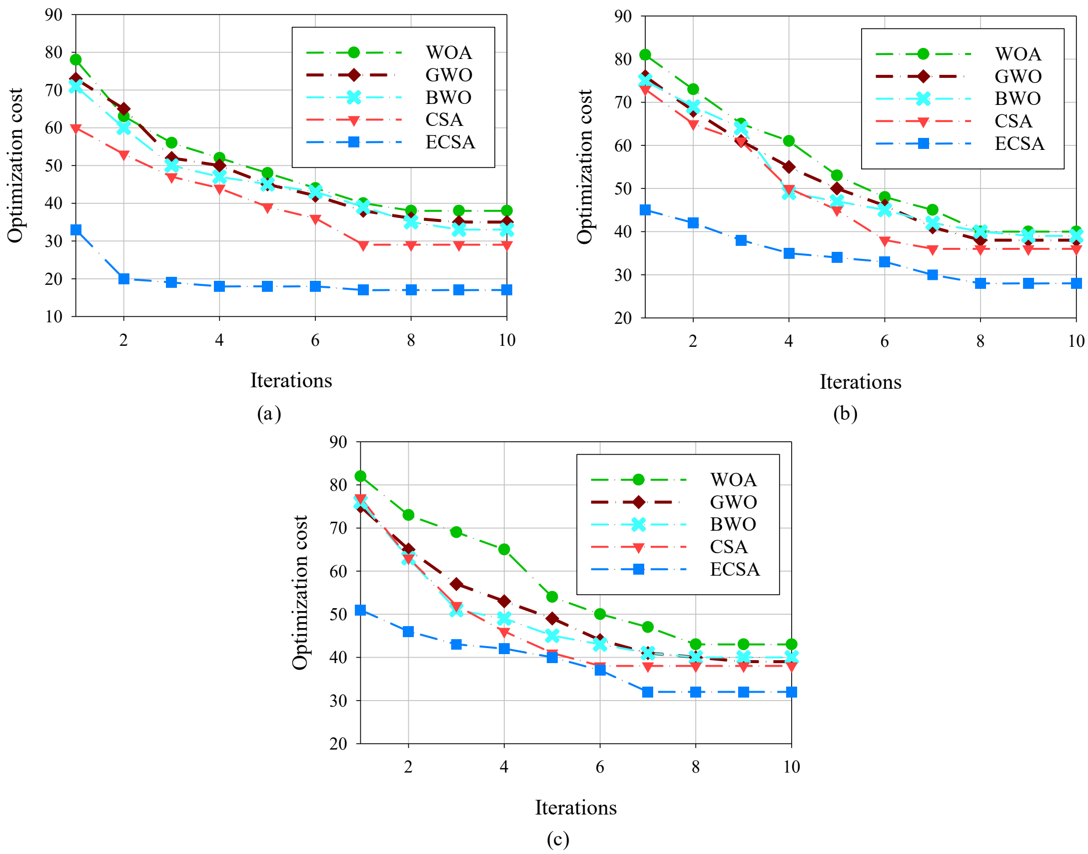

Fig. 4. Cost function convergence of algorithms across three WSN scenarios: (a) 50 sensor nodes, (b) 100 sensor nodes, (c) 150 sensor nodes.

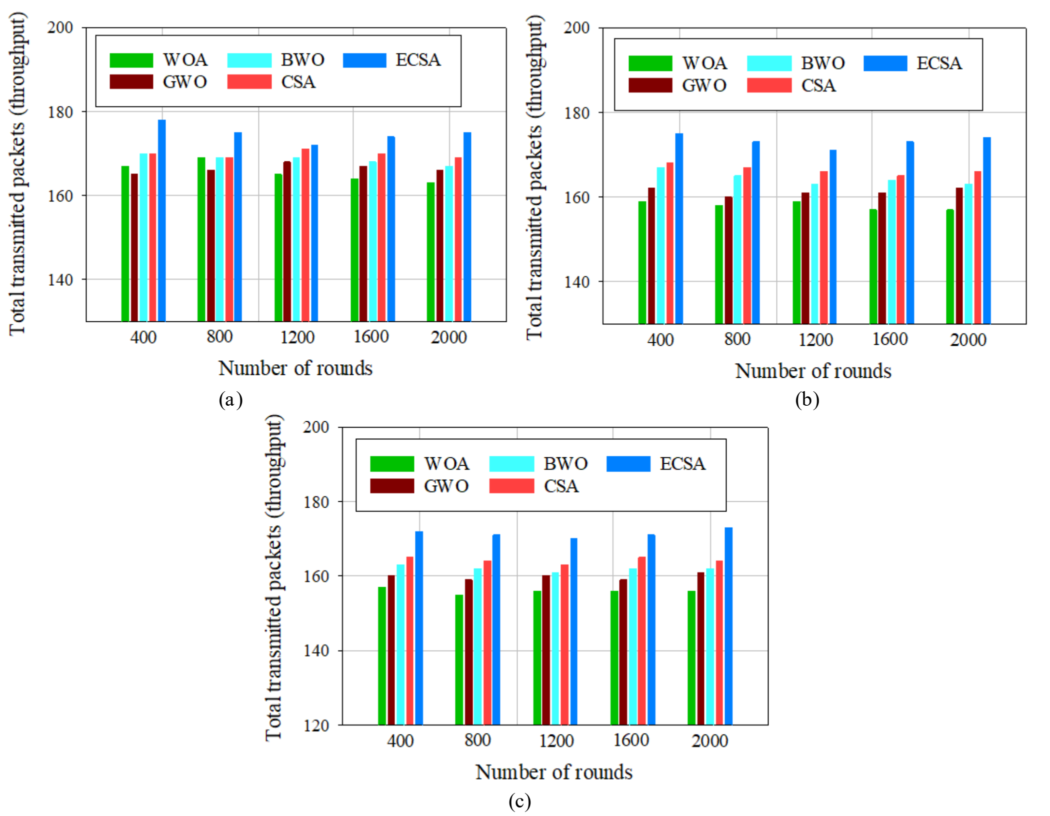

Fig. 5. Throughput performance of algorithms across different rounds for (a) 50 nodes, (b) 100 nodes, and (c) 150 nodes.

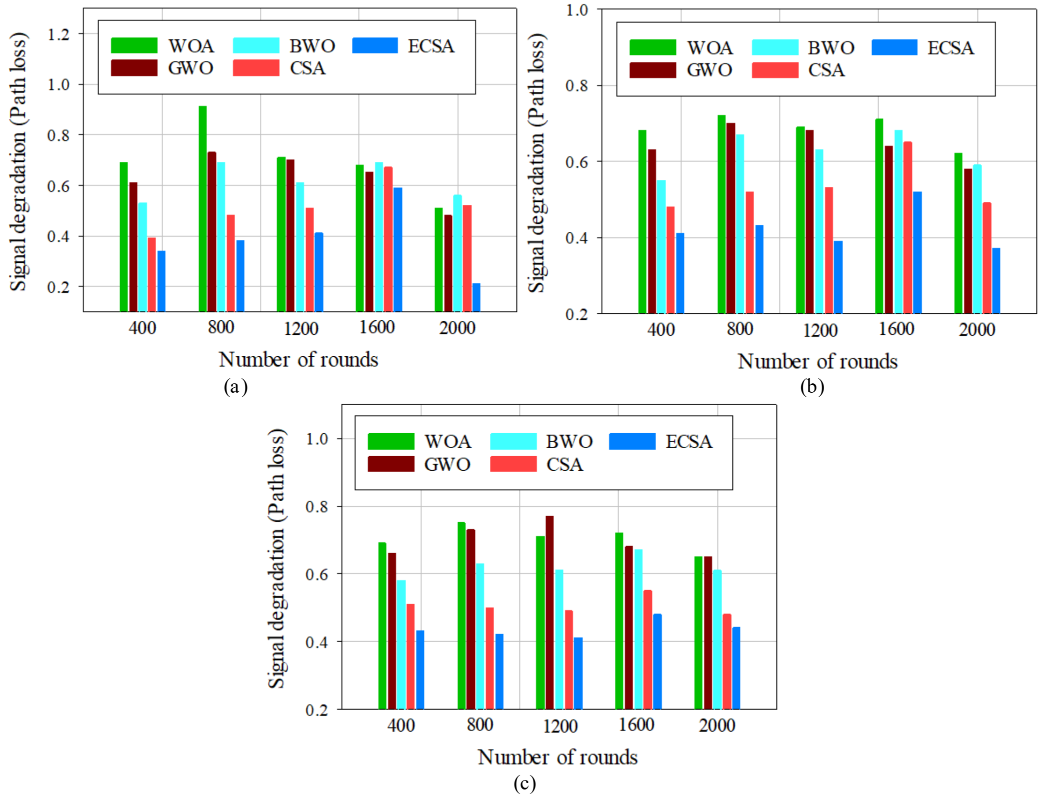

Fig. 6. Path loss performance of algorithms across different rounds for (a) 50 nodes, (b) 100 nodes, and (c) 150 nodes.

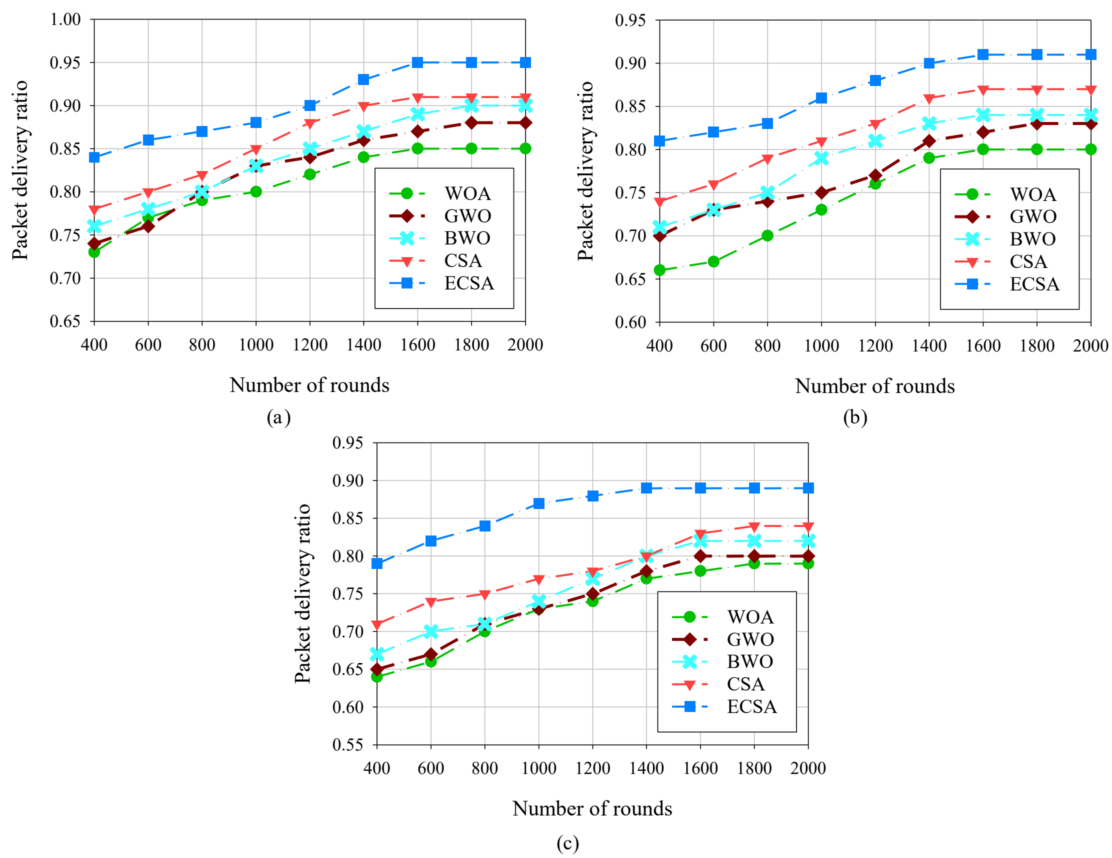

Fig. 7. Packet delivery ratio performance of algorithms across different rounds for (a) 50 nodes, (b) 100 nodes, and (c) 150 nodes.

The performance of ECSA in improving network throughput was confirmed by evaluating the volume of data delivered successfully against time. Fig. 5 shows that ECSA outpaces heuristic algorithms consistently by achieving superior throughput in all cases. Better throughput is the direct consequence of smart CH election, less path loss, and energy-aware transmission scheduling. This proves ECSA's ability to sustain data-intensive WSN applications with improved transmission efficiency.

The path loss was compared under three node-density configurations as a representative factor of signal quality and energy consumption. As shown in Fig. 6, ECSA outperforms in reducing path loss until the 2000th round. Furthermore, in the first and second scenarios, the path loss is temporarily higher than in CSA at the advanced stages, and it might indicate a necessity to refine it for longer-duration deployments in the future. The ECSA shows fewer path loss values and validates the proposed routing model's credibility and robustness.

The data delivery reliability of the protocol was checked using PDR, which is presented in Fig. 7. ECSA has a consistently low rate of losing PDR compared to other routing protocols in all scenarios. The reduced rate of losing PDR results from the algorithm's stability and efficient selection of the CH, reducing the rate of dropping and discarding packets in communication. Therefore, ECSA provides superior delivery reliability in critical WSN applications.

The protocol's sustainability was analyzed by measuring the active node count per simulation round. As indicated by Fig. 8, ECSA retained a significantly higher number of alive nodes across the three cases than baseline strategies. In scenario 2, ECSA offers superior node survival across transmission rounds. This demonstrates its energy-conservation properties and suggests fewer nodes reach their energy boundaries earlier. Superior node survivability confirms the efficiency of ECSA in balancing energy load distributions when choosing CHs.

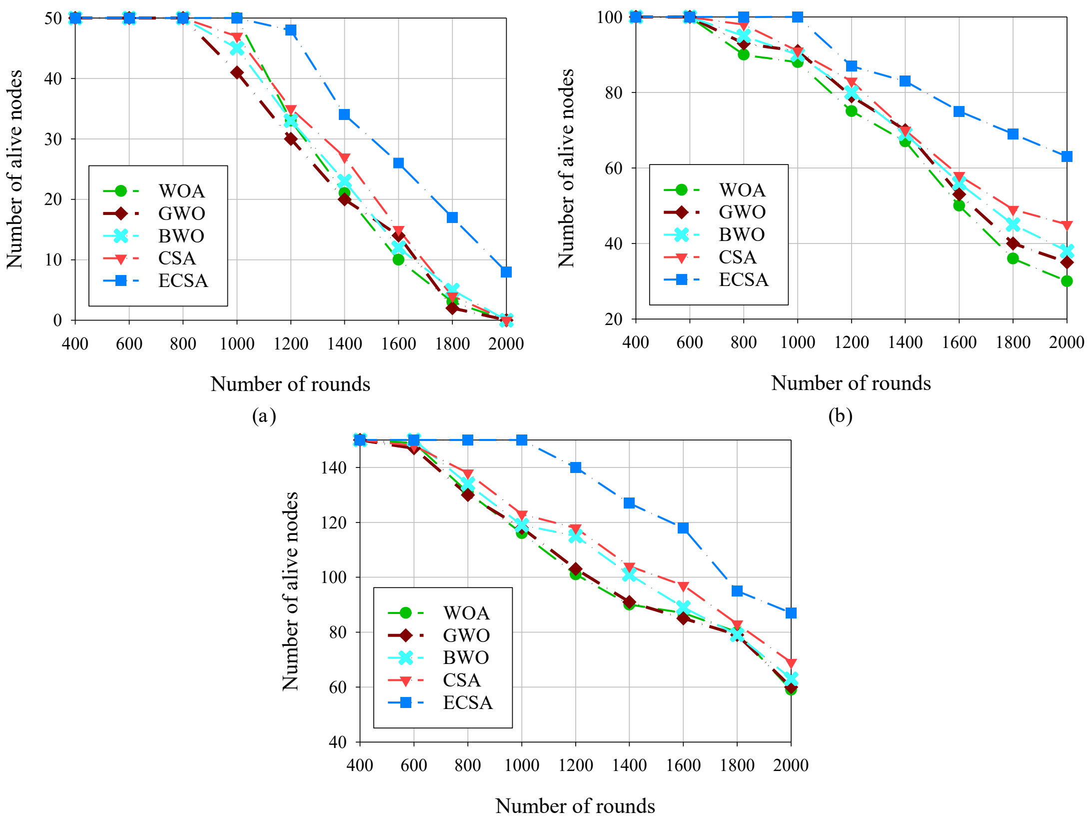

Fig. 8. Number of alive nodes of algorithms across different rounds for (a) 50 nodes, (b) 100 nodes, and (c) 150 nodes.

VI. Discussion

The superior simulation results of ECSA on all evaluation parameters can directly be attributed to intrinsic advancements in CSA. One key aspect involves adding an adaptive tournament selection policy to facilitate selection for updated positions. Compared to the initial CSA, in which randomly selected peers guide crows, ECSA allows crows to be guided to the fittest peers from a dynamically sized pool of candidates. Indeed, as demonstrated in the convergence results, the technique resulted in quicker convergence and more robust solution quality, particularly when network densities are high. Moreover, the linear increase in the tournament size per iteration permitted the algorithm to expand its search at the beginning and intensify exploitation towards the latter phase, which lent it to minimal energy consumption and maximum node survival in all test cases.

In addition, the advanced evasion process utilized by ECSA contributed significantly to optimizing route performance. In contrast to the standard CSA that triggers random relocation on evasion, ECSA incorporates a focused evasion process by using global best and average location information for the population. This ensures informed and active exploratory behavior even when AP is high. Consequently, ECSA resulted in lower path loss and higher PDR, particularly at high node density and extended round simulation. Improved throughput performance further confirms that the advancements in pursuit (guide selection) and evasion (movement policy) acted synergistically to produce superior route decisions, energy balancing, and overall robust protocol performance in WSN scenarios.

Though the proposed ECSA-based routing protocol provides superior energy efficiency and robustness over existing methods, the study has some drawbacks. First, it was conducted within simulated networks with pre-assumed network models that do not capture fundamental WSN dynamics. Furthermore, although the cooperative island model provides superior population diversity, computational complexity increases with the size of the network, such that large-scale networks may lack scalability in very dense sensor environments. Finally, security-related issues, such as resistance to malicious nodes, have not been specifically addressed. These drawbacks present potential areas for future work, such as hardware-based verification, optimization for scalability, and the addition of security-aware mechanisms.

VII. Conclusion

The paper introduced ECSA for energy-efficient routing in WSNs by hybridizing a cooperating island model with adaptive tournament selection. From a theoretical standpoint, the paper first applied a structured population model in CSA for CH selection to address two essential problems: premature convergence and limited population diversity. Apart from WSNs, the model provides a generic framework for integrating swarm intelligence strategies with hierarchical clustering mechanisms. An experimental study on networks containing 100 nodes confirmed that ECSA outperformed CSA, BWO, GWO, and WOA. In detail, ECSA achieved 22–30% lower optimization cost, 4.8–10.8% higher throughput, 24.4–40.3% lower path loss, 4.5–13.7% higher PDR, and 40.1–109.1% more alive nodes. These results confirm the robustness, scalability, and energy-saving capabilities of the approach if applied at a large scale in WSN.

In addition, the study also has its limitations. The analysis was conducted in a simulated environment without external dynamics, such as hardware variation, environmental interference, or malicious nodes. Furthermore, the cooperative island model entails additional computational overhead that may hinder scalability in ultra-dense networks. The future study will therefore focus on 1) protocol verification over hardware testbeds, 2) lowering computational complexity for optimization of scalability, as well as 3) extending the model for the addition of security-aware routing.

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