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An Efficient Cluster Head Selection Approach in MANET using Enhanced Elephant Herding Optimization based on Chaos Theory and the Simplex Method

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Abstract: In Mobile Ad Hoc Networks (MANETs), choosing an efficient cluster-head (CH) is very important to ensure network stability, scalability and communication efficiency. However, existing clustering algorithms are prone to premature convergence, unstable cluster formation, high re-affiliation rates and high control-message overhead under dynamic network conditions. In order to solve these problems, this paper presents a Chaos-Simplex Elephant Herding Optimization (CS-EHO) algorithm for the cluster-head selection in MANETs. The proposed approach employs chaotic population initialization to increase the diversity of search and avoid the local optima, and the simplex-based local search to improve the exploitation capability and the convergence accuracy. The performance of the proposed CS-EHO is compared with GWOCA, EHO, HBA, MPSO, ABC and DGA using four clustering metrics, namely, average number of clusters, cluster lifetime, re-affiliation rate and control-message overhead, for different network sizes, node speeds and transmission ranges. The experimental results show that CS-EHO always outperforms all benchmark algorithms. For a network size of 500 nodes with a transmission range of 100 m, CS-EHO produced only 26 clusters in comparison with 32, 37, 54, 59, 65 and 102 clusters for GWOCA, EHO, HBA, MPSO, ABC and DGA respectively. CS-EHO achieved cluster lifetime of 79% and 80% for transmission ranges of 100 m, 200 m respectively with a low re-affiliation rate of 0.0372 and control overhead of 0.0032 under high mobility (80 km/h). The hybridization of chaotic exploration and simplex based exploitation significantly improves the cluster-head selection ability of EHO. The proposed CS-EHO framework gives rise to more stable clusters, reduces the cost of cluster maintenance, lowers the communication overhead and improves the scalability of the network. Therefore, CS-EHO is an effective and robust clustering solution for highly dynamic MANET scenarios.

Keywords: Cluster Head Selection, Elephant Herding Optimization, Chaos Theory, Simplex Method, MANET.

1. Introduction

MANETs are self-organizing wireless networks that have no centralized infrastructure and do not use centralized administration or reference points on a base station [1]. MANETs have a lot of challenges in ensuring stability and efficiency of communication because of their decentralized systems, dynamic topology, limited bandwidth, and limited access to energy [2]. Clustering has been extensively used as an efficient method of increasing the scale, decreasing routing overhead, and enhancing energy efficiency in MANETs. In cluster-based architectures, the Cluster Head (CH) is important in order to coordinate communication, intra- and inter-cluster routing, as well as data aggregation. Hence, to achieve network stability and extend the network lifetime, there is a need to choose a cluster head that is an optimal choice [3, 4]. Deterministic rules and fixed parameters are major in the conventional methods of selecting the cluster head, such as Lowest-ID, Highest-Degree, and Weighted Clustering Algorithm (WCA). Even though these methods are straightforward and their implementation is easy, they are not suitable to accommodate the common topology change and the different node mobility in dynamic MANET conditions [5]. Consequently, the clusters tend to be unstable, which causes re-clustering, a higher re-affiliation rate and too much overhead of control. Besides, these conventional techniques can keep on picking the same nodes as cluster heads, leading to uneven power consumption and premature node breakdown that eventually reduces the overall performance of the network [4, 6].

To address these shortcomings, metaheuristic optimization methods like the Genetic Algorithm (GA) [4], Particle Swarm Optimization (PSO) [7, 8] and EHO

[9] have been proposed to select a cluster head. Such algorithms offer superior global search and flexibility to the traditional approaches [10]. Nevertheless, conventional metaheuristic methods continue to be plagued by some of the following weaknesses: early convergence, the lack of population diversity, and local exploitation capability. Specifically, standard EHO can encounter less efficient exploration in the case that the starting population is not diversified, and its exploration mechanism is not adequately scanning through the promising solutions in highly dynamic network conditions [11].

In order to solve these problems, this paper suggests an effective cluster head selection algorithm, which is an improved EHO algorithm with the additions of the Chaos Theory [12, 13] and the Simplex method [14, 15]. In the proposed method, a chaos-based initialization technique is proposed to generate a very diverse population at the beginning of the optimization process. Unlike the traditional EHO implementations based on random initialization, the proposed chaotic mapping mechanism can be utilized to distribute the candidate solutions uniformly over the search space, which enhances the population diversity and reduces the chance of early stagnation. This initialization step builds a more solid basis for further exploration and improves the EHO's ability to detect promising search areas. The main methodological contribution of the proposed framework is the adaptive coordination between the EHO and the local refinement based on the simplex method. Instead of applying local search through the optimization process, the simplex mechanism is selectively used to refine only the elite solutions discovered by EHO. This design keeps the exploration ability of EHO and introduces the targeted exploitation when promising regions are identified. Thus, the framework provides a more efficient trade-off between global exploration and local intensification than traditional hybrid approaches, which conduct both processes separately or at predetermined intervals. In addition, the proposed CS-EHO framework creates a cooperative feedback framework between the two optimization stages. The better solutions found by simplex search are not taken as final results, but are added to the population of EHO and take part in the next clan evolution. Such two-way information exchange enables local refinements to influence the directions of subsequent global searches. Consequently, the optimization process is synergistic, not merely a sequential combination of the existing techniques. Thus, the methodological contribution of CS-EHO is the adaptive search schedule, elite-guided refinement strategy, and cooperative feedback architecture. These components together improve the convergence accuracy, maintain the population diversity, and increase the overall search efficiency of the optimization process.

A multi-objective fitness function is developed to measure CH candidates based on the important network parameters such as residual node energy, node degree, mobility, and link quality. The combination of these metrics provides energy-conscious, mobility-sensitive, and quality-conscious cluster formation of the proposed method. This research paper has the ultimate objective of creating a powerful and intelligent clustering mechanism that improves stability across networks and the longevity of networks in dynamic MANET settings. These goals are to reduce the re-affiliation rate and control overhead, make the cluster lifetime and number of clusters as large as possible, and bring energy consumption at nodes to a balance. The significant contributions of the work are as follows,

- The offered CS-EHO approach brings the combination of a chaos-based population initialization scheme and a simplex method-based local search strategy for selecting optimal CHs in MANET.
- Chaotic sequences, as opposed to purely random initialization, are more likely to explore the entire search space, are more effective at exploration, and are less likely to get stuck in local optima early on.
- The local search strategy based on the Simplex is integrated into the EHO framework, which boosts the exploitation phase. Although traditional EHO puts much attention on exploration based on clans, the proposed approach optimizes elite solutions
- The approach proposed is a mobility-conscious and energy-balanced multi-objective fitness model that considers residual energy, node degree, node mobility, and node direction simultaneously.
- The approach makes clusters more stable by reducing the rate of re-affiliation, thus limiting the restructuring of clusters now and then due to node mobility. This has a direct positive impact on the reduction of control overhead and consistency of routing.

The rest of the paper is structured in the following way. Section 2 outlines the corresponding literature on the topic of cluster head selection and clustering methods based on swarm intelligence used in MANETs. Section 3 is a description of the fitness parameters and formulation to be applied in the selection of optimal cluster heads. Section 4 discusses the research methods. Section 5 explains the output of the experiment and gives a discussion and performance analysis. Lastly, Section 6 concludes the research work and provides potential future improvements.

2. Related Work

MANETs have dynamic topology, limited battery resources, and decentralised management, so clustering and CH selection are very important to sustain network stability, energy efficiency, and Quality of

Service (QoS). Many recent researchers have investigated bio-inspired optimization systems, hybrid intelligence, and machine learning systems to resolve such problems (Table 1). The Clustering Algorithm, a Gray Wolf Optimization-based (GWOCA) [16], was suggested to eliminate inefficiency in energy consumption and fluctuating stability in highly dynamic MANETs. Their scheme balances the load distribution and is responsive to the topology variation, with a reduction of delay of 30.66 percent and better scalability than traditional clustering schemes, including CBRP. Patil *et al.* (2025) [17], in another study, compared PSO and ACO with QoS optimization, determining that ACO performed better in delay, PDR, and throughput, whereas PSO exhibited a slightly better energy saving. Yilmaz *et al.* (2025) [18] proposed the Hybrid Adaptive Clustering Algorithm in Dynamic MANETs (HACADM) based on the combination of WCA, GSA optimization, and Enhanced-DBSCAN Clustering. Their two-stage process enhanced load balancing and the network lifetime and reached up to 46.38% of remaining energy improvement over current methods. The Hybrid Dual Optimization Machine Learning Model (HDOMLM) was proposed by KS *et al.* (2025) [19], with PSO creating an initial cluster and an optimized ML classifier identifying CH nodes based on the measures of mobility, delay, and energy. The result of the simulation indicated that there was an increase of 56 percent in residual energy and enhanced network lifetime. Pise *et al.* (2025) [20] used Ant Colony Optimization (ACO) in VANET clustering, which also shows better adaptability and minimizes the packet loss by using pheromone-based CH selection. On the same note, Abbas *et al.* (2025) [21] also merged BOA with ACO in a hybrid model to improve the reliability of routing and energy efficiency. There is also a Cuckoo Search Optimization-based clustering protocol (CSOA) of inter-domain routing suggested by Saha *et al.* (2025) [22], which greatly enhanced throughput and cut down routing overheads. A hybrid IHHO-FJSO model was proposed by Al-Jawahry *et al.* (2025) [23], which aims at maximizing the life of the network and minimizing delay by simultaneously optimizing clustering and routing. Hussein *et al.* (2025) [24] proposed a Coverage K-Means Routing Protocol (CKRP) wherein the network is divided into zones, and CH election is done through density-aware clustering with better routing reliability than AODV-based schemes. Clustering that is security-conscious has also been of concern. A recent framework [25] combined CH selection using reinforcement learning, the management of trust, and lightweight encryption to provide more robustness against attacks and less energy usage. Past literature also offers the background approaches. Agrawal and Rathi (2024) [26] proposed a mobility-aware cluster-head selection scheme for MANETs that improved throughput and energy efficiency. Suresh Kumar *et al.* (2022) [27] and Arulprakash *et al.* (2023) [28] focused on energy-conscious routing combined with clustering, with ORS and tweaked AVOA -MMF optimization methods. The proposed algorithm, Binary Waterwheel Plant Algorithm (BWPA), by Devarayasamudram *et al.* (2024) [29], is the joint selection of CH and routing that is optimized by maximizing node lifetime and path efficiency. Liu *et al.* (2024) [30] designed a hybridized 2-CH model, which is a GWO-WOA model, to minimize the frequency of CH re-elections and energy consumption. The latest developments are also based more on hybrid metaheuristics and AI-based decision-making. Fauzan *et al.* [31] (2026) proposed EGWO-NN to select adaptive CHs with the help of neural networks, whereas Aslam *et al.* (2026) [32] suggested Secretary Bird Optimization (SBOA), which can be used to provide better load balancing and cluster stability in ad hoc networks on UAVs. Mala *et al.* (2025) [33] expounded the clustering research to secure multipath routing by combining stochastic optimization with neural networks, which provides a 96 % detection rate and low energy usage.

The Group Search Chronological Optimizer (GSCO) has been suggested by Nallusamy *et al*. [34] to be used in MANETs to select cluster heads and geographic routing. The algorithm combines GSC and a chronological updating approach to select CHs based on multi-objective criteria, like residual energy, trust, delay, distance, data rate, and geographic data. Their model showed better energy consumption and delay, and improved the reliability of routing by using the multi-criteria optimization. The many fitness parameters add complexity to computations and decision latency. A Genetic PSO (GPSO) method developed by Gayatri *et al.* (2022) [35] integrates GA and PSO to facilitate the QoS-based multipath routing based on clustering. The hybridization is better in convergence behavior than standalone GA, and has better network lifetime due to the equalization of energy consumption across CHs. Still, genetic operations combined with swarm updates increased the processing time and need parameters fine-tuning. These hybrid structures might not be the best with the MANET nodes that are limited in terms of calculations. Udaya *et al.* (2024) [36] used Lion Swarm Optimization (LSO) with Elliptic Curve Cryptography (ECC) to conduct CH selection and secure routing together with the other one. The strategy enhances throughput, the ratio of packet delivery, and network lifetime, besides identifying malicious nodes. Though these are beneficial, when the optimization is combined with the cryptographic operations, the overhead of computation and energy consumption is raised, which might narrow the scalability of large MANET exploitation, where a lightweight clustering is anticipated. According to Kumar *et al.* (2025) [37], A hybrid GWO-PSO approach to dynamic CH selection and routing based on congestion in the Enhanced Swarm Distributed Energy-Efficient Clustering (ES-DEEC) protocol. However, hybrid swarm models such as GWO-PSO involve a series of iterative update processes, which increase the complexity and convergence time of the algorithm, especially for larger networks.

Table 1. Comparative analysis of CH selection algorithms

Ref No.	Method	Key Contributions	Merits	Demerits
[16]	GWO-based Clustering Algorithm	Improved energy efficiency and stability in dynamic MANETs	Reduced delay and better scalability	May suffer from premature convergence
[17]	PSO vs ACO	Comparative QoS optimization	ACO improves delay, PDR, and throughput; PSO saves energy	Trade-off between energy and QoS
[18]	HACADM (WCA + GSA + DBSCAN)	Two-stage hybrid clustering	Improved load balancing, 46.38% energy gain	High computational complexity
[19]	HDOMLM (PSO + ML)	ML-based CH selection after clustering	56% residual energy improvement	Requires training and a dataset
[20]	ACO (VANET)	Pheromone-based CH selection	Reduces packet loss, adaptive	Slow convergence in large networks
[21]	BOA + ACO	Hybrid routing and clustering	Improved reliability and energy efficiency	Increased algorithm complexity
[22]	CSOA	Cuckoo Search-based clustering	Improved throughput, reduced overhead	Random search may be unstable
[23]	IHHO-FJSO	Joint clustering and routing optimization	Increased network lifetime, reduced delay	Complex hybrid design
[24]	CKRP (K-Means)	Density-based CH selection	Better routing reliability	Sensitive to cluster initialization
[25]	Reinforcement Learning + Security	Trust-based secure clustering	Robust against attacks, energy efficient	Training overhead
[26]	IROA	Multi-objective CH selection	Improved throughput and energy efficiency	Higher complexity
[27]	ORS	Energy-aware routing & clustering	Efficient routing	Limited scalability
[28]	AVOA-MMF	Optimized clustering	Improved energy efficiency	Parameter tuning needed
[29]	BWPA	Joint CH selection & routing	Maximizes lifetime & path efficiency	New method, limited validation
[30]	GWO-WOA (2-CH Model)	Reduces CH re-election frequency	Lower energy consumption	May increase coordination overhead
[31]	EGWO-NN	NN-based adaptive CH selection	Intelligent decision-making	Requires training data
[32]	SBOA	Optimization for UAV MANETs	Better load balancing & stability	Limited to UAV scenarios
[33]	Stochastic + NN	Secure multipath routing	96% detection accuracy	High computational cost
[34]	GSCO	Multi-objective CH selection	Improved reliability, energy, and delay	High computation & latency
[35]	GPSO (GA + PSO)	QoS-based multipath routing	Better convergence, energy balance	High processing time
[36]	LSO + ECC	Secure clustering & routing	High security, throughput	High energy & computation cost
[37]	GWO-PSO (ES-DEEC)	Congestion-aware CH selection	Improved energy efficiency	Increased convergence time
[38]	Elephant Herding Optimization (EHO)	Optimal CH selection and stable clustering in MANET	Improves network lifetime and reduces clustering overhead	Limited adaptability under high mobility scenarios
[39]	Genetic Algorithm (Dynamic GA)	Dynamic load-balanced clustering with topology awareness	Ensures fairness and adapts to topology changes	High computational complexity
[7]	Particle Swarm Optimization (PSO)	Multi-objective CH selection considering energy and mobility	Enhances network lifetime and reduces re-clustering	Premature convergence problem
[40]	Honey Bee Algorithm	Efficient clustering using multiple parameters	Reduces control overhead and improves stability	Increased decision complexity due to multiple parameters

Devi *et al.* (2023) [38] proposed cluster head selection in MANET based on EHO. Emphasizes the establishment of stable clusters with dynamic topology. Enhances network lifetime and minimizes clustering overhead compared to current approaches. Cheng *et al.* (2013) [39] developed a new GA for formulating the dynamic load-balanced clustering problem. Make sure that there is a fair allocation of nodes among cluster heads. Manages topology efficiently at the expense of increased computation. Khatoon *et al.* (2017) [7] developed PSO-based multi-objective clustering. Makes CH choices based on energy, mobility, and connectivity. Increases the lifetime of the network and decreases the frequency of re-clustering. Ahmad *et al.* (2017) [40] developed a new Honey bee algorithm to form a cluster. Makes use of numerous parameters such as energy, mobility, and node degree. Stable clustering with less control overhead.

Though a lot of advancement has been made in the area of clustering and the selection of CH of MANETs, there are a number of challenges that still cannot be addressed. Most of the current methods are based on traditional swarm intelligence methods, including PSO, GWO, ACO, EHO, and SSO. These methods are better in terms of energy efficiency and QoS, but in general, they rely on random population starting and iteration to the existing optimal solution. This usually results in premature convergence, whereby the algorithm gets stuck in local optima and never finds globally optimum CH configurations. This is especially bad in MANET environments where the mobility of nodes is very fast, and it is constantly changing the optimization landscape.

To address these disadvantages, the proposed CS-EHO incorporates chaotic initialization to enhance the diversity of the population and eliminate local optima, whereas simplex-based local search speeds up the convergence and further refines the optimal solutions. This mixture provides a balance between exploration and exploitation, minimizes computation, and allows quicker and more resilient CH selection as applicable to very dynamic and resource-constrained MANET settings. The suggested CS-EHO technique overcomes the inefficiencies of current clustering techniques because it reduces convergence instability, minimizes the number of computations, offers better adaptability to mobility, and increases the level of scalability, which is the reason why it is more applicable in real-time and large-scale MANET applications.

3. Cluster Head Selection

Cluster heads (CHs) are chosen among the members of a set of mobile nodes depending on some weight (fitness) value, and the ability of a communication device to act as a cluster head. Figure 1 shows the architecture of MANET. Figure 2 shows the framework of CHs selection in MANET. In order to determine the suitability of the node for the CH role, there are several parameters that are taken into consideration, which are node-specific, as explained below.

3.1 Node Energy ($Energy_{node}$)

The most significant factor in CH selection is the residual energy. A communication device that has more remaining energy can better serve as a CH because it can be used to perform longer communication and coordination activities. On the other hand, a node with a small residual energy is selected with an insignificant probability as a CH.

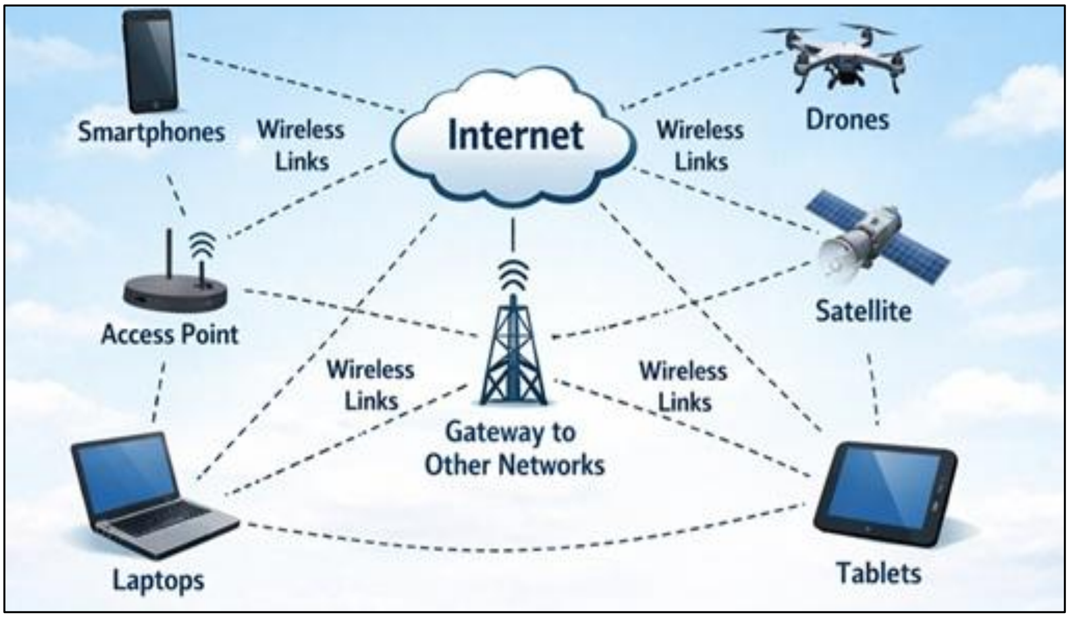

Figure 1. Architecture of MANET.

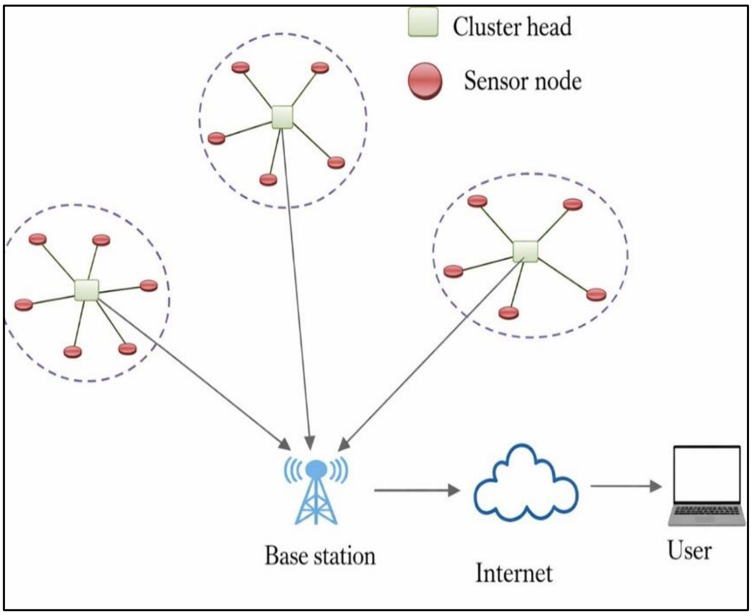

Figure 2. Framework of CHs selection in MANET.

3.2 Node Degree ($Degree_{node}$)

The degree of a node is the number of nodes adjacent to a transmission range. The more nodes, the higher the node degree, the higher the likelihood of being chosen as a CH is because it is be able to serve more members of the cluster. Superior nodes are said to be poor node candidates of the CH role.

3.3 Node Mobility ($Mobility_{node}$)

The mobility of nodes has a great impact on the stability of a cluster. CHs are communication devices that are comparatively mobile to their neighbours, and nodes with very dissimilar mobility patterns are not suited. Estimation of node mobility is conducted in terms of speed as well as direction, as follows:

- *Node speed* ($Speed_{node}$) - A communication device whose speed is similar to that of its neighbours can be viewed as an optimal candidate of CH. Devices having radically different speeds cannot be good neighbours.
- *Node direction* ($Direction_{node}$) - A communication device that works in a similar direction with its neighbors is the most advisable to the CH role, whereas the least preferable is a node that has a different direction.

$$Mobility_{node} = Speed_{node} + Direction_{node} \tag{1}$$

3.4 Node Quality ($Quality_{node}$)

The quality of nodes indicates the distance and degree of connection between nodes. Good neighbours are those neighbours whose distance is within a single hop, and those outside two hops are regarded as bad neighbours. A node that has more satisfactory neighbours is held as the one that is better suited to serve as a CH. Thus, the following formula can be used to determine a communication device's weight:

$$x_i = Energy_{node} + Quality_{node} + Mobility_{node} + Direction_{node} \tag{2}$$

Where, $Energy_{node}$ is the remaining energy, $Direction_{node}$ is the direction of node, $Mobility_{node}$ is the mobility of communication and $Quality_{node}$ is the quality of neighbours. To facilitate the formation of balanced and non-overlapping clusters, the Euclidean distance between the CHs is taken into consideration, such that the CHs are evenly distributed throughout the network. Optimization of an ad hoc environment to create optimal clusters is defined with the following objective function:

$$min\, F = \sum_{i=1}^{n} \sum_{j=1}^{k} w_{ij} (x_i - c_j)^2 \tag{3}$$

$$w_{ij} = 0\ or\ 1\ (i = 1,2, \dots .n. j = 1,2, \dots ..k \tag{4}$$

Where, n is the total number of communication devices. k is the total number of clusters selected. $x_i \in \mathbb{R}^n$ is represent the fitness values of i^{th} node. $c_j \in \mathbb{R}^n$ represent the average fitness of the j^{th} cluster head. Cluster member indicator w_{ij} defined as follows,

$$w_{ij} = \begin{cases} 1 & node\ i\ belongs\ to\ cluster\ j \\ 0 & otherwise \end{cases} \tag{5}$$

The average fitness is indicated by c_j which is measured as follows,

$$C_j = \frac{1}{N_j} \sum_{j=1}^{k} w_{ij} x_i \tag{6}$$

Here, x_i is the fitness value of the communication device. N_j is the total number of nodes in the cluster. The goal is to reduce the mean distance between cluster members and their respective CHs:

$$Cf_j = \frac{1}{k} \sum_{j=1}^{k} d(x, CH_j) \tag{7}$$

$d(x, CH_j)$ Represents the Euclidean distance between an arbitrary node x and the j^{th} cluster head. x Indicates a node of the one-hop or two-hop neighbourhood CH_j.

4. Research Methods

4.1 EHO Approaches

EHO is a population swarm intelligence algorithm that is based on the social behaviour of elephants in herding in clans with a matriarch. In EHO, an elephant corresponds to a candidate solution of a d-dimensional search space, and to enhance diversity, the entire population is grouped into various clans. Let $X_{ij}^t = \{X_{ij1}^t, X_{ij2}^t, \ldots\ldots, X_{ijd}^t\}$ represents the position of the i^{th} elephant and j^{th} clan at iteration t. An objective function $f(X)$ is used to determine the quality of all the elephants of a given clan, and the matriarch of that clan is picked as the best individual. EHO uses the clan updating operator as its main search mechanism, a model that is used to explain the preference of the matriarch of the elephants to follow them. The rank of each of the elephants is changed by driving him towards the best of the elephants of his clan, according to

$$X_{i,j}^{t-1} = X_{best,j}^t + \alpha r(X_{best,j}^{t-1} - X_{i,j}^{t-1}) \tag{8}$$

$X_{best,j}^t$ is represent the position of the matriarch. r is denotes a uniformly distributed random number in the range between 0 and 1. $\alpha \in [0,1]$ is a control parameter that defines the impact of the matriarch. This operator focuses on exploitation by directing inferior solutions to promising areas of the search space. In order to ensure the structural stability of every clan and prevent over-convergence of one person to another, EHO alters the location of the matriarch with the help of the clan center. The mean position of all the elephants in the clan is calculated as the clan center, in which the value is obtained as follows.

$$X_{center,j}^t = \frac{1}{n_j}\sum_{i=1}^{n_j} X_{i,j}^t \tag{9}$$

n_j is the number of elephants in clan j. The matriarch position is then updated as follows,

$$X_{best,j}^{t+1} = \beta . X_{center}^t \tag{10}$$

Where, $\beta \in [0,1]$ is a scaling factor that determines the direction of the movement of the matriarch towards the clan centre. This process assists in maintaining the diversity of the population and minimizes premature convergence. To enhance exploration in the search space, EHO adds a separating operator that mimics the natural behavior of male elephants leaving the clan. The worst performer among the elephants of a particular clan is re-initiated randomly within the search limits with the help of the following equation,

$$X_{worst,j}^{t+1} = X_{min} + r.(X_{max} - X_{min}) \tag{11}$$

Where are X_{min} and X_{max} represent the upper and lower limits of the search space, respectively. This operator also adds new candidate solutions, thus enhancing exploration and allowing the algorithm to get out of local optima. Once all elephants are updated, boundary control is deployed to make solutions feasible. Every dimension is modified based on the following,

$$X_{i,j,d}^{t+1} = \begin{cases} X_{min,d}, & if \ X_{i,j,d}^{t+1} < X_{min,d}, \\ X_{max,d}, & if \ X_{i,j,d}^{t+1} < X_{max,d}, \\ X_{i,j,d}^{t+1} & otherwise \end{cases} \tag{12}$$

This process is repeated until some termination is met, e.g., the maximum number of iterations. Minimization problems are then solved in the global best way as follows,

$$X_{global} = \arg \underset{x}{min} f(x) \tag{13}$$

On the whole, EHO ensures a successful balance of exploration and exploitation by its separation and update mechanism in the clan.

4.2 Simplex Method

Spendley *et al.* (1962) [41] invented the simplex method. It is defined by a set of points that is one larger than the set of dimensions of the search space. Fast searching is just one of the numerous attributes of the simplex method, including minimal computation space, small local search limits, and speedy searching of the data [42, 43]. The step-wise procedure of the SM method is given below,

Step 1: Assess all solutions in the population. Choose the global best (X_g) and second best (X_b) assuming that (X_s) is the worst solution to be replaced. These three fitness values are referred to as (X_g) , $f(X_b)$ and $f(X_s)$.

Step 2: The midpoint (X_c) between two positions, such as global best (X_g) and second best (X_b) is calculated using the formula below,

$$X_c = \frac{X_g + X_b}{2} \tag{14}$$

Step 3: The reflection point (X_r) is calculated as follows,

$$X_r = X_c + \alpha(X_c - X_s) \tag{15}$$

Here, α is the reflection coefficient, which is set to 1.

Step 4: The reflection point and global best are compared and operated. In case $f(X_r) < f(X_g)$, the following equation is to be done.

$$X_e = X_c + \gamma(X_r - X_c) \tag{16}$$

Where γ is the extension coefficient, and values are usually set to 2. Then, compare the fitness value of the extension point and the global best. If $(X_e < X_g)$ then (X_s) should be replaced with (X_e) and (X_r) is substituted by (X_s).

Step 5: Comparison between (X_r) and (X_s) is done. In case $f(X_r) > f(X_s)$, then the comparison operation ought to be implemented with the help of the next equations.

$$X_t = X_c + \beta\,(X_s - X_c) \tag{17}$$

Where, β represent the coefficient of condense and normally, the coefficient is put at 0.5. Then, the evaluation is made between the fitness values of the condense point (X_t) and the point(X_s). If$f(X_t) < f(X_s)$, then (X_s) should be replaced withX_t. Otherwise, (X_r) is substituted by (X_s).

Step 6: The shrink operations are obtained to find the condensation point (X_w) which is defined as follows,

$$X_w = X_c - \beta(X_s - X_c) \tag{18}$$

Here, β represent the shrink coefficient. If $f(X_w) < f(X_s)$, then (X_s) must be replaced by (X_w). Otherwise (X_w) is replaced with(X_s).

4.3 Chaos Theory

The application of chaotic search in optimization is due to its good ergodicity and pseudo-random nature [44]. In contrast to a simple random search, chaotic sequences are formed based on deterministic nonlinear equations but have complex and unpredictable plots. One typical chaotic generator is the logistic map:

$$ch_{k+1} = \mu ch_k(1 - ch_k) \tag{19}$$

Where $0 < ch_k < 1$ and$\mu = 4$. The system is completely chaotic and has a positive Lyapunov exponent (λ) which means that it is sensitive to initial conditions. As a result of this property, the chaotic sequence may be densely contained in the interval between 0 and 1. it is effective in local optimization since it investigates the nearby regions in a detailed manner.

4.4 Proposed CS-EHO

The proposed CS-EHO algorithm is developed to efficiently select optimal CHs in a MANET, where dynamic topology, node mobility, and limited battery power pose significant challenges. Algorithms 1, 2 and 3 are shows proposed CS-EHO, simplex method, and repairing process. In MANET clustering, CHs play a vital role in coordinating intra-cluster communication and forwarding inter-cluster data; therefore, improper CH selection may result in excessive energy consumption and frequent re-clustering. To address these issues, CS-EHO integrates chaos theory for population initialization and the simplex method for position updating within the EHO framework. The proposed CS-EHO algorithm integrates chaos theory and the Simplex search mechanism into the classical EHO framework to enhance population diversity, global exploration, and local exploitation. The simplex method itself is continuously optimizing, in this work a simplex method is used as a local search operator in a continuous domain, with each solution being represented as a real-valued vector: to make it discrete again, a discretization function is applied after each simplex operation to map the continuous values to binary CH decisions. A repair mechanism is also employed to support feasibility. Each elephant is encoded as a continuous-valued vector of dimension equal to the number of nodes, where each element represents the likelihood of a node being selected as a cluster head. The continuous vector is transformed into a discrete CH configuration using a threshold-based binarization (or top-K selection), followed by a repair mechanism to ensure feasibility with respect to energy and connectivity constraints. The motivation behind this hybridization is to overcome the limitations of conventional EHO, such as random initialization bias, premature convergence, and slow convergence speed in complex and high-dimensional search spaces. In the proposed method, chaos theory is first employed for population initialization to enhance solution diversity and global exploration. Instead of random initialization, chaotic sequences are generated using the logistic map, expressed as

$$x_{k+1} = \mu x_k(1 - x_k) \tag{20}$$

Where $x_k \in (0,1)$ is the chaotic variable at iteration k, and the control parameter $\mu$is set to 4 to ensure fully chaotic behavior. The generated chaotic values are mapped to the MANET search space using a carrier transformation given by

$$X_{i,d} = X_{min,d} + x_k(X_{max,d} - X_{min,d}) \tag{21}$$

Where $X_{i,d}$ represents the d^{th} decision variable of the i^{th} candidate CH, and $X_{min,d}$ and $X_{max,d}$ denote the lower and upper bounds of that variable. This chaos-based initialization ensures ergodic traversal of the search space and improves the likelihood of selecting energy-efficient and stable CH candidates. Each candidate solution represents a potential CH configuration and is evaluated using a multi-objective fitness function. The CH selection problem is formulated as an optimization task where the objective is to maximize network performance by considering residual energy, node degree, mobility, and distance. The fitness function for a node i is defined as

$$F_i = w_1E_i + w_2D_i + w_3M_i + w_4D_i \tag{22}$$

Where E_i is the residual energy, D_i is the node degree, M_i denotes node mobility, D_i represents the direction of nodes, and w_1, w_2, w_3, and w_4 are weighting coefficients satisfying$\sum w_j = 1$. Nodes with higher fitness values are more suitable for CH selection. After initialization, the population is divided into clans according to the EHO strategy. Each clan is led by a matriarch, who corresponds to the best candidate CH in that clan. The position of each elephant (candidate CH) is updated toward the matriarch using the clan updating operator, given by

$$X_{i,j}^{t+1} = X_{i,j}^{t} + \alpha \cdot r \cdot \left(X_{best,j}^{t} - X_{i,j}^{t}\right) \tag{23}$$

Where $X_{best,j}^{t}$ is the matriarch of the j^{th} clan, α is a control parameter, and $r \in (0,1)$ is a random number. This operator enhances global exploitation by guiding candidate CHs toward high-quality solutions. To further prevent premature convergence, a separation operator is applied, where the worst-performing elephant in each clan is reinitialized using chaotic values. This step enhances exploration and enables the algorithm to escape local optima, which is critical in highly dynamic MANET environments. For local exploitation and fine-tuning of elite solutions, the proposed CS-EHO incorporates the Simplex method for position updating. Let the simplex consist of $n + 1$ elite candidate solutions in an n-dimensional space. The centroid of the simplex is computed as

$$X_c = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{24}$$

Based on fitness evaluation, reflection, expansion, contraction, and shrink operations are performed to generate improved candidate CH solutions. These operations allow CS-EHO to accurately refine promising CH candidates without requiring gradient information, making it suitable for nonlinear and discrete MANET optimization problems. Overall, the proposed CS-EHO algorithm effectively balances global exploration through chaos-based initialization and EHO clan updating and local exploitation through Simplex-based position refinement. This hybrid optimization framework enables the selection of optimal, energy-efficient, and stable cluster heads, thereby reducing re-clustering overhead, extending network lifetime, and improving overall MANET performance. The integration of the Simplex method within the EHO position updating phase enables adaptive local exploitation, complementing the global search behavior induced by clan updating and chaotic initialization. This hybrid mechanism ensures a balanced exploration–exploitation trade-off, where chaos enhances global diversity and the Simplex method refines solution quality in later iterations. The proposed CS-EHO algorithm effectively combines the ergodicity and randomness of chaotic sequences with the geometric efficiency of the Simplex method, resulting in faster convergence, improved solution accuracy, and robust optimization performance. The Figure 3 shows the flowchart of proposed CH selection approach.

5. Experimental Results and Analysis

The usefulness, reliability, and applicability of the proposed CS-EHO-based cluster-head selection scheme in MANETs depend heavily on experimental findings and their systematic interpretation. Because MANET environments are highly dynamic and resource-constrained, theoretical formulation alone is not sufficient to demonstrate practical applicability. Experimental analysis provides quantitative evidence of the effectiveness of the proposed method under different network conditions. The results confirm that CS-EHO is effective in selecting stable and energy-efficient cluster heads because it balances global exploration and local exploitation.

Algorithm 1. CS-EHO algorithm

Input: Population size (Number of mobile nodes (N)), number of clusters (K), number of clans, maximum iterations (Max_{Iter}), objective function $(f(X))$, Threshold value (T), and Node parameters

Output: Optimal set of CHs

Begin

1. Initialize elephant population using chaotic values within search bounds
2. Divide the population into multiple clans
3. Evaluate the fitness of all elephants
4. Identify the matriarch (best elephant) in each clan
5. For each elephant
6. If $f(X) \geq T$
7. $CH_j = 1$
8. Else
9. $CH_j = 0$
10. End if
11. End for
12. Repairing process using Algorithm 3
13. Determine the global best elephant
14. While the termination condition is not satisfied
15. For each clan
16. For each elephant except the matriarch
17. Update elephant position toward the clan matriarch
18. End for
19. Update the matriarch position using clan information
20. End for
21. For each clan
22. Identify the worst elephant (poor CH configuration)
23. Reinitialize the worst elephant using chaotic values (Generate new CH set)
24. End for
25. Select elite elephants from the population
26. For each selected elite elephant

27. Construct a simplex around the current CH solution using Algorithm 2
28. Replace the CH solution if an improved configuration is found
29. End for
30. Apply boundary control to all elephants
31. Re-evaluate the fitness of the population
32. Update clan matriarchs and the global best CH solution
33. For each node
34. If $f(X) \geq T$
35. $CH_j = 1$
36. Else
37. $CH_j = 0$
38. End if
39. End for
40. Repairing process using Algorithm 3
41. End while
42. Return the global best CH set

End

CS-EHO is compared with current strategies, including GWOCA [16], EHO [38], ABC [45], DGA [39], MPSO [7], and the Honey Bee Algorithm (HBA) [40]. MATLAB 2002R is used to implement the comparison experiments. The findings indicate measurable improvements in the key performance indicators. This verification demonstrates that the introduction of chaos theory improves population diversity, whereas the simplex technique leads to faster convergence toward optimal solutions. The simulation environment (Table 2) is designed to realistically evaluate the proposed CS-EHO cluster-head selection method in a dynamic MANET. The scalability study covers both sparse and dense networks in a 1000 m × 1000 m area with 50–500 mobile nodes. Nodes move according to the Random Waypoint Mobility model at speeds of up to 80 km/h, allowing evaluation under highly dynamic topology changes. The pause time is set to 5 s. Wireless communication is modeled using IEEE 802.11b with a data rate of 16 Mbps and the Two-Ray Ground propagation model. CBR traffic with 512-byte packets is used to maintain a steady data load for fair performance comparison. Mobile-node communication is simulated using omnidirectional antennas with transmission ranges of 100–200 m. To obtain statistically sound results, each scenario is run for 20 minutes and averaged over 100 independent repetitions. The performance metrics are cluster lifetime, number of clusters, re-affiliation rate, and control overhead, which reflect stability, efficiency, adaptability, and communication cost. The reward and penalty parameters (0.1 each) encourage CS-EHO to prefer nodes with higher energy, better connectivity, and lower mobility, thereby improving cluster stability and reducing unnecessary re-clustering. Table 3 shows the parameter settings of the proposed CS-EHO.

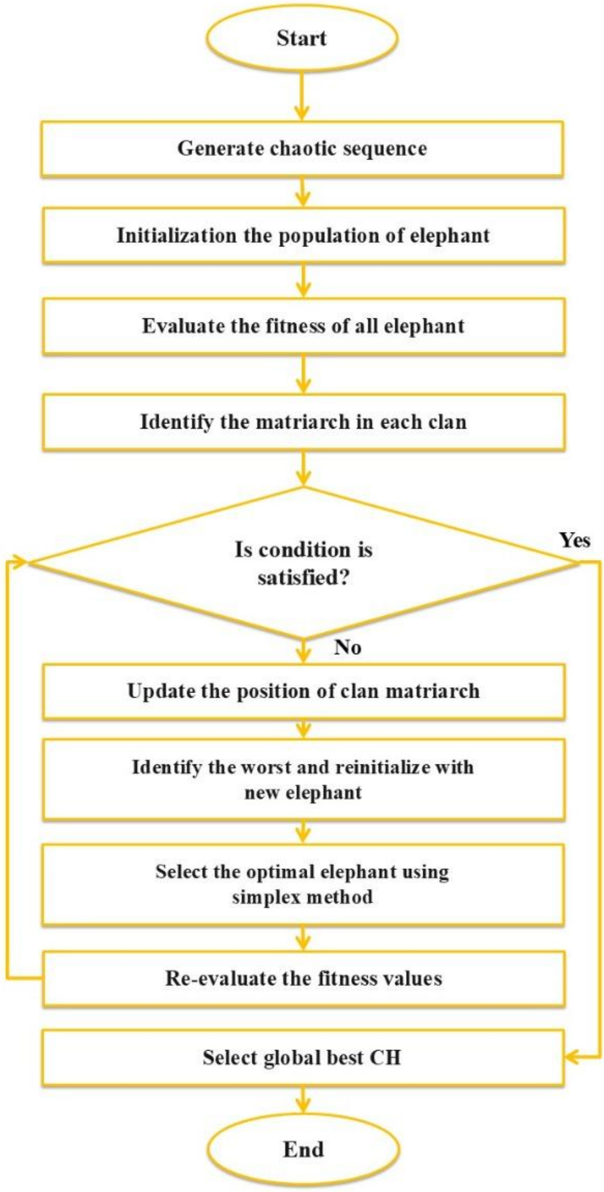

Figure 3. Flowchart of the proposed CS-EHO method for CH selection.

5.1 Performance Metrics

The following measures are used to assess the performance of the proposed CS-EHO scheme:

- *Cluster lifetime* is the period during which a node remains a cluster head (CH). It indicates the stability of the clustering scheme. A longer cluster lifetime implies better resistance to node mobility. Cluster lifetime is likely to decrease when the movement patterns of neighboring nodes are highly dissimilar

Table 2. Simulation parameters

Parameter	Values
Simulation area	1000 m × 1000 m
Number of mobile nodes	50 – 500
Node deployment	Random and uniform distribution
Node mobility model	Random Waypoint Mobility
Pause time	5s
Node speed	1 – 80 km/h
MAC protocol	IEEE 802.11 (CSMA/CA)
Propagation model	Two-ray ground
Channel capacity	16 Mbps
Antenna type	Omnidirectional
Antenna transmission range	100 – 200 m
Data packet size	512 bytes
Traffic type	Constant Bit Rate (CBR)
Traffic generation rate	20 packets/second
Queuing model	Store-and-forward queue
Neighbor awareness	Nodes are aware of neighbors' mobility
Simulation duration	20 minutes
Number of simulation runs	100 independent runs
Result averaging	Average of 100 runs
Proposed method	CS-EHO
Penalty Parameter	0.1
Reward Parameter	0.1
Performance Metrics	Cluster lifetime, Number of clusters, Re-affiliation rate, Control overhead

Table 3. Parameter settings of CS-EHO

Parameter	Values	Role in CH Selection
Population Size (N)	**40**	Number of candidate CH solutions explored
Number of Clans (C)	4	Subgroups for local search diversity
Elephants per Clan N_c	N/C	Controls intra-clan exploitation
Maximum Iterations (Max_{Iter})	50	Termination condition
Matriarch Influence Factor (α)	0.5	Guides elephants toward the best CH in the clan
Clan Updating Factor β	0.5	Controls convergence speed
Separation Operator Probability P_{sep}	0.3	Maintains diversity by relocating the worst elephant
Dimension of Solution (D)	Number of mobile Nodes	Each dimension corresponds to one MANET node
Fitness Function $f(x)$	Multi-objective	Evaluates the suitability of CH
Chaotic Initialization Parameter (for CS-EHO) λ	4	Enhances population diversity
Local Search Coefficient S_c	1.0	Refines the best CH solution locally

- *Number of Clusters:* The number of clusters is used to denote how many partitions are created once the algorithm is executed. This measure has a direct impact on the size of the cluster. The number of clusters can be large to reduce latency, energy use, channel contention, scheduling overhead, and control overhead, but too many clusters could reduce routing efficiency.

- *Re-affiliation Rate:* The frequency with which a mobile node shifts the associated cluster head is referred to as the re-affiliation rate. Re-affiliation is a process where the existing CH either abandons its position or goes out of communication. This measure is a negative ratio of the lifetime of the cluster and a good indicator of the stability of a cluster.
- *Control Overhead:* Control overhead is the count of control messages that are exchanged in forming and maintaining clustering. It is calculated in the number of control packets sent per second. Reduced control overhead means it has a more efficient and scalable clustering algorithm.

5.2 Results Analysis and Discussion

Results analysis and discussion are essential components of research because they demonstrate the practical effectiveness of the proposed method. For cluster-head selection in MANETs, this section shows that CS-EHO enhances network performance in terms of energy efficiency, stability, and cluster lifetime through measurable outcomes. It translates the theoretical formulation into experimentally validated results. This part not only presents the numerical results and tables but also explains the reasons for the observed improvements.

5.2.1 Number of Clusters

This experiment evaluates the number of clusters formed as the number of nodes increases from 50 to 500 in steps of 50. The Random Waypoint mobility model is used for node movement. The simulation area, maximum node speed, and radio radius are fixed according to the simulation setup. The performance results for a transmission range of 100 m are presented in Table 4. The table shows the mean number of clusters (or CHs) with respect to network size. It clearly shows that the number of clusters increases with the number of nodes for all algorithms. The results reveal that the CS-EHO scheme performs better than the other clustering schemes considered in this study. The experiment is then repeated for a transmission range of 200 m, and the results are given in Table 5.

Table 5 also shows an increase in the number of clusters as the network size grows, while CS-EHO consistently yields the lowest number of clusters among the compared methods.

Table 4. Network size versus the average number of clusters with a transmission range of 100 *m*

Number of Nodes	CS-EHO (Mean ± SD)	GWOCA (Mean ± SD)	EHO (Mean ± SD)	HBA (Mean ± SD)	MPSO (Mean ± SD)	ABC (Mean ± SD)	DGA (Mean ± SD)
50	4.00 ± 0.15	5.00 ± 0.18	7.00 ± 0.21	11.00 ± 0.32	13.00 ± 0.39	16.00 ± 0.48	22.00 ± 0.61
100	5.00 ± 0.18	7.00 ± 0.22	9.00 ± 0.26	16.00 ± 0.44	18.00 ± 0.51	21.00 ± 0.57	27.00 ± 0.73
150	7.00 ± 0.21	9.00 ± 0.27	12.00 ± 0.33	20.00 ± 0.52	23.00 ± 0.61	26.00 ± 0.69	33.00 ± 0.84
200	10.00 ± 0.26	12.00 ± 0.32	15.00 ± 0.39	25.00 ± 0.63	27.00 ± 0.71	30.00 ± 0.78	40.00 ± 0.95
250	12.00 ± 0.29	15.00 ± 0.37	18.00 ± 0.45	29.00 ± 0.72	31.00 ± 0.79	34.00 ± 0.86	48.00 ± 1.08
300	14.00 ± 0.33	18.00 ± 0.43	21.00 ± 0.51	34.00 ± 0.81	36.00 ± 0.89	39.00 ± 0.97	55.00 ± 1.22
350	17.00 ± 0.37	21.00 ± 0.49	25.00 ± 0.58	38.00 ± 0.91	41.00 ± 1.00	45.00 ± 1.09	65.00 ± 1.39
400	20.00 ± 0.42	24.00 ± 0.56	29.00 ± 0.66	43.00 ± 1.02	47.00 ± 1.12	52.00 ± 1.22	78.00 ± 1.61
450	23.00 ± 0.47	28.00 ± 0.64	33.00 ± 0.74	48.00 ± 1.13	53.00 ± 1.24	58.00 ± 1.35	88.00 ± 1.84
500	26.00 ± 0.53	32.00 ± 0.72	37.00 ± 0.83	54.00 ± 1.25	59.00 ± 1.37	65.00 ± 1.49	102.00 ± 2.08

Table 5. Network size versus the average number of clusters with a transmission range of 200 *m*

Number of Nodes	CS-EHO (Mean ± SD)	GWOCA (Mean ± SD)	EHO (Mean ± SD)	HBA (Mean ± SD)	MPSO (Mean ± SD)	ABC (Mean ± SD)	DGA (Mean ± SD)
50	6.00 ± 0.18	10.00 ± 0.30	13.00 ± 0.39	19.00 ± 0.56	26.00 ± 0.73	30.00 ± 0.84	34.00 ± 0.95
100	9.00 ± 0.24	13.00 ± 0.37	17.00 ± 0.48	26.00 ± 0.71	36.00 ± 0.94	43.00 ± 1.12	52.00 ± 1.31
150	11.00 ± 0.28	16.00 ± 0.45	20.00 ± 0.56	30.00 ± 0.82	45.00 ± 1.12	53.00 ± 1.34	62.00 ± 1.52
200	15.00 ± 0.34	20.00 ± 0.53	26.00 ± 0.69	36.00 ± 0.95	52.00 ± 1.26	60.00 ± 1.47	69.00 ± 1.68
250	18.00 ± 0.39	24.00 ± 0.62	31.00 ± 0.81	42.00 ± 1.06	57.00 ± 1.37	66.00 ± 1.58	74.00 ± 1.79
300	22.00 ± 0.45	28.00 ± 0.71	36.00 ± 0.93	47.00 ± 1.17	64.00 ± 1.48	71.00 ± 1.70	79.00 ± 1.91
350	25.00 ± 0.50	32.00 ± 0.80	41.00 ± 1.04	52.00 ± 1.28	69.00 ± 1.59	76.00 ± 1.82	83.00 ± 2.03
400	29.00 ± 0.56	36.00 ± 0.89	45.00 ± 1.15	57.00 ± 1.39	76.00 ± 1.72	82.00 ± 1.96	88.00 ± 2.15
450	33.00 ± 0.62	40.00 ± 0.98	48.00 ± 1.23	60.00 ± 1.48	81.00 ± 1.84	87.00 ± 2.08	92.00 ± 2.24
500	36.00 ± 0.68	43.00 ± 1.07	51.00 ± 1.31	64.00 ± 1.57	85.00 ± 1.95	91.00 ± 2.20	97.00 ± 2.36

Table 4 shows the average number of clusters generated by CS-EHO, GWOCA, EHO, HBA, MPSO, ABC, and DGA for network sizes ranging from 50 to 500 nodes with a 100 m transmission range. For all algorithms, the average number of clusters increases as the number of nodes increases, which is expected because larger networks require more cluster heads to maintain connectivity and efficient communication. However, the rate of increase differs among the algorithms, reflecting their clustering efficiency. The proposed CS-EHO consistently produces the minimum average number of clusters for every network size. For example, at 50 nodes, CS-EHO forms only 4 clusters, whereas GWOCA, EHO, HBA, MPSO, ABC, and DGA form 5, 7, 11, 13, 16, and 22 clusters, respectively. At 250 nodes, CS-EHO generates 12 clusters, which is substantially lower than GWOCA (15), EHO (18), HBA (29), MPSO (31), ABC (34), and DGA (48). For the largest network of 500 nodes, CS-EHO requires only 26 clusters, while GWOCA, EHO, HBA, MPSO, ABC, and DGA require 32, 37, 54, 59, 65, and 102 clusters, respectively. This corresponds to reductions of about 18.8%, 29.7%, and 51.9%, 55.9%, 60.0%, and 74.5% compared with the competing methods, confirming the superior clustering efficiency of CS-EHO at a 100 m transmission range.

Table 5 presents the relationship between network size and the average number of clusters when the transmission range is increased to 200 m. As in the previous experiment, the number of clusters increases with network size because more nodes require more cluster heads to support effective communication. Even under this setting, CS-EHO consistently yields the minimum number of clusters among all compared algorithms. For a network of 50 nodes, CS-EHO forms 6 clusters, whereas GWOCA, EHO, HBA, MPSO, ABC, and DGA produce 10, 13, 19, 26, 30, and 34 clusters, respectively. At 250 nodes, CS-EHO creates 18 clusters, compared with 24, 31, 42, 57, 66, and 74 clusters for the competing methods. For the largest network of 500 nodes, CS-EHO produces 36 clusters, while GWOCA, EHO, HBA, MPSO, ABC, and DGA produce 43, 51, 64, 85, 91, and 97 clusters, respectively. These results demonstrate that the proposed algorithm maintains efficient clustering even at higher node densities and larger transmission ranges.

5.2.2 Cluster Lifetime

This metric examines how node speed affects cluster lifetime. Higher node mobility reduces cluster lifetime. In this study, simulation experiments were carried out by varying the number of mobile nodes from 50 to 500. To evaluate the performance of the proposed approach under different network conditions, the antenna transmission range was also varied between 100 m and 200 m. Node speed varies from 1 to 80 km/h, and the mean cluster duration in seconds is measured. The proposed clustering scheme is superior to the others in terms of cluster stability, as shown in Table 6. In CS-EHO, member nodes remain connected to the CH for a considerably longer duration. This can be attributed to the fact that the relative mobility of mobile nodes is taken into account, and the most stable node is selected as the cluster head. The transmission range is then extended to 200 m, as shown in Table 7, while the other parameters remain the same. These results are used to examine the influence of radio transmission range on cluster lifetime. The findings show that cluster lifetime can be extended when the transmission range is increased. With greater radio coverage, CH neighbors remain within range for a longer period, thereby increasing cluster lifetime. The effect of node mobility on cluster lifetime is shown in Table 6 for a transmission range of 100 m. The cluster lifetime of all algorithms decreases as node speed increases from 10 km/h to 80 km/h because of more frequent topology changes and link breakages. However, the proposed CS-EHO consistently achieves the highest cluster lifetime at all mobility levels. Specifically, the cluster lifetime of CS-EHO decreases from 96.00 at 10 km/h to 79.00 at 80 km/h, while GWOCA, EHO, HBA, MPSO, ABC, and DGA decrease to 62.00, 56.00, 54.00, 39.00, 34.00, and 30.00, respectively, at the highest mobility level. At 80 km/h, CS-EHO prolongs cluster lifetime by 27.42%, 41.07%, 46.30%, 102.56%, 132.35%, and 163.33% compared with GWOCA, EHO, HBA, MPSO, ABC, and DGA, respectively. At 50 km/h, CS-EHO achieves a cluster lifetime of 88.00 in comparison with 81.00, 76.00, 65.00, 51.00, 50.00, and 49.00 for GWOCA, EHO, HBA, MPSO, ABC, and DGA, respectively, corresponding to improvements of 8.64%, 15.79%, 35.38%, 72.55%, 76.00%, and 79.59%. These results show that CS-EHO can effectively maintain stable clusters and reduce frequent cluster reformation under high mobility. The performance of cluster lifetime for a transmission range of 200 m is shown in Table 7. Similar to the 100 m case, cluster lifetime decreases with increasing node speed for all algorithms. However, CS-EHO always maintains the longest cluster duration throughout the experiment. At 80 km/h, CS-EHO achieves a cluster lifetime of 80.00, while GWOCA, EHO, HBA, MPSO, ABC, and DGA achieve 71.00, 67.00, 56.00, 44.00, 39.00, and 35.00, respectively. This corresponds to performance gains of 12.68%, 19.40%, 42.86%, 81.82%, 105.13%, and 128.57% over the competing approaches. Under low-mobility conditions (10 km/h), CS-EHO reaches the maximum cluster lifetime of 98.00 and outperforms GWOCA, EHO, HBA, MPSO, ABC, and DGA by 3.16%, 5.38%, 11.36%, 15.29%, 20.99%, and 28.95%, respectively. The enhanced performance of CS-EHO is due to its ability to balance exploration and exploitation through chaotic initialization and simplex-based local search, which leads to effective cluster-head selection and improved cluster stability under different mobility conditions.

Table 6. Node speed versus cluster duration with a transmission range of 100 m

Node Speed (km/h)	CS-EHO (Mean ± SD)	GWOCA (Mean ± SD)	EHO (Mean ± SD)	HBA (Mean ± SD)	MPSO (Mean ± SD)	ABC (Mean ± SD)	DGA (Mean ± SD)
10	96.00 ± 1.12	93.00 ± 1.30	90.00 ± 1.48	85.00 ± 1.76	79.00 ± 2.04	75.00 ± 2.18	71.00 ± 2.31
20	94.00 ± 1.18	90.00 ± 1.42	86.00 ± 1.56	80.00 ± 1.88	70.00 ± 2.15	68.00 ± 2.29	65.00 ± 2.43
30	92.00 ± 1.24	87.00 ± 1.50	83.00 ± 1.64	74.00 ± 1.96	64.00 ± 2.26	62.00 ± 2.38	60.00 ± 2.52
40	90.00 ± 1.31	85.00 ± 1.61	82.00 ± 1.72	69.00 ± 2.08	55.00 ± 2.41	55.00 ± 2.53	54.00 ± 2.66
50	88.00 ± 1.39	81.00 ± 1.73	76.00 ± 1.84	65.00 ± 2.17	51.00 ± 2.55	50.00 ± 2.68	49.00 ± 2.81
60	85.00 ± 1.46	76.00 ± 1.84	71.00 ± 1.96	62.00 ± 2.29	47.00 ± 2.68	44.00 ± 2.81	41.00 ± 2.95
70	82.00 ± 1.54	71.00 ± 1.98	65.00 ± 2.11	59.00 ± 2.41	43.00 ± 2.82	39.00 ± 2.96	35.00 ± 3.12
80	79.00 ± 1.62	62.00 ± 2.14	56.00 ± 2.28	54.00 ± 2.56	39.00 ± 2.97	34.00 ± 3.13	30.00 ± 3.28

Table 7. Node speed versus cluster duration with a transmission range of 200 m

Node Speed (km/h)	CS-EHO (Mean ± SD)	GWOCA (Mean ± SD)	EHO (Mean ± SD)	HBA (Mean ± SD)	MPSO (Mean ± SD)	ABC (Mean ± SD)	DGA (Mean ± SD)
10	98.00 ± 1.05	95.00 ± 1.21	93.00 ± 1.37	88.00 ± 1.65	85.00 ± 1.88	81.00 ± 2.01	76.00 ± 2.14
20	96.00 ± 1.12	93.00 ± 1.29	90.00 ± 1.46	82.00 ± 1.79	79.00 ± 2.01	75.00 ± 2.13	72.00 ± 2.25
30	94.00 ± 1.19	90.00 ± 1.38	87.00 ± 1.55	78.00 ± 1.92	74.00 ± 2.15	69.00 ± 2.28	65.00 ± 2.41
40	92.00 ± 1.27	88.00 ± 1.47	84.00 ± 1.64	74.00 ± 2.06	64.00 ± 2.31	61.00 ± 2.43	58.00 ± 2.56
50	89.00 ± 1.35	84.00 ± 1.58	81.00 ± 1.74	69.00 ± 2.18	59.00 ± 2.47	53.00 ± 2.60	47.00 ± 2.73
60	86.00 ± 1.44	80.00 ± 1.71	76.00 ± 1.86	63.00 ± 2.32	53.00 ± 2.61	47.00 ± 2.74	41.00 ± 2.88
70	83.00 ± 1.53	76.00 ± 1.84	72.00 ± 1.98	60.00 ± 2.46	49.00 ± 2.77	44.00 ± 2.90	39.00 ± 3.04
80	80.00 ± 1.63	71.00 ± 1.98	67.00 ± 2.11	56.00 ± 2.61	44.00 ± 2.94	39.00 ± 3.06	35.00 ± 3.19

5.2.3 Re-Affiliation Rate

This section presents a series of simulation experiments to determine the effects of radio transmission range and node mobility speed on the re-affiliation rate. The re-affiliation rate is the number of times a mobile node switches cluster heads per unit time. A mobile node joins a new cluster when the existing CH relinquishes its role or when the node can no longer remain connected to its CH. The re-affiliation rate increases when mobile nodes move at higher speeds because they leave their clusters more frequently. The Random Waypoint mobility model is used in these experiments; 50 mobile nodes are deployed in the simulation area, and the transmission range of each mobile node is 200 m. The node speed varies between 1 and 80 km/h to quantify the mean re-affiliation rate. The mean re-affiliation rate at different node speeds is given in Table 8. CS-EHO has the lowest re-affiliation rates compared with the other schemes, as shown in the table. The obtained results on cluster lifetime also suggest that the algorithm performs well. This positive effect arises because the CHs are selected based on relative mobility and other significant measures. As a result, CH lifetime is extended, and member nodes leave their existing clusters at a much lower rate. We also study the impact of radio transmission range on the re-affiliation rate, and the results are presented in Table 9. The transmission range is increased from 100 m to 400 m in increments of 50 m. Table 9 shows the re-affiliation rate of all schemes under different transmission-range settings.

Table 8 shows the re-affiliation rate under different node mobility conditions. We observe that the re-affiliation rate increases for all clustering algorithms as node speed increases from 10 km/h to 80 km/h because of more frequent topology changes and node movement between clusters. However, the proposed CS-EHO consistently achieves the minimum re-affiliation rate at all mobility levels. In particular, the re-affiliation rate of CS-EHO increases from 0.0016 at 10 km/h to 0.0372 at 80 km/h. For GWOCA, EHO, HBA, MPSO, ABC, and DGA, the corresponding values at the highest mobility level are 0.0488, 0.0604, 0.0806, 0.0879, 0.0947, and 0.1015, respectively. At 80 km/h, the re-affiliation rate of CS-EHO is 23.77%, 38.41%, 53.85%, 57.68%, 60.72%, and 63.35% lower than those of GWOCA, EHO, HBA, MPSO, ABC, and DGA, respectively.

Table 8. Performance comparisons of re-affiliation rate with different node speeds

Node Speed (km/h)	CS-EHO (Mean ± SD)	GWOCA (Mean ± SD)	EHO (Mean ± SD)	HBA (Mean ± SD)	MPSO (Mean ± SD)	ABC (Mean ± SD)	DGA (Mean ± SD)
10	0.0016 ± 0.00008	0.0032 ± 0.00014	0.0051 ± 0.00021	0.0108 ± 0.00039	0.0186 ± 0.00062	0.0214 ± 0.00072	0.0242 ± 0.00081
20	0.0029 ± 0.00011	0.0054 ± 0.00020	0.0079 ± 0.00029	0.0176 ± 0.00056	0.0274 ± 0.00087	0.0302 ± 0.00096	0.0331 ± 0.00105
30	0.0051 ± 0.00018	0.0077 ± 0.00027	0.0104 ± 0.00036	0.0271 ± 0.00081	0.0365 ± 0.00112	0.0398 ± 0.00120	0.0432 ± 0.00129
40	0.0076 ± 0.00024	0.0117 ± 0.00036	0.0158 ± 0.00048	0.0374 ± 0.00108	0.0482 ± 0.00143	0.0520 ± 0.00154	0.0559 ± 0.00165
50	0.0124 ± 0.00036	0.0175 ± 0.00051	0.0226 ± 0.00067	0.0508 ± 0.00144	0.0561 ± 0.00162	0.0663 ± 0.00186	0.0765 ± 0.00211
60	0.0203 ± 0.00058	0.0299 ± 0.00085	0.0395 ± 0.00112	0.0617 ± 0.00173	0.0669 ± 0.00188	0.0768 ± 0.00213	0.0868 ± 0.00239
70	0.0281 ± 0.00079	0.0380 ± 0.00107	0.0478 ± 0.00135	0.0719 ± 0.00199	0.0748 ± 0.00206	0.0842 ± 0.00231	0.0936 ± 0.00256
80	0.0372 ± 0.00104	0.0488 ± 0.00136	0.0604 ± 0.00168	0.0806 ± 0.00222	0.0879 ± 0.00241	0.0947 ± 0.00260	0.1015 ± 0.00278

Table 9. Performance comparisons of re-affiliation rate versus radio transmission range

Transmission Range (m)	CS-EHO (Mean ± SD)	GWOCA (Mean ± SD)	EHO (Mean ± SD)	HBA (Mean ± SD)	MPSO (Mean ± SD)	ABC (Mean ± SD)	DGA (Mean ± SD)
100	0.0369 ± 0.00103	0.0480 ± 0.00134	0.0591 ± 0.00164	0.0685 ± 0.00189	0.0716 ± 0.00197	0.0732 ± 0.00201	0.0748 ± 0.00205
150	0.0268 ± 0.00076	0.0408 ± 0.00115	0.0547 ± 0.00153	0.0648 ± 0.00181	0.0701 ± 0.00194	0.0729 ± 0.00200	0.0756 ± 0.00207
200	0.0227 ± 0.00065	0.0381 ± 0.00107	0.0534 ± 0.00149	0.0596 ± 0.00167	0.0664 ± 0.00184	0.0698 ± 0.00193	0.0731 ± 0.00201
250	0.0194 ± 0.00057	0.0345 ± 0.00098	0.0496 ± 0.00139	0.0537 ± 0.00152	0.0611 ± 0.00172	0.0642 ± 0.00180	0.0672 ± 0.00188
300	0.0166 ± 0.00049	0.0259 ± 0.00076	0.0351 ± 0.00102	0.0491 ± 0.00140	0.0546 ± 0.00156	0.0575 ± 0.00164	0.0604 ± 0.00171
350	0.0149 ± 0.00045	0.0223 ± 0.00067	0.0296 ± 0.00088	0.0388 ± 0.00115	0.0421 ± 0.00128	0.0474 ± 0.00140	0.0526 ± 0.00151
400	0.0132 ± 0.00041	0.0190 ± 0.00059	0.0248 ± 0.00076	0.0299 ± 0.00093	0.0358 ± 0.00109	0.0425 ± 0.00126	0.0491 ± 0.00142

Similarly, at 50 km/h, the proposed approach achieves a re-affiliation rate of only 0.0124, whereas GWOCA, EHO, HBA, MPSO, ABC, and DGA record 0.0175, 0.0226, 0.0508, 0.0561, 0.0663, and 0.0765, respectively, corresponding to reductions of 29.14%, 45.13%, 75.59%, 77.90%, 81.30%, and 83.79%. These results show that CS-EHO can reduce changes in cluster membership and identify more stable cluster structures even in highly dynamic network environments.

Table 9 illustrates the impact of radio transmission range on the re-affiliation rate. The re-affiliation rate for all algorithms decreases as the transmission range increases from 100 m to 400 m because wider communication coverage enhances cluster connectivity and reduces frequent cluster switching. However, the re-affiliation rate of CS-EHO remains the smallest throughout the evaluation. At a transmission range of 400 m, the re-affiliation rate of CS-EHO is 0.0132, whereas the corresponding values are 0.0190, 0.0248, 0.0299, 0.0358, 0.0425, and 0.0491 for GWOCA, EHO, HBA, MPSO, ABC, and DGA, respectively. This corresponds to reductions of 30.53%, 46.77%, 55.85%, 63.13%, 68.94%, and 73.12% over the competing methods. Similarly, when the transmission range is set to 100 m, the re-affiliation rate of CS-EHO is 0.0369, which is better than GWOCA, EHO, HBA, MPSO, ABC, and DGA by 23.13%, 37.56%, 46.13%, 48.46%, 49.59%, and 50.67%, respectively. The better performance of CS-EHO is attributed to its improved cluster-head selection scheme. It balances exploration and exploitation through chaotic initialization and simplex-based local refinement, resulting in more stable clusters and a large reduction in re-affiliation events under different network conditions.

5.2.4 Control Message Overhead

Control message overhead is the number of messages sent per second during cluster formation. Cluster formation in MANET clustering algorithms requires multiple message exchanges. This section presents the findings of experiments conducted to observe message exchanges during cluster formation. The simulation tests in this category involve the random deployment of 50 mobile nodes within a 1000 m × 1000 m simulation area. The nodes move randomly according to the Random Waypoint mobility model. The initial transmission range of the mobile nodes is 200 m. The node speed varies between 10 and 80 km/h in steps of 10. These experiments are repeated with increased transmission range. Tables 10 and 11 present the simulation results.

Table 10. Node speed versus control message overhead with a transmission range of 100 m

Node Speed (km/h)	CS-EHO (Mean ± SD)	GWOCA (Mean ± SD)	EHO (Mean ± SD)	HBA (Mean ± SD)	MPSO (Mean ± SD)	ABC (Mean ± SD)	DGA (Mean ± SD)
10	0.00060 ± 0.00003	0.00080 ± 0.00003	0.00100 ± 0.00004	0.00200 ± 0.00008	0.00300 ± 0.00012	0.00375 ± 0.00015	0.00450 ± 0.00018
20	0.00110 ± 0.00004	0.00155 ± 0.00006	0.00200 ± 0.00008	0.00250 ± 0.00010	0.00350 ± 0.00014	0.00435 ± 0.00017	0.00520 ± 0.00021
30	0.00140 ± 0.00005	0.00185 ± 0.00007	0.00230 ± 0.00009	0.00270 ± 0.00011	0.00410 ± 0.00016	0.00490 ± 0.00020	0.00570 ± 0.00023
40	0.00170 ± 0.00006	0.00205 ± 0.00008	0.00240 ± 0.00010	0.00310 ± 0.00012	0.00470 ± 0.00018	0.00560 ± 0.00022	0.00650 ± 0.00026
50	0.00200 ± 0.00007	0.00245 ± 0.00009	0.00290 ± 0.00011	0.00340 ± 0.00014	0.00540 ± 0.00021	0.00630 ± 0.00025	0.00720 ± 0.00029
60	0.00230 ± 0.00008	0.00285 ± 0.00011	0.00340 ± 0.00013	0.00370 ± 0.00015	0.00610 ± 0.00024	0.00700 ± 0.00028	0.00790 ± 0.00032
70	0.00270 ± 0.00009	0.00330 ± 0.00012	0.00390 ± 0.00015	0.00420 ± 0.00017	0.00680 ± 0.00027	0.00745 ± 0.00030	0.00810 ± 0.00033
80	0.00320 ± 0.00011	0.00370 ± 0.00014	0.00420 ± 0.00016	0.00470 ± 0.00019	0.00770 ± 0.00031	0.00825 ± 0.00033	0.00880 ± 0.00035

Table 11. Node speed versus control message overhead with a transmission range of 200 m

Node Speed (km/h)	CS-EHO (Mean ± SD)	GWOCA (Mean ± SD)	EHO (Mean ± SD)	HBA (Mean ± SD)	MPSO (Mean ± SD)	ABC (Mean ± SD)	DGA (Mean ± SD)
10	0.00062 ± 0.00003	0.00106 ± 0.00004	0.00150 ± 0.00006	0.00220 ± 0.00009	0.00260 ± 0.00010	0.00335 ± 0.00013	0.00410 ± 0.00016
20	0.00068 ± 0.00003	0.00144 ± 0.00006	0.00220 ± 0.00009	0.00260 ± 0.00010	0.00330 ± 0.00013	0.00395 ± 0.00016	0.00460 ± 0.00018
30	0.00045 ± 0.00002	0.00148 ± 0.00006	0.00250 ± 0.00010	0.00290 ± 0.00012	0.00390 ± 0.00016	0.00450 ± 0.00018	0.00510 ± 0.00020
40	0.00110 ± 0.00004	0.00185 ± 0.00007	0.00260 ± 0.00010	0.00300 ± 0.00012	0.00440 ± 0.00018	0.00510 ± 0.00020	0.00580 ± 0.00023
50	0.00135 ± 0.00005	0.00223 ± 0.00009	0.00310 ± 0.00012	0.00320 ± 0.00013	0.00520 ± 0.00021	0.00590 ± 0.00024	0.00660 ± 0.00026
60	0.00170 ± 0.00006	0.00260 ± 0.00010	0.00350 ± 0.00014	0.00360 ± 0.00014	0.00590 ± 0.00024	0.00685 ± 0.00027	0.00780 ± 0.00031
70	0.00205 ± 0.00007	0.00293 ± 0.00012	0.00380 ± 0.00015	0.00410 ± 0.00016	0.00640 ± 0.00026	0.00740 ± 0.00030	0.00840 ± 0.00034
80	0.00260 ± 0.00009	0.00345 ± 0.00014	0.00430 ± 0.00017	0.00450 ± 0.00018	0.00730 ± 0.00029	0.00805 ± 0.00032	0.00880 ± 0.00035

Control overhead is reduced by extending the radio transmission range, although this comes at the expense of additional energy use. As the transmission range increases, the re-affiliation rate decreases and cluster lifetime increases. Thus, the residual node energy is taken into account when selecting CHs in our algorithm. As shown in Tables 10 and 11, the proposed CS-EHO achieves the lowest control message overhead compared with the other methods. CS-EHO also exhibits the lowest re-affiliation rate and the longest cluster lifetime among the compared schemes. In this way, CS-EHO minimizes re-clustering and supports stable cluster formation. The reduction in re-clustering directly lowers the control message overhead.

The control message overhead under various node mobility conditions for a transmission range of 100 m is shown in Table 10. The control overhead increases for all clustering algorithms as node speed increases from 10 km/h to 80 km/h. This is because increased mobility leads to more frequent cluster-maintenance operations and topology updates. However, the proposed CS-EHO consistently achieves the lowest control overhead at all mobility levels. Specifically, the CS-EHO overhead increases from 0.00060 at 10 km/h to 0.00320 at 80 km/h, while GWOCA, EHO, HBA, MPSO, ABC, and DGA reach 0.00370, 0.00420, 0.00470, 0.00770, 0.00825, and 0.00880, respectively, at the highest mobility level. The corresponding reductions achieved by CS-EHO over GWOCA, EHO, HBA, MPSO, ABC, and DGA at 80 km/h are 13.51%, 23.81%, 31.91%, 58.44%, 61.21%, and 63.64%, respectively. Similarly, at 50 km/h, the overhead of the proposed method is only 0.00200, corresponding to reductions of 18.37%, 31.03%, 41.18%, 62.96%, 68.25%, and 72.22% with respect to GWOCA, EHO, HBA, MPSO, ABC, and DGA, respectively. These results show that CS-EHO is effective in reducing cluster-maintenance signaling and improving communication efficiency even in highly dynamic network environments.

The same trend can be observed for the transmission range of 200 m, as shown in Table 11. All algorithms exhibit an increase in control message overhead as node speed increases, but CS-EHO consistently has the lowest overhead throughout the evaluation. For CS-EHO, the control overhead is 0.00260 at 80 km/h. For GWOCA, EHO, HBA, MPSO, ABC, and DGA, the overhead values are 0.00345, 0.00430, 0.00450, 0.00730, 0.00805, and 0.00880, respectively. Thus, CS-EHO achieves reductions of 24.64%, 39.53%, 42.22%, 64.38%, 67.70%, and 70.45% over the competing methods. Under low-mobility conditions (10 km/h), CS-EHO has an overhead of only 0.00062, while GWOCA, EHO, HBA, MPSO, ABC, and DGA have overhead values of 0.00106, 0.00150, 0.00220, 0.00260, 0.00335, and 0.00410, respectively. These correspond to reductions of 41.51%, 58.67%, 71.82%, 76.15%, 81.49%, and 84.88%, respectively. The enhanced performance of CS-EHO is based on its effective cluster-head selection process, which minimizes unnecessary cluster reconfigurations and control-message exchanges by integrating the benefits of chaotic initialization and simplex-based local optimization. CS-EHO provides a scalable and communication-efficient clustering framework for MANETs under different mobility conditions.

The improved efficiency of the proposed CS-EHO algorithm is due to the integrated effect of chaotic initialization and simplex-based local search within the EHO framework. Traditional clustering methods generally suffer from premature convergence, lack of population diversity, and limited ability to adapt effectively to dynamic changes in network topology during cluster-head selection [46]. These limitations lead to frequent cluster reformation, unstable cluster-head assignment, increased node re-affiliations, and excessive control-message exchanges. To address these issues, the proposed CS-EHO enhances both global exploration and local exploitation in the optimization process. The chaotic initialization mechanism produces a highly diverse initial population of candidate cluster-head solutions. In contrast to random initialization, chaotic sequences distribute solutions more evenly across the search space, increasing the chances of finding high-quality cluster-head configurations in the early stages of optimization. This increase in diversity helps the optimization process avoid getting trapped in local optima and allows the algorithm to explore multiple promising regions simultaneously. Hence, cluster-head selection is based on a more comprehensive consideration of network characteristics such as node connectivity, mobility, neighborhood density, and cluster stability. Furthermore, the simplex-based local search improves the exploitation ability of the original EHO algorithm. Once promising solutions are identified, the simplex search performs localized refinement to improve cluster-head placement and the quality of cluster formation. This refinement process allows the algorithm to converge to more stable cluster structures while remaining computationally efficient. Hence, the selected cluster heads are more robust to topology changes caused by node mobility and have increased operational lifetime [47]. From the network point of view, stable cluster-head selection directly affects all clustering performance metrics. As a result, cluster joining and leaving procedures are required less often. Cluster members associated with longer-lasting cluster heads experience fewer re-affiliation events. This reduces control-message exchanges for cluster maintenance and hence lowers control overhead. At the same time, less cluster reconfiguration improves cluster lifetime and network stability because communication paths remain valid for longer periods. Fewer re-affiliations also reduce routing disruptions and packet loss, thereby increasing overall network reliability.

The advantage of CS-EHO is particularly prominent under high-mobility conditions. As node speed increases, the MANET topology changes more frequently, causing link breakages and cluster instability in conventional algorithms. However, the adaptive search capability of CS-EHO identifies cluster heads with better mobility characteristics and stronger connectivity relationships. It also helps maintain stable clusters under high mobility, thereby reducing the need for cluster re-creation and keeping the network organized and efficient. Moreover, the algorithm is scalable as network size and transmission range increase. Larger networks create more complex optimization problems because of the greater number of node interactions and clustering possibilities. CS-EHO handles this complexity through a balanced exploration-exploitation strategy that maintains solution diversity while refining high-quality candidates. Similarly, larger transmission ranges improve node connectivity, and CS-EHO takes full advantage of this to build more stable and sustainable cluster structures. The experimental results show that CS-EHO is a well-balanced optimization framework that can select highly stable cluster heads, reduce cluster-maintenance operations, minimize control overhead, reduce re-affiliation rates, and prolong cluster lifetime. Due to the synergistic benefits of chaos-enhanced exploration and simplex-assisted exploitation, CS-EHO outperforms GWOCA, EHO, HBA, MPSO, ABC, and DGA across different network densities, transmission ranges, and mobility scenarios, providing a highly effective clustering solution for MANETs.

5.3 Convergence Analysis

The convergence performance of the proposed CS-EHO algorithm is shown in Figures 4–7 together with GWOCA, EHO, HBA, MPSO, ABC, and DGA. Convergence behavior assesses the optimization ability of each algorithm in terms of solution quality, convergence rate, exploration-exploitation tradeoff, and search stability during the iterative process of cluster-head selection. As shown in Figure 4, the average number of clusters decreases gradually with increasing optimization iterations and finally reaches a stable equilibrium point. The proposed CS-EHO algorithm exhibits a faster convergence rate and finds the minimum cluster number compared with the competing algorithms. This better performance is due to the combination of chaotic population initialization and improved exploitation mechanisms, which increase population diversity in the initial search process and avoid premature convergence. Thus, CS-EHO efficiently finds the optimal cluster-head configuration with balanced cluster distribution and lower clustering complexity.

Figure 5 shows the convergence analysis of average cluster duration. Cluster lifetime increases monotonically with the number of iterations until a stable optimum is achieved. The proposed CS-EHO algorithm converges in about 70–80 iterations and has the highest cluster duration among all compared methods. The increased cluster duration indicates improved cluster stability, enhanced cluster-head sustainability, and reduced cluster-maintenance operations.

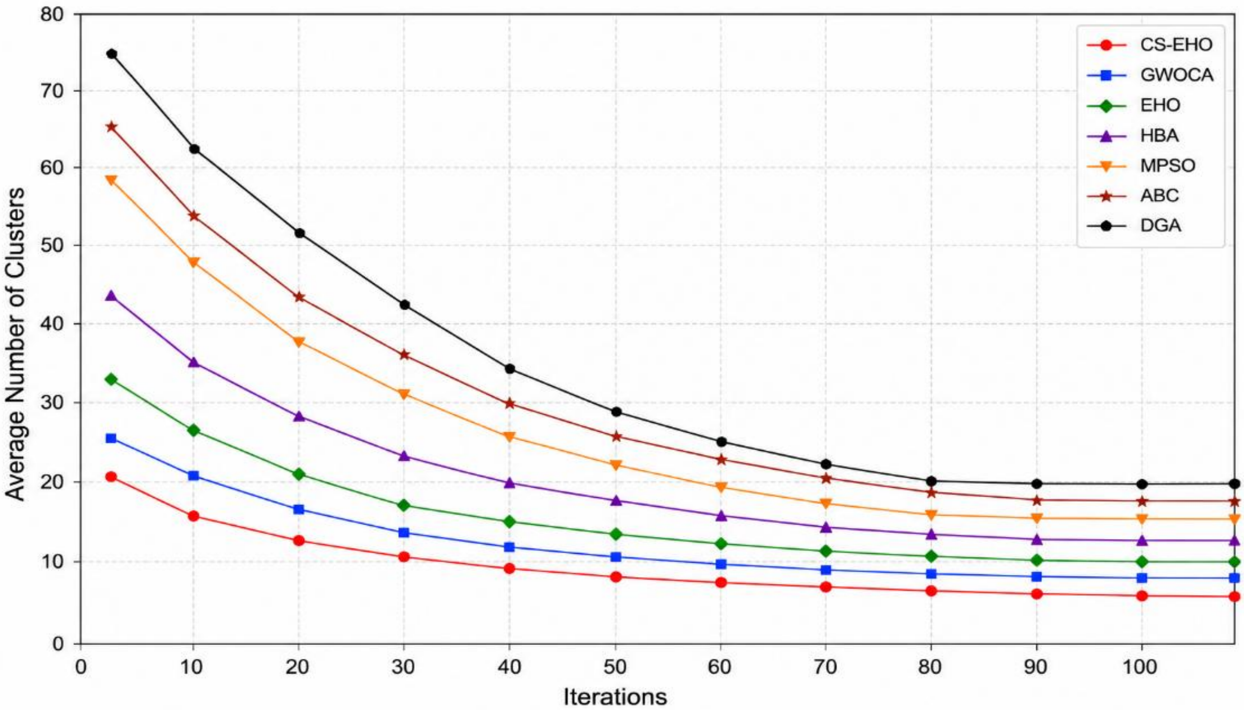

Figure 4. Convergence analysis of the average number of clusters for different algorithms.

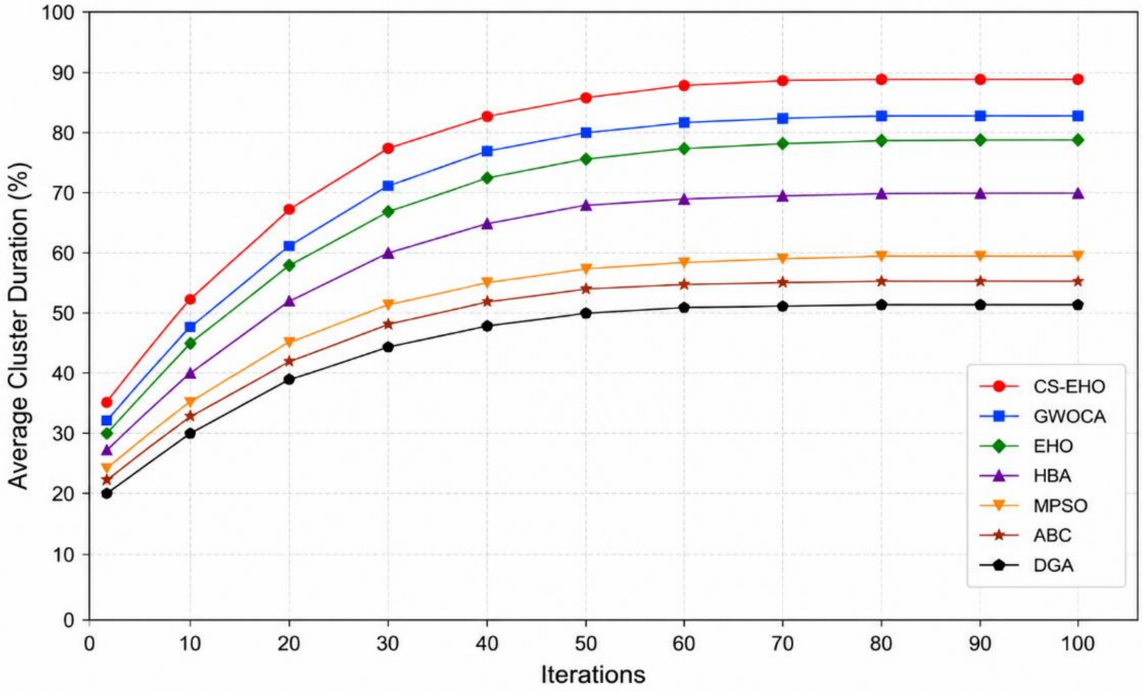

Figure 5. Convergence analysis of the average cluster durations for different algorithms.

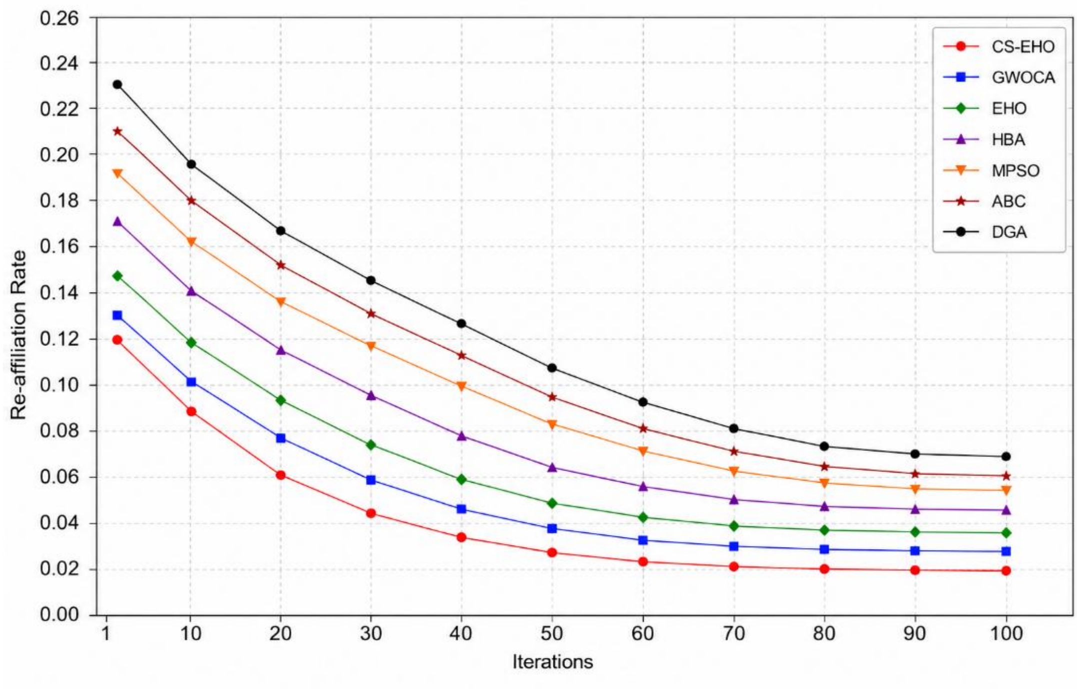

Figure 6. Convergence analysis of the average re-affiliation rate for different algorithms.

Moreover, the convergence pattern shows the ability of CS-EHO to balance global exploration and local exploitation effectively, which contributes to its ability to escape local optima and achieve robust cluster formation under dynamic network conditions. Figure 6 shows the convergence properties of the average re-affiliation rate. The re-affiliation rate decreases quickly in the early iterations and then gradually stabilizes as the search approaches the global optimum. The results show that the proposed CS-EHO algorithm has the lowest re-affiliation rate and the fastest convergence compared with the other algorithms considered. This behavior demonstrates the effectiveness of the proposed fitness-driven cluster-head selection strategy in minimizing node migration between clusters. A low re-affiliation rate indicates better cluster stability, lower topology fluctuations, lower signaling overhead, and better adaptability to node mobility. All these are important requirements in highly dynamic MANET environments.

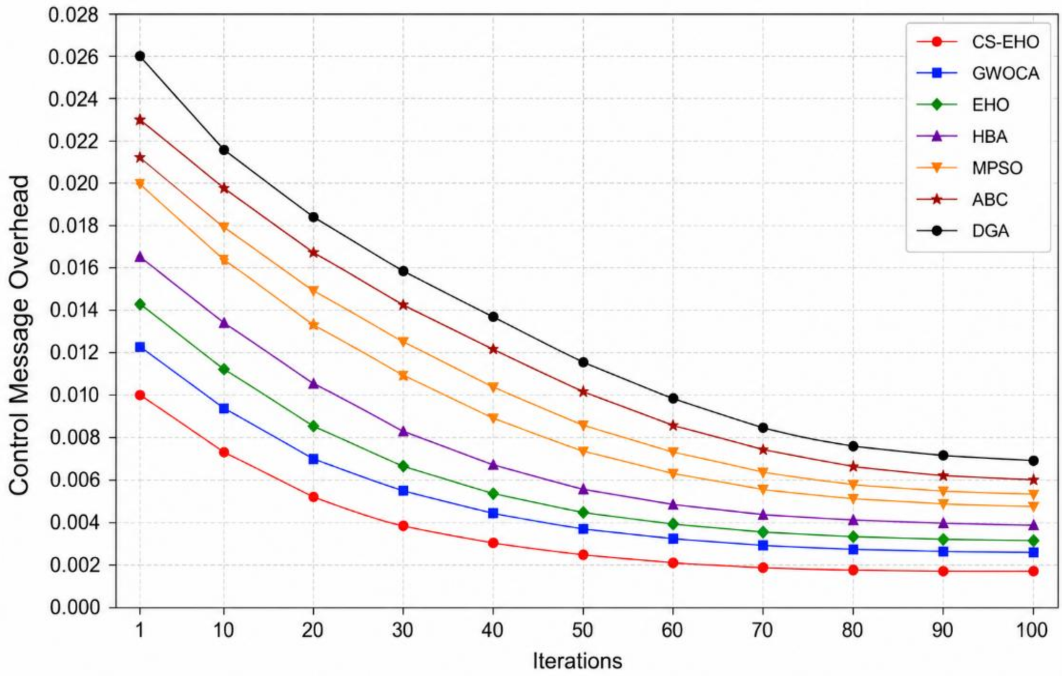

Figure 7. Convergence analysis of the control message overhead for different algorithms.

Figure 7 presents the convergence behavior of control message overhead. The overhead values decrease consistently throughout the optimization process and eventually stabilize after approximately 80 iterations. The proposed CS-EHO algorithm achieves the minimum control overhead compared with GWOCA, EHO, HBA, MPSO, ABC, and DGA. The reduced overhead reflects efficient cluster maintenance, fewer cluster reconfiguration messages, and lower communication costs. Furthermore, the fast convergence implies that the proposed algorithm not only efficiently reduces routing control traffic but also preserves clustering efficiency and network connectivity.

From an optimization perspective, the convergence profiles indicate that CS-EHO has better search ability, a stronger capacity to maintain population diversity, higher convergence accuracy, and a greater ability to avoid local optima. Chaos-assisted initialization promotes exploration through greater search-space diversification, while the exploitation mechanism speeds up local refinement around promising solutions. Therefore, the proposed CS-EHO achieves a good balance between exploration and exploitation, leading to faster convergence, better solution quality, and higher robustness than the benchmark algorithms. The convergence analysis demonstrates the effectiveness of the proposed CS-EHO algorithm for cluster-head selection in MANETs. The algorithm consistently converges to globally competitive solutions, minimizing the number of clusters, re-affiliation rate, and control message overhead while maximizing cluster duration. These results demonstrate the scalability, stability, and optimization efficiency of the proposed clustering framework under different network environments.

5.4 Comparison with State-of-the-Art Methods

The proposed CS-EHO algorithm was compared with six representative clustering methods: GWOCA [16], EHO [38], ABC [45], DGA [39], MPSO [7], and HBA [40]. While these methods have been proven effective for CH selection in MANETs, they have inherent limitations in clustering stability, scalability, and communication efficiency under highly dynamic network conditions. GWOCA uses the hunting behavior and social dominance of grey wolves to find suitable CHs. Its main advantage is good global search capability and relatively fast convergence. However, it relies heavily on the leader wolves (alpha, beta, and delta), which may lead to premature convergence and reduced solution diversity in large-scale MANETs. As node mobility increases, GWOCA has difficulty maintaining stable cluster structures, which increases cluster reformation and control overhead. CS-EHO addresses these drawbacks through chaotic initialization, which greatly enhances population diversity and prevents the search procedure from becoming trapped in local optima. EHO is inspired by the clan-updating and separating behaviors of elephant herds. In the early stage of optimization, EHO offers a simple structure and good exploration capability. However, the exploitation ability of the standard EHO is relatively weak, leading to slow convergence and suboptimal cluster-head selection. As a result, high-mobility environments lead to poor cluster stability. CS-EHO addresses this limitation by using simplex-based local search, which enhances exploitation efficiency and allows more accurate refinement of candidate cluster-head solutions.

HBA has good exploration ability because of its digging and honey-searching mechanisms. The algorithm can escape from local optima effectively during the search process. However, excessive exploration may degrade convergence stability and generate unstable cluster-head assignments in MANETs. This results in more cluster-maintenance operations and reduced cluster lifetime. In contrast, CS-EHO achieves a better balance between exploration and exploitation, which ensures stable cluster-head selection while maintaining strong global search capability. MPSO has fast convergence and lower computational complexity. The information-sharing mechanism between particles enables efficient optimization in the early stages of the search. However, as the iterations proceed, MPSO suffers from premature convergence and loss of diversity. This problem is exacerbated in dense MANETs, where optimal cluster-head positions vary continuously because of node mobility. CS-EHO uses chaotic population generation and simplex refinement to adapt continuously to the dynamic network environment, thereby mitigating this problem.

ABC is based on the foraging behavior of employed bees, onlooker bees, and scout bees to explore the solution space. ABC is known for its robustness and simplicity. However, high-quality solutions are often obtained only after many iterations, which can increase computational overhead and reduce responsiveness in fast-changing MANET environments. Additionally, clustering decisions may be unstable because of the random scout-bee phase. CS-EHO overcomes these weaknesses by accelerating convergence through simplex-based local optimization while preserving adequate search diversity through chaos theory. DGA uses adaptive genetic operations such as selection, crossover, and mutation to search for optimal cluster-head configurations. DGA has strong global optimization capability and the ability to adapt to changing environments. However, genetic operations generally increase computational complexity and may produce unstable solutions because of the excessive randomness of crossover and mutation processes. Furthermore, DGA may require many generations to converge to near-optimal solutions. CS-EHO improves optimization efficiency by avoiding unnecessary random operations and narrowing the search to promising areas through chaotic exploration and simplex exploitation. The superior performance of CS-EHO is attributed to the complementary combination of chaos theory and simplex-based local search in the EHO framework. Chaotic initialization enhances population diversity and improves exploration by distributing candidate solutions more uniformly across the search space. This prevents premature convergence and increases the chances of finding good cluster-head configurations. The promising solutions are then further refined by simplex-based local search, which improves exploitation capability and accelerates convergence toward optimal cluster structures.

Thus, CS-EHO consistently produces fewer clusters, longer cluster durations, lower re-affiliation rates, and lower control-message overhead than GWOCA [16], EHO [38], ABC [45], DGA [39], MPSO [7], and HBA [40]. The experimental results show that CS-EHO reduces the number of clusters by up to 74.51%, improves cluster lifetime by 163.33%, reduces the re-affiliation rate by 83.79%, and reduces control overhead by 84.88%. These improvements demonstrate the effectiveness of CS-EHO in overcoming the exploration-exploitation imbalance, premature convergence, unstable cluster formation, and high maintenance overhead of existing clustering algorithms. Thus, the proposed CS-EHO framework offers a more reliable, scalable, and efficient clustering solution for highly dynamic MANET environments.

6. Conclusion

A highly effective cluster head selection algorithm was described in this paper in relation to MANETs, which is based on the improved EHO algorithm combined with the Chaos Theory and the Simplex method. The suggested hybrid framework was aimed at overcoming the drawbacks of traditional clustering algorithms and usual metaheuristic methods, especially in regard to the early convergence, low population diversity, volatile cluster formation, and unbalanced energy usage. The proposed method enhanced exploration performance by introducing chaotic population initialisation, which promoted a good spread of candidate solutions throughout the search space. Local search mechanism integrated with Simplex enhanced the exploitation stage so that the promising cluster head configurations could be optimized and refined. The outcomes of the simulation have proved that the suggested Chaos-Simplex improved EHO has a noticeable advantage over traditional and standard metaheuristic-based clustering techniques. All these have a direct impact on the increased stability of the network and network life. In general, the hybrid optimization framework that is proposed offers a powerful, scalable, and efficient approach to cluster head selection in MANETs.

The proposed CS- EHO algorithm for cluster head selection in MANETs has shown promising performance, but some limitations still exist. Firstly, the performance assessment was restricted to clustering-related metrics such as cluster lifetime, number of clusters, re-affiliation rate, and control overhead. Network-level performance metrics such as residual energy, PDR, throughput, E2ED, and cluster-head reselection frequency are not considered. The proposed method has been validated in a specific simulation environment and network setup. Further study is required to evaluate its performance in highly dynamic mobility patterns, heterogeneous node capabilities, varying traffic load, and large-scale MANET deployments.

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Authors Contribution Statement

S. Usha Devi: Conceptualization, Methodology, Validation, Data curation, Formal analysis, Writing – Original manuscript. K. Preetha: Formal analysis, Writing – review & editing. Both the authors read and approved the final version of this manuscript.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

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