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Balancing and Optimizing Network Parameters Using a Multi-Objective Hippopotamus Optimization Algorithm for Cluster-Based Routing in MANETs

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Abstract – Mobile Ad-Hoc Network (MANET) is a wireless network, which are connected in a self-healing and self-configured manner without any fixed infrastructure. One of the main challenges in MANETs is the development of an efficient Clustering and Routing Algorithm (CRA) that can select Cluster Heads (CH) and paths based on performance metrics related to node or path qualities. Various CRAs have been developed using metaheuristic algorithms like Grey Wolf Optimization (GWO), Ant Colony Optimization (ACO), etc. However, most of these algorithms focus on a single objective to improve clustering and routing performance based on specific metrics like delay or energy usage. Hence, this manuscript introduces a novel Multi-Objective Hippopotamus Optimization Algorithm-based CRA (MOHOA-CRA) for MANETs. This algorithm aims to address the challenges of efficient CH selection and optimal path determination in dynamic MANET environments. It considers multiple factors such as node density, energy consumption, mobility and hop count to optimize network performance. It executes two main phases: optimal CH selection and path selection, both leveraging the capabilities of the HOA. Extensive simulations comparing MOHOA-CRA with existing algorithms demonstrate its superior performance across various metrics including energy consumption, Normalized Routing Load (NRL), throughput, End-to-End Delay (E2D), and packet loss. The results show significant improvements, especially in networks with high node counts. For example, in a network with 1000 nodes, MOHOA-CRA achieves a mean energy consumption of 15.4%, NRL of 60, throughput of 131 Kbps, mean E2D of 200 ms, and packet loss of 8.5%, outperforming existing algorithms.

Index Terms – MANET, CH Selection, Path Selection, Metaheuristic Algorithm, Multi-Objective, Hippopotamus Optimization Algorithm.

1. INTRODUCTION

MANETs are self-sufficient networks of wireless devices that function independently of centralized control points like Base Stations (BS). These networks operate in a decentralized manner where individual nodes communicate directly with each other in a multi-hop fashion [1]. Though MANETs are vital in several applications like military, agriculture, etc., there are still numerous considerable issues regarding movement, performance, efficiency and routing [2-3]. To combat these issues various routing strategies have been devised including proactive, reactive and hybrid approaches [4].

On the other hand, the mobility of mobile nodes poses a significant challenge for proactive routing protocols. The constantly varying network topology due to node mobility requires routing protocols to have mechanisms in place to mitigate the impact on the routing process. Additionally, the movement of nodes suffers from potential communication disruptions and packet loss, further complicating the routing task, especially in applications where uninterrupted communication is crucial [5]. Reactive protocols address the limitations of proactive protocols by only maintaining active traffic data. Pathfinding is initiated upon request when a node requires to send data to a specific destination. If the node does not have an active route, it broadcasts request packets [6].

The Ad-hoc On-demand Distance Vector (AODV) is a reactive routing protocol frequently employed in MANETs due to its simple flooding mechanism, which can lead to broadcast storms and excessive redundant traffic in densely populated network areas. This can overload network resources, causing issues such as packet loss, latency, and low throughput [7-8]. While AODV saves energy by only performing routing operations, when necessary, it lacks native energy awareness and mechanisms to prevent excessive energy consumption. Additionally, it may not be easily

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customizable to optimize energy usage or throughput for specific applications.

To overcome the challenges faced by AODV in MANETs, various versions of the AODV routing protocol have been developed incorporating metaheuristic optimization schemes. For instance, Sarkar et al. [9] introduced an Enhanced-Ant-AODV routing protocol that integrates ACO to improve QoS in MANETs. They selected the optimal data transfer route depending on the pheromone route value which was determined by factors such as end-to-end reliability, congestion, hop count and remaining node energy along the route. The route with the highest pheromone value was chosen for data transfer. However, additional QoS parameters such as available bandwidth and node density were required to select a more robust path. To address this limitation, Safari et al. [10] proposed a Cross-Layer Adaptive Fuzzy (CLAF) based AODV (CLAF-AODV) routing protocol for MANETs. They employed a 2-stage Fuzzy Logic (FL) approach and cross-layer design technique to identify nodes that are more likely to participate in broadcasting, considering factors such as performance (data throughput, waiting time), reliability (device power, signal quality) and flexibility to network size. These studies used a single-objective algorithm to enhance the routing performance of AODV based on a specific metric. While these protocols enable AODV customization by choosing various performance indicators, it limits optimization to a single metric, such as delay or energy usage. The main objective of this paper is improving the cluster stability and route selection for obtaining better QoS metrics by proposing a new optimization algorithm with additional metrics which decides optimal size of the clusters, optimal CH selection and efficient path selection through inter cluster formation for efficient transmission of packets.

1.1. Key Contributions

This manuscript introduces a novel multi-objective CRA based on the HOA to improve the performance of MANETs. The study consists of two main phases: (i) Optimal CH selection and (ii) Path selection. The selection process considers factors such as neighborhood degree, energy consumption, mobility, and hop count of each mobile node in the network. Initially, optimal CHs are selected, and Hello messages are broadcasted to neighboring nodes within their communication range to form clusters. Subsequently, the best routing path is determined by the MOHOA based on the specified factors. Then, the information is transmitted along the route through selected path, aiming to achieve multiple objectives such as higher throughput, lower NRL, reduced packet loss, lower energy consumption, and minimum E2D.

The following sections are structures in the following manner. Section 2 explores existing studies. Section 3 explains the proposed protocol, and Section 4 showcases its effectiveness. Section 5 provides a summary of the findings and indicates possible future directions.

2. LITERATURE SURVEY

The use of new and improved metaheuristic approaches in CRAs for MANETs shows promise in reducing energy depletion and extending lifespan. This section reviews some of the latest CRAs for MANETs. Jegadeesan et al. [10] introduced a Reliable Fuzzy based Cross-Layer Route Selection method for adaptable data transmission in MANETs. They determined the most efficient shortest route by managing data archiving incongruities through queue storage.

Sugitha et al. [11] introduced a clustering technique for ad hoc networks using a Robust Spatial Gabriel Graph (RS-GG). They clustered primary and secondary users based on network theory and predicted weighted delays to identify adjacent nodes within each cluster. Data transfer routes were established if multi-route decision-making criteria were met An Adaptive Mobility-Aware Clustering (AMAC) based on the hybrid Artificial Bee Colony with Particle Swarm Optimization (ABC-PSO) [12] was presented to select CHs and ensure network longevity in MANETs. The mobility of nodes was considered in selecting inter-CH for data transfer by finding the next closest node.

Tawfeeq [13] proposed a new method for selecting CHs in MANETs to improve network efficiency using Connectivity Probability (CP) calculated from the Poisson probability and residual energy of each node. The Poisson distribution, determined by a parameter lambda, predicts the likelihood of an event. Lambda represents the average distance between a node and the BS within their communication range. By multiplying lambda and residual energy, CP was calculated to identify nodes with the highest CP values for CH selection. However, the throughput was low and packet loss was high since the mobility factors were not encountered during CH and path selection. Khudair Madhloom et al. [14] introduced the quantum-inspired ACO algorithm for MANETs to optimize gateways and form new routes. They integrated Grover's amplitude amplification and time-driven quantum evolution to encode routes through continuous updates to the pheromone distribution.

Rajeshkumar et al. [15] suggested an enhanced Multi-Objective PSO (MOPSO) algorithm for MANETs to optimize the number of clustered MANETs and minimize energy loss in nodes. Arulprakrash et al. [16] developed an Energy-efficient Modified African Vulture and Modified Mayfly (E-MAVMMF) method for MANETs. This approach employed a two-tiered system: CH selection utilizing a modified African Vulture Optimization Algorithm (AVOA) incorporating Brownian movement and optimal route selection utilizing a Modified Mayfly Algorithm (MMF) augmented with a refined mutation phase inspired by the Symbiotic Organism Search (SOS) algorithm.

Reka et al. [17] developed an efficient energy management clustering technique using Enhanced Chicken Swarm Optimization with Adaptive Position Routing Protocol (ECSO-APRP) for MANETs. The ECSO algorithm was used to form clusters and select cluster heads (CHs), followed by APRP implementation on CHs to reduce transmissions using network coding. Saravanan et al. [18] developed a Modified K-Means Philippine Eagle (MKMPE) optimization for secure routing in MANET. It selects primary CHs based on node trust values using modified K-means scheme. After that, it uses Philippine eagle optimization to find energy-efficient and secure data transfer routes.

Patil and Kohle [19] introduced the Cluster-based Genetic Routing Protocol (CGRP) for time-sensitive WSNs. The mutation operator was employed to determine the optimal position for carrying genetic information across chromosomes, hence lowering routing costs. Hu et al. [20] proposed the CHHFO protocol, which combines FL with the collaborative Harris Hawks Optimization (HHO) strategy for improving network longevity. The FL system considers factors like residual energy, proximity to the central BS and neighboring node count to choose the best CHs. The collaborative Harris Hawks optimization uses innovative coding schemes to select the ideal relay CH for data transmission. Table 1 provides a summary of the studies discussed above, outlining the methodology employed as well as the advantages and disadvantages.

Table 1 Summary of Related Works

Ref. No.	Methodology Used	Advantages	Disadvantages
[10]	Reliable Fuzzy based Cross-Layer Route Selection	Higher queuing storage	Due to inadequate path maintenance, significant packet loss persisted, hindering effective data transmission.
[11]	RS-GG	Good E2D	Throughput low when multi-route decision-making criteria were met
[12]	ABC-PSO	Better PDR	High delay and energy consumption.
[13]	CP for cluster selection	Better energy utilization	Low throughput and high packet loss
[14]	Quantum-inspired ACO	High Throughput.	High Energy consumption
[15]	MOPSO	Minimize energy loss	Throughput remained low
[16]	E-MAVMMF	Optimal route selection	Throughput low for high mobility
[17]	ECSO-APRP	Reduce retransmission	High mean E2D
[18]	MKMPE	Energy efficient	Throughput was found low
[19]	CGRP	Lowering routing cost	Latency is high
[20]	HHO	High throughput	More energy consumption

2.1. Research Gap

Current methods for CRA in MANETs often use single-objective optimization algorithms, which can limit their effectiveness in addressing multiple critical network performance metrics simultaneously. While these algorithms can optimize for specific parameters like energy usage, delay, or throughput, they do not consider the complex interactions between different network characteristics. This single-objective approach may result in suboptimal network performance, as improvements in one factor may come at the expense of others. To tackle this challenge, multi-objective optimization techniques are needed to balance and optimize multiple network parameters concurrently, offering a more comprehensive approach to MANET clustering and routing.

3. PROPOSED METHODOLOGY

This section offers an in-depth explanation of the proposed methodology in MANETs. A visual representation of the study can be found in Figure 1. Initially, CHs are selected from the mobile nodes using the HOA. The selection process considers multiple objective factors such as node density, energy consumption, node mobility, and hop count to choose the best CHs. Once the CHs are chosen, they broadcast HELLO messages to neighbor nodes within their transmission range and form clusters based on received acknowledgements (ACKs). Additionally, a path search and optimal path selection phase is included to find stable routes for reliable data transmission. Finally, the algorithm's performance is

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evaluated in terms of throughput, energy efficiency, NRL, delay, and packet loss.

3.1. Preliminaries

3.1.1. Network Model

In MANET, data is transferred between mobile nodes as portrayed in Figure 2. The MANET network model can be represented as a graph $G = (V, E)$, where V denotes mobile nodes and E denotes the connections between them. The node set is represented as $V = \{x_1, \dots, x_m, \dots, x_n\}; 1 \leq m \leq n$, where n is the overall nodes. The set of connections is denoted as $E = \{l_1, \dots, l_z\}$, where z is the overall connection used to connect two nodes. The MANET network is constructed by considering metrics like power, number of transmissions and retransmissions, and the total quantity of adjacent nodes.

Consider the following scenario: source node S sends data segments to the designated node D. The set of CHs is denoted as $C = \{c_1, \dots, c_r, \dots, c_v\}; 1 \leq r \leq v$, where v is the overall CHs. Additionally, the set of paths between S and D is represented as $P = \{p_1, \dots, p_u\}$, where u is the count of available paths between S and D. Each segment is transferred by the nodes in a queuing manner and every data segment has a fixed capacity.

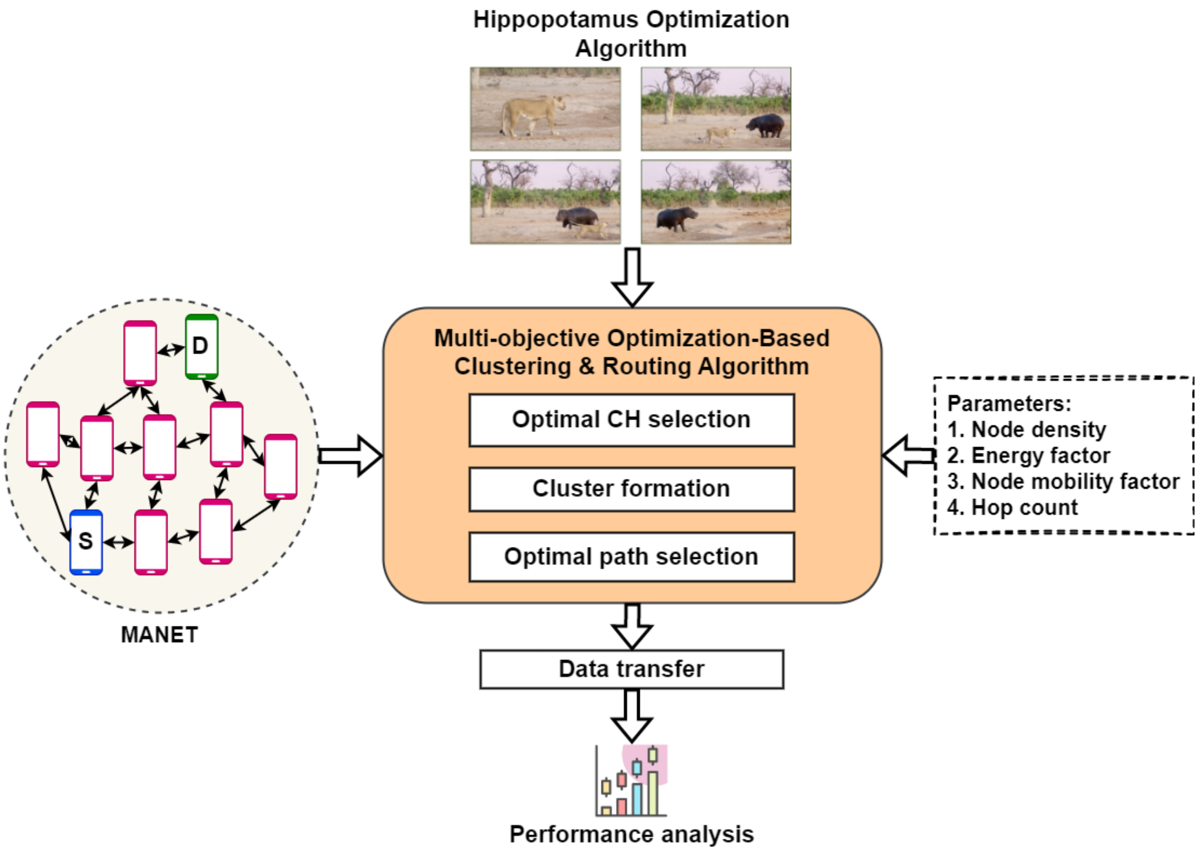

Figure 1 Diagrammatic Representation of the Proposed Study

The process of selecting the optimal CH and route for data transmission is explained below. Each node consumes a significant amount of power to transmit packets. To address this issue, an energy and mobility-aware reliable CH and path selection method is employed.

3.1.2. Hippopotamus Optimization Algorithm

The hippopotamus is a fascinating mammal found in Africa, known for its semi-aquatic lifestyle in rivers and ponds. They live in social groups called pods or bloats, with 10-30 members. Adult hippos can stay underwater for up to 5 minutes and are herbivores, mainly eating grass and plants. They are one of the most dangerous mammals due to their powerful jaws and aggressive behavior. Male hippopotamuses can reach a staggering weight of approximately 4,500 kilograms, dwarfing females who typically weigh around 1,360 kilograms. These herbivores have voracious appetites with females consuming approximately 34 kilograms of vegetation daily. They defend themselves from predators by opening their jaws and emitting a loud vocalization. When threatened, they can retreat at 30 km/hr speed to water bodies for safety.

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The HOA is inspired by three key behavioral patterns observed in hippopotamuses. These include young hippos' tendency to wander away from the group, defensive responses when under attack, and fleeing from predators by seeking water bodies. Young hippos' curiosity can lead them to wander off and become vulnerable to predators. When threatened, hippos defend themselves by facing predators with their jaws and vocalizations. Predators like lions and hyenas avoid confrontation with hippos due to their powerful jaws. Hippos instinctively flee from danger and seek refuge in water bodies to escape predators.

3.1.2.1. Theoretical Framework of HOA

The HOA, a population-based optimization technique, uses hippopotamuses as search agents to solve optimization problems. Each hippopotamus represents a candidate solution, with its location within the solution space corresponding to decision variable values. The population of hippopotamuses is represented as a matrix. This algorithm starts with random initial solutions generated by,

$$P_i: p_{i,j} = lb_j + rand_{ij} \cdot (ub_j - lb_j), i = 1, \dots, N;\ j = 1, \dots, m \tag{1}$$

In Eq. (1), P_i is the location of the i^{th} candidate solution, $p_{i,j}$ indicates its j^{th} decision variable, N refers to the size of the hippopotamus population, m denotes the amount of decision variables in the problem, $rand_{i,j}$ is the arbitrary value ranging [0,1], lb_j and ub_j define the minimum and maximum margin of the j^{th} decision variable, correspondingly. The hippopotamus population is represented by the population matrix (P) as follows in Eq. (2):

$$P = \begin{bmatrix} P_1 \\ \vdots \\ P_i \\ \vdots \\ P_N \end{bmatrix}_{N\times m} = \begin{bmatrix} p_{1,1} & \cdots & p_{1,j} & \cdots & p_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ p_{i,1} & \cdots & p_{i,j} & \cdots & p_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ p_{N,1} & \cdots & p_{N,j} & \cdots & p_{N,m} \end{bmatrix}_{N\times m} \tag{2}$$

Candidate solutions in decision variables determine the fitness values, as:

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{3}$$

In Eq. (3), F denotes the vector of the obtained fitness value and F_i denotes the fitness value achieved for i^{th} hippopotamus. The optimal solution is the one with the highest fitness value. This best member is updated in each iteration as candidate solutions are updated.

Stage 1 – Exploration (Update of Hippopotamus Location in the River)

Hippopotamus herds consist of adult females, calves, adult males, and a dominant male leader. The dominant male is determined through an objective function based on minimizing or maximizing values. Hippos gather closely together for protection, with dominant males guarding the herd and territory. Females surround the dominant males, and when males reach maturity, they are expelled from the herd. Expelled males must compete for dominance or attract females. Equation (4) represents the positioning of male hippos in the herd's habitat.

$$P_i^{M_{hippo}}: p_{i,j}^{M_{hippo}} = p_{i,j} + rand_1 \times (D_{hippo} - I_1 p_{i,j}), i = 1, \dots, \left[\frac{N}{2}\right]; j = 1, \dots, m \tag{4}$$

$$h = \begin{cases} I_2 \times \overrightarrow{rand}_1 + (\sim Q_1) \\ 2 \times \overrightarrow{rand}_2 - 1 \\ \overrightarrow{rand}_3 \\ I_1 \times \overrightarrow{rand}_4 + (\sim Q_2) \\ rand_5 \end{cases} \tag{5}$$

$$\mathcal{T} = e^{\left(-\frac{t}{T}\right)} \tag{6}$$

$$P_i^{FB_{hippo}}: p_{i,j}^{FB_{hippo}} = \begin{cases} p_{i,j} + h_1 \times (D_{hippo} - I_2 \mu_i), & T > 0.6 \\ \Xi, & Otherwise \end{cases} \tag{7}$$

$$\Xi = \begin{cases} p_{i,j} + h_2 \times (\mu_i - D_{hippo}), & rand_6 > 0.5 \\ lb_j + rand_7 (ub_j - lb_j), & Otherwise \end{cases}, i = 1, \dots, \left[\frac{N}{2}\right]; j = 1, \dots, m \tag{8}$$

In Eqns. (4) – (8), $P_i^{M_{hippo}}$ is male hippopotamus location, D_{hippo} is the dominant hippopotamus position (the hippopotamus with the highest suitability in the current cycle), $rand_1, rand_2, rand_6, rand_7$ are an arbitrary value ranging [0,1], I_1, I_2 are the integer values between 1 and 2. $P_i^{FB_{hippo}}$ is the female or immature hippopotamus location within the herd, $\overrightarrow{rand}_1, \dots, \overrightarrow{rand}_4$ are an arbitrary vector ranging [0,1], t is the current iteration, T represents the maximum number of cycles, μ_i represents the average values of a randomly selected group of hippopotamuses, including an equal chance of selecting the current hippopotamus (P_i), and Q_1, Q_2 are arbitrary integer values that can be one or zero.

Young hippopotamuses typically stay close to their mothers, but their curiosity can sometimes lead them to wander away from the herd. If the value of $\mathcal{T} > 0.6$, it signifies that the young hippopotamus has achieved independence from its parent (as per Eq. (6)). If the value of $rand_6$ exceeds 0.5 (as per Eq. (8)), it indicates that the young hippopotamus has moved away from its mother but is still near the herd or has strayed from the group. Eqns. (7) and (8) simulate the

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behavior of immature and female hippopotamuses. h_1 and h_2 are numbers arbitrarily chosen from the five cases in Eq. (5).

The location update of male, female, or immature hippopotamuses within the herd is defined as follows:

$$P_i = \begin{cases} P_i^{M_{hippo}}, & F_i^{M_{hippo}} < F_i \\ P_i, & Otherwise \end{cases} \tag{9}$$

$$P_i = \begin{cases} P_i^{FB_{hippo}}, & F_i^{FB_{hippo}} < F_i \\ P_i, & Otherwise \end{cases} \tag{10}$$

In Eqns. (9) – (10), F_i is the objective function. Utilizing h vectors in I_1 and I_2 scenarios enhances global search and exploration in the HOA, improving overall performance.

Stage 2 – Exploration (Hippopotamus Defense against Predators)

Hippopotamuses live in herds for safety and security, as their large size can deter predators. However, young or sick hippos may be vulnerable to predators like crocodiles, lions, and hyenas. When threatened, hippos will vocalize loudly and may approach the predator to drive it away. The predator's position in the search space is represented as follows:

$$Predator: Predator_j = lb_j + \overrightarrow{rand}_8 \times (ub_j - lb_j), j = 1, \dots, m \tag{11}$$

In Eq. (11), $\overrightarrow{rand}_8$ is an arbitrary vector ranging between 0 and 1.

$$\vec{D} = \left|Predator_j - p_{i,j}\right| \tag{12}$$

In Eq. (12), $\vec{D}$ denotes the distance between hippopotamus and predator. During this stage, the hippopotamus exhibits defensive tactics based on the factor $F_{Predator_j}$ to safeguard them from predators. If $F_{Predator_j} < F_i$, signifying imminent danger, the hippopotamus swiftly turns toward the predator and advances toward it to deter its approach. If $F_{Predator_j} > F_i$, the hippopotamus exhibits a more restrained turning motion toward the predator, signaling its territorial presence and discouraging further attack.

$$P_i^{hippo_R}: p_{i,j}^{hippo_R} = \begin{cases} \overrightarrow{RL} \oplus Predator_j + \left(\frac{a}{c - d \times \cos(2\pi g)}\right) \times \left(\frac{1}{\vec{D}}\right), & F_{Predator_j} < F_i \\ \overrightarrow{RL} \oplus Predator_j + \left(\frac{a}{c - d \times \cos(2\pi g)}\right) \times \left(\frac{1}{2\vec{D} + \overrightarrow{rand}_9}\right), & F_{Predator_j} \geq F_i \end{cases}$$

$$i = \left[\frac{N}{2}\right] + 1, \left[\frac{N}{2}\right] + 2, \dots, N; j = 1, \dots, m \tag{13}$$

In Eq. (13), $P_i^{hippo_R}$ represents the location of the hippopotamus facing the predator, a refers to the uniform arbitrary number between 2 and 4, c is a uniform arbitrary value between 1 and 1.5, d is a uniform arbitrary number between 2 and 3, g is a uniform arbitrary value between -1 and 1, $\overrightarrow{rand}_9$ represents an arbitrary vector with dimensions $1 \times m$, and $\overrightarrow{RL}$ represents a Levy distribution used for abrupt variations in the location of predator while attacking the hippopotamus. The Levy movement model is defined as follows:

$$\mathcal{L}evy(\vartheta) = 0.05 \times \left(\frac{\omega \times \sigma_\omega}{|v|^{\frac{1}{\vartheta}}}\right) \tag{14}$$

$$\sigma_\omega = \left[\frac{\Gamma(1+\vartheta)\sin\left(\frac{\pi\vartheta}{2}\right)}{\Gamma\left(\frac{(1+\vartheta)}{2}\right)\vartheta 2^{\frac{(\vartheta-1)}{2}}}\right]^{\frac{1}{\vartheta}} \tag{15}$$

In Eqns. (14) & (15), ω and v are the arbitrary numbers in [0,1], respectively, ϑ is a constant ($\vartheta = 1.5$), Γ represents the Gamma function. According to Eq. (16), if $F_i^{hippo_R} \geq F_i$, it implies that a hippopotamus has been lost to predation and will require replacement within the herd. If not, the predator will retreat and the hippopotamus will rejoin the group. The global search process improved significantly in the second stage, complementing the prior stage to avoid local minimum traps.

$$P_i = \begin{cases} P_i^{hippo_R}, & F_i^{hippo_R} < F_i \\ P_i, & F_i^{hippo_R} \geq F_i \end{cases} \tag{16}$$

Stage 3 – Exploitation (Hippopotamus Escaping from the Predator)

When confronted by multiple predators or unable to deter a single threat, a hippopotamus will attempt to evade the situation by retreating to the nearest body of water. Predators such as lions and hyenas generally avoid aquatic environments, providing the hippopotamus with a temporary respite. This behavior is simulated by generating a random location nearby the current location of the hippopotamus, as defined in Eqns. (17) – (20). If the new location enhances the cost function value, it means the hippopotamus reached a more secure location.

$$lb_j^{local} = \frac{lb_j}{t}, ub_j^{local} = \frac{ub_j}{t}, \text{where } t = 1, \dots, T \tag{17}$$

$$P_i^{hippo_E}: p_{i,j}^{hippo_E} = p_{i,j} + rand_{10} \times \left(lb_j^{local} + \tau\left(ub_j^{local} - lb_j^{local}\right)\right), i = 1, \dots, N; j = 1, \dots, m \tag{18}$$

In Eq. (18), $P_i^{hippo_E}$ denotes the location of the hippopotamus searched for the nearest safe place, τ is an arbitrary vector chosen from three scenarios s in Eq. (19).

$$s = \begin{cases} 2 \times \overrightarrow{rand}_{11} - 1 \\ rand_{12} \\ rand_{13} \end{cases} \tag{19}$$

In Eq. (19), $\overrightarrow{rand}_{11}$ is an arbitrary vector between 0 and 1, whereas $rand_{10}$ and $rand_{13}$ are arbitrary numbers created

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within the range of 0 and 1. As well, $rand_{12}$ is a normally distributed arbitrary number in Eq. (20),

$$P_i = \begin{cases} P_i^{hippo_E}, & F_i^{hippo_E} < F_i \\ P_i, & F_i^{hippo_E} \geq F_i \end{cases} \quad (20)$$

Following each cycle of HOA, all individuals within the population are adjusted according to the specified stages. This modification procedure, following Eqns. (4–20), continues until the final iteration. The most promising outcome is consistently monitored and recorded throughout the algorithm's operation. Upon the algorithm's conclusion, the most suitable candidate, (i.e.,) the dominant hippopotamus solution is identified as the optimal solution.

3.2. Determination of Node Factors and Fitness Function for Optimal CH Selection

3.2.1. Node Degree

The neighborhood of a mobile node i (Γ_i) consists of nodes directly connected to it within its communication range (R_i). This defines the degree of node i.

$$\Gamma_i = \{j, such\ that\ d(i,j) < R_i \ \&\ i \neq j\} \quad (21)$$

In Eq. (21), $d(i,j)$ denotes the distance between nodes i and j, which is calculated as:

$$d(i,j) = \sqrt{\left(\mathrm{x}_i - \mathrm{x}_j\right)^2 + \left(\mathrm{y}_i - \mathrm{y}_j\right)^2} \quad (22)$$

In Eq. (22), $(\mathrm{x}_i, \mathrm{y}_i)$ and $(\mathrm{x}_j, \mathrm{y}_j)$ denote the x and y coordinates of nodes i and j, respectively. So, the node degree of a node i (ND_i) represents the cardinality of the set Γ_i in In Eq. (23) as:

$$ND_i = |\Gamma_i| \quad (23)$$

3.2.2. Energy Factors

Energy consumption is a critical factor in selecting efficient CH nodes in MANET. Since nodes in the network operate on battery power, their limited energy reserves must be considered when selecting CH nodes for data transmission. The algorithm proposed in this study is designed to optimize energy usage during transmission and receiving states by utilizing the Coulomb counting technique to estimate the energy levels of nodes. This approach is aimed at enhancing network performance and prolonging the battery endurance of the nodes. To achieve this, energy depletion for each node state, including E_{init}^i, E_{res}^i and $E_{consumed}^i$ is calculated using a common radio energy model. If $E_{init}^i(t)$ is the initial energy of node i at t, then the residual energy of i at time $t+\tau$ $\left(E_{res}^i(t+\tau)\right)$ is calculated as:

$$E_{res}^i(t+\tau) = E_{init}^i(t) - E_{consumed}^i(t+\tau) \quad (24)$$

In Eq. (24), $E_{consumed}^i(t+\tau)$ represents the energy consumption of i over period τ, accounting for broadcast, delivery, control packet transfer, and internal functions. As well, the energy consumption is determined based on circuitry power, packet quantity, and time spent in various states. The energy used by i in a transmission model $\left(E_{TR}^i(t+\tau)\right)$ for sending ꞑ packets can be calculated as:

$$E_{TR}^i(t+\tau) = ꞑ \times P_{TR}^i(t+\tau) \quad (25)$$

In Eq. (25), $P_{TR}^i(t+\tau)$ represents the power consumption for transferring ꞑ data and control packets with adjacent nodes at $t+\tau$. Similarly, the energy consumption of i in reception mode to receive ɱ data and control packets at τ is calculated as:

$$E_{receive}^i(t+\tau) = ɱ \times P_{RX}^i(t+\tau) \quad (26)$$

In Eq. (26), $P_{RX}^i(t+\tau)$ represents the power used by i for control packet exchange and receiving ɱ packets at τ. Nodes also consume energy for internal functions such as processing, monitoring, and data manipulation at τ, denoted as $E_{OP}^i(t+\tau)$. As a result, the total energy consumption of i at τ for transmission, reception, and operation states is calculated as Eq. (27):

$$E_{consumed}^i(t+\tau) = E_{TR}^i(t+\tau) + E_{RX}^i(t+\tau) + E_{OP}^i(t+\tau) \quad (27)$$

Moreover, the residual energy of i at τ is determined as Eq. (28):

$$E_{res}^i(t+\tau) = E_{init}^i(t) - \left\{E_{TR}^i(t+\tau) + E_{RX}^i(t+\tau) + E_{OP}^i(t+\tau)\right\} \quad (28)$$

3.2.3. Mobility Factors

Every node picks a random spot within the simulated area as its target and travels toward it at a steady speed selected from a range between 0 and V_{max}, where V_{max} represents the node's maximum speed. Upon reaching its destination, the node pauses for a period, T_{pause}, before choosing another random location and repeating this cycle until the simulation concludes.

So, the mobility value of each node i is calculated based on its mean relative velocity and mean distance as:

$$M_i = \sqrt{\left(\ln\left(1 - \frac{V_{mean}(i)}{V_{max}(i)}\right)\right)^2 + \frac{d_{mean}(i)}{d_{max}(i)}} \quad (29)$$

In Eq. (29), $V_{max}(i)$ and $d_{max}(i)$ are the maximum velocity and distance of node i, respectively. $V_{mean}(i)$ represents the mean relative velocity of i, which is determined as:

$$V_{mean}(i) = \frac{1}{ND_i}\sum_{j=1, j\neq i}^{ND_i}\left|V_i - V_j\right| \quad (30)$$

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In Eq. (30), V_i and V_j are the velocity of nodes i and j. Additionally, $d_{mean}(i)$ is the mean distance between each node i towards its set of neighbors and calculated by Eq. (31)

$$d_{mean}(i) = \frac{1}{ND_i}\sum_{j=1,j\neq i}^{ND_i}\sqrt{\left(\mathrm{x}_i - \mathrm{x}_j\right)^2 + \left(\mathrm{y}_i - \mathrm{y}_j\right)^2} \quad (31)$$

3.2.4. Hop Count

It represents the quantity of intermediary nodes that data must traverse to journey from a starting point (s) to a target destination (d) within a MANET. It is denoted as $\left(H(s,d)\right)$ and calculated by

$$H(s,d) = N_{path} - 1 \quad (32)$$

In Eq. (32), N_{path} represents the total number of nodes on the specific path.

3.3. MOHOA for CH Selection

The fitness function is designed to optimize energy usage and reduce E2D by considering node density, residual energy, mobility, and number of hops within the cluster. The algorithm selects cluster head nodes based on these factors, expressed as an optimization challenge addressed through the HOA. The fitness function (F_i) for each node i is calculated using a weighted sum rule as follows:

$$F_i = w_1\frac{ND_i}{ND_{max}} + w_2\frac{E_{res}^i}{E_{max}} + w_3\frac{M_i}{M_{max}} + w_4\frac{H(s,d)}{H_{max}} \quad (33)$$

In Eq. (33), w_1, w_2, w_3 and w_4 are the weight values assigned to each factor to balance their importance in CH selection. Also, $ND_{max}, E_{max}, M_{max}$ and H_{max} are normalization factors representing the maximum values of node density, residual energy, mobility, and hop count in the network, respectively. These factors can help achieve multiple objectives like throughput, energy efficiency, routing load, and delay. Figure 2 demonstrates the CH selection process using MOHOA, and Algorithm 1 provides a detailed pseudocode.

Input: n number of mobile nodes and C clusters

Output: Optimal CHs for C clusters

1. Begin
2. Initialize the number of hippopotamus (N), which is equal to n and the maximum iteration (T);
3. Generate the initial location of each hippopotamus using Eq. (1);
4. Calculate the fitness function values of each individual in the initial population based on Eq. (33);
5. $while(t \leq T)$
6. Update dominant hippopotamus location based on fitness function value criteria;
7. $for\left(i = 1{:}\frac{N}{2}\right)$
8. Determine the new place for i^{th} hippopotamus by Eqns. (4) & (7);
9. Update location of the i^{th} hippopotamus by Eqns. (9) & (10);
10. $end\ for$
11. $for\left(i = 1 + \frac{N}{2}{:}N\right)$
12. Create arbitrary location for predators by Eq. (11);
13. Determine the new location for i^{th} hippopotamus by Eq. (13);
14. Update the location of i^{th} hippopotamus by Eq. (16);
15. $end\ for$
16. Compute new limits for decision variables using Eq. (17);
17. $for(i = 1{:}N)$
18. Determine the new location for i^{th} hippopotamus by Eq. (18);
19. Update the location of i^{th} hippopotamus by Eq. (20);
20. $end\ for$
21. Store the optimal candidate solution obtained so far,
22. $end\ while$
23. Return the optimal CH nodes found by HOA
24. End

Algorithm 1 MOHOA for Optimal CH Selection

3.4. MOHOA for Optimal Path Determination

During path creation, the source node sends a route discovery message to find the subsequent intermediary node on the optimal path to the destination. The packet is multicast to neighbors to locate the destination, with the hop count initially set to zero. Intermediate nodes check for duplicate entries in their local table based on the originating address and request ID. If it's a new route, a route confirmation message is transmitted back to the originating node; otherwise, the packet is discarded. The process continues until the route request reaches the destination, which then generates a route confirmation packet. Each node increments the hop count to track the distance from the destination. Nodes check for candidate nodes for the next hop, and if there are multiple candidates, the target destination is regarded as a component of the potential solution. Only nodes with at least one element in the candidate solution can implement the HOA. The potential solution of a node can have multiple elements while neighboring nodes may have fewer. The set of candidate solutions is denoted as $\mathscr{k}$.

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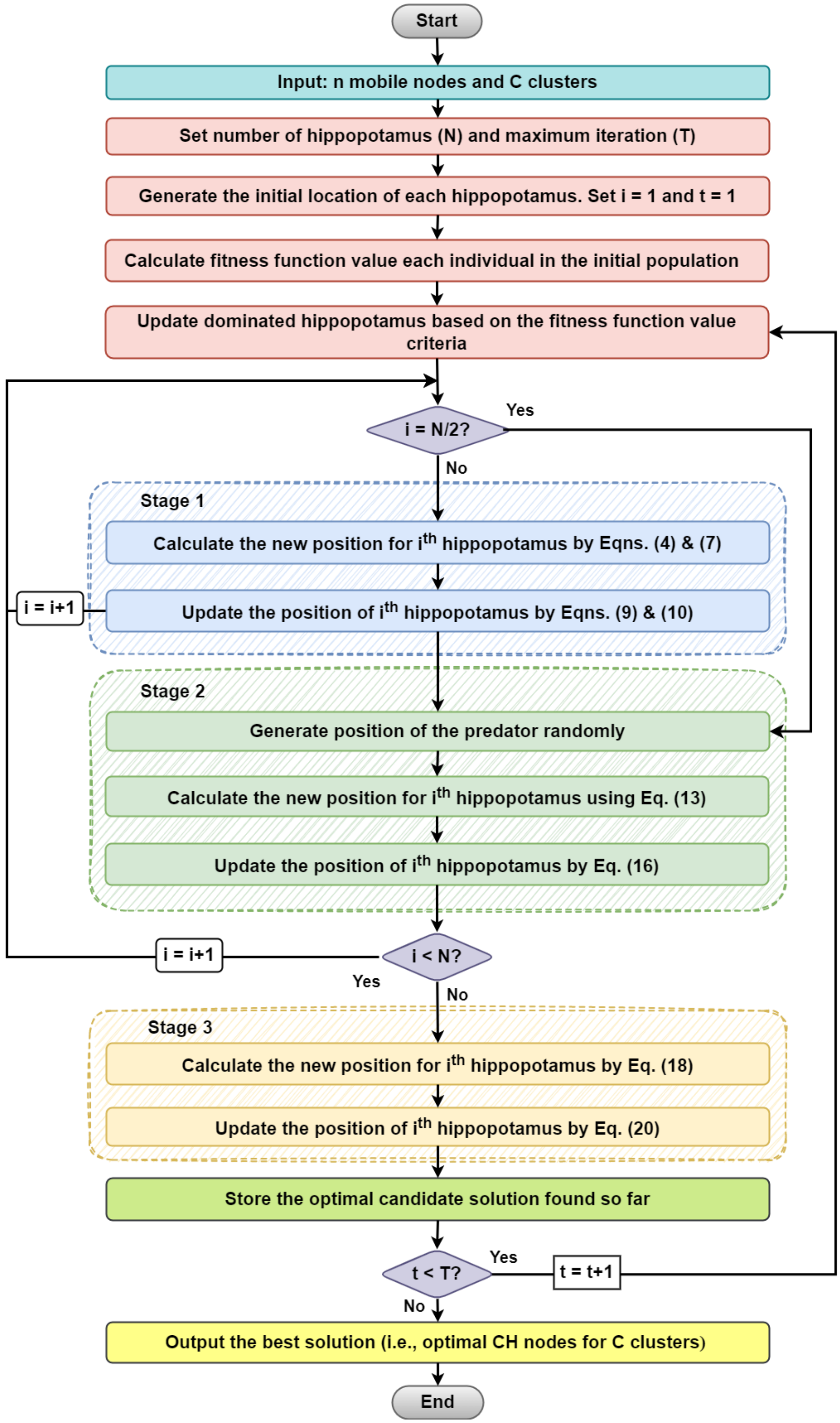

Figure 2 Flow Diagram of MOHOA-Based CH Selection

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Let $(\mathrm{x}_j, \mathrm{y}_j)$ represent the position of the solution of element K_i on the X and Y axes. $(\mathrm{x}_{ij}, \mathrm{y}_{ij})$ represent the coordinates of the chosen subsequent intermediary node on the path to the j^{th} destination node. Each node with candidate solutions selects m random solutions, where $m = N$ is the population size of the HOA. In summary, the main points are:

Throughout the pathfinding process, the originating node generates a route confirmation message that is received by the hops. Each hop has a routing schedule with available routes to the destination. The hop point verifies its routing table for a candidate node as the next hop. Nodes with a candidate node increment a variable and send a route request message to their neighbors. The message includes information on node density, movement rate, number of intermediary nodes and energy status of nearby nodes. This allows each intermediate node to evaluate the usefulness of its candidate solution by Eq. (34)

$$F_{total}(K) = \frac{ND_K}{ND_{max}} + \frac{E_{res}^K}{E_{max}} + \left(1 - \frac{M_K}{M_{max}}\right) + \left(1 - \frac{H(K)}{H_{max}}\right) \quad (34)$$

The best candidate solution is stored in k_{best}. For each candidate solution k_i, the vectors x_i and y_i are computed, followed by the three different stages in HOA. A comprehensive pseudocode outlining the process of identifying the optimal route through the use of HOA is provided in Algorithm 2.

Input: Set of candidate solutions (nodes) $\mathscr{k}$ for each intermediate node

Output: Optimal path from the originating node to the target destination

1. Begin
2. Initialize the number of hippopotamus (N), which is equal to $\mathscr{k}$ and the maximum iteration (T);
3. Generate the initial location of each hippopotamus using Eq. (1);
4. Calculate the fitness function values of each individual in the initial population based on Eq. (34);
5. $while(t \leq T)$
6. Update dominant hippopotamus location based on fitness function value criteria;
7. $for\left(i = 1 : \frac{N}{2}\right)$
8. Determine the new place for i^{th} hippopotamus by Eqns. (4) & (7);
9. Update location of the i^{th} hippopotamus by Eqns. (9) & (10);
10. $end\ for$
11. $for\left(i = 1 + \frac{N}{2} : N\right)$
12. Create arbitrary location for predators by Eq. (11);
13. Determine the new location for i^{th} hippopotamus by Eq. (13);
14. Update the location of i^{th} hippopotamus by Eq. (16);
15. $end\ for$
16. Compute new limits for decision variables using Eq. (17);
17. $for(i = 1 : N)$
18. Determine the new location for i^{th} hippopotamus by Eq. (18);
19. Update the location of i^{th} hippopotamus by Eq. (20);
20. $end\ for$
21. Store the optimal candidate solution obtained so far;
22. $end\ while$
23. Return the optimal route to the destination node found by HOA for data transmission;
24. End

Algorithm 2 MOHOA for Optimal Path Determination

Thus, selecting the best CHs and routing paths can help achieve multiple goals like increased throughput, lower E2D, improved energy efficiency, reduced NRL, and minimized packet loss.

4. SIMULATION RESULTS

This section evaluates the proposed MOHOA-CRA against existing methods like ABC-PSO [12], E-MAVMMF [16], ECSO-APRP [17], and MKMPE [18].

4.1. Simulation Environment

The simulation codes for the proposed and existing algorithms were implemented on a laptop with a 1TB HDD, 4GB RAM, and an Intel® Core™ i5-4210 CPU @ 2.80GHz running Windows 10 64-bit. Python 3.7 software was used for the simulation. Multiple simulation runs were performed for each case with varying parameter values, and the average data from these runs was selected.

Table 2 Simulation Parameters

Parameters	Values
No. of nodes	1400
Node mobility	1 – 5 m/s
Simulation area	1500×1500 m^2

Queue length	30 packets
MAC layer	IEEE 802.11
Traffic class	Constant Bit Rate (CBR)
Packet size	512 bytes
Communication range	220 m
Mean node degree	3 – 5
Mobility model	Random way point
Propagation model	Free space
Channel bandwidth	2 Mbps
Carrier frequency	2.4 GHz
Initial energy	100 J
Transceiver energy	0.6 J
Receiver power	0.35 J
Node pause time	0.5 sec
Simulation period	200 sec

Table 2 presents the network configuration simulation parameters of both existing and proposed algorithms to conduct a fair comparison.

4.2. Mean Energy Consumption

It represents the mean energy utilized by the mobile nodes while simulating. It is determined as follows Eq. (35):

$$E_{mean} = \frac{1}{n}\sum_{i=1}^{n}\left(E_{init}^{i} - E_{res}^{i}\right) \quad (35)$$

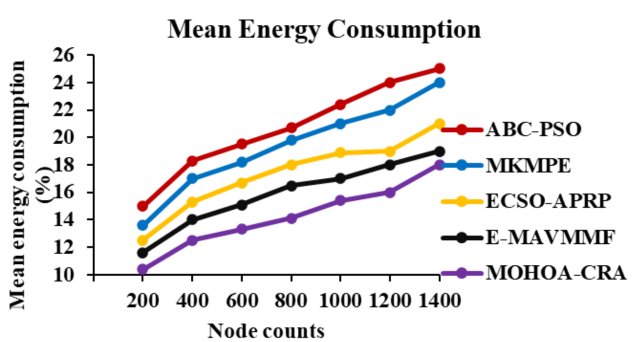

Figure 3 Comparison of Mean Energy Consumption for Different Node Counts

In Eq. (35), E_{init}^{i} is the initial energy of node i, E_{res}^{i} is the residual energy of i at the end of simulation period, and n is the quantity of mobile nodes.

Figure 3 shows the energy consumption of MOHOA-CRA and existing algorithms across various network sizes. MOHOA-CRA demonstrates a notable decrease in energy consumption compared to the other algorithms. For instance, with 1000 nodes, MOHOA-CRA reduces energy consumption by 31.25%, 26.67%, 18.52%, and 9.41% compared to ABC-PSO, MKMPE, ECSO-APRP, and E-MAVMMF, respectively. The reason for energy minimization of the prospeod work is considered energy factors calculated from Eq. (24) to Eq. (28) is utilized in the selection of the path. Because energy factors is the one key, factors for selecting best path through optimization algorithm.

4.3. Normalized Routing Load

It is calculated as the proportion of the total quantity of routing control messages transmitted by each node to the total quantity of data packets received at the target destination.

$$NRL = \frac{\sum RPkt_{TR}}{\sum DPkt_{RX}} \quad (36)$$

In Eq. (36), $RPkt_{TR}$ and $DPkt_{RX}$ are the transmitted control packets and received data packets, respectively.

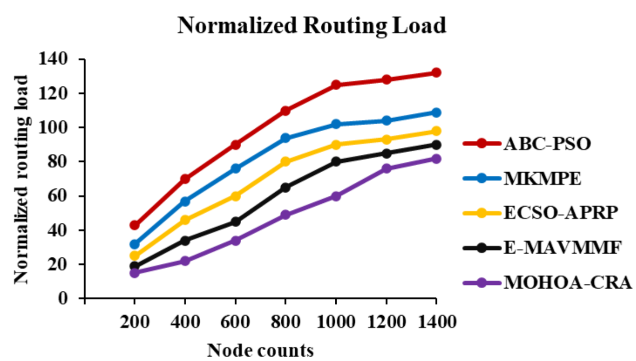

Figure 4 Comparison of NRL for Different Node Counts

Figure 4 plots the NRL of the proposed MOHOA-CRA with existing algorithms across different numbers of nodes. The results show a statistically significant reduction in NRL with the MOHOA-CRA compared to ABC-PSO, MKMPE, ECSO-APRP, and E-MAVMMF. For instance, with 1000 nodes, the average NRL reduction is 52% for MOHOA-CRA compared to ABC-PSO, 41.18% compared to MKMPE, 33.33% compared to ECSO-APRP, and 25% compared to E-MAVMMF. The findings indicate that the proposed algorithm's use of HOA enhances network performance by considering the varying node density to select CH and paths. This leads to effective dynamic transmission decisions in MOHOA-CRA that reduce redundant routing packets. The parameters used considered for mobility factor, node degree and hop count are used to select more stable path. So, that packet transmission is processed in the less overhead nodes. This is the reason for reducing overhead of transmission.

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4.4. Throughput

It quantifies the amount of data successfully transmitted to the target nodes within a specific timeframe. It is measured in kilobits per second (Kbps).

$$Throughput = \frac{byte_{RX} \times 8}{t_{sim} \times 1024} \quad (37)$$

In Eq. (37), $byte_{RX}$ represents the quantity of received bytes and t_{sim} represents the simulation period.

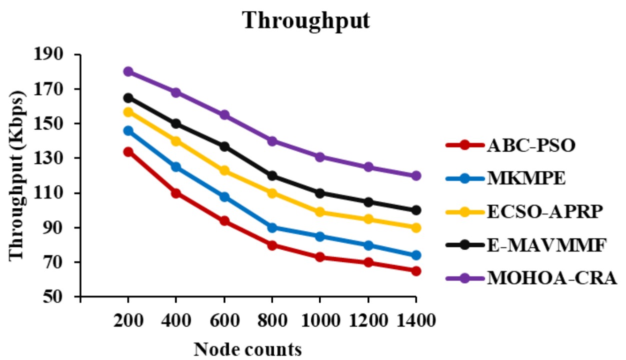

Figure 5 Comparison of Throughput for Different Node Counts

Figure 5 illustrates the mean throughput comparison of MOHOA-CRA and existing algorithms across various network sizes. MOHOA-CRA outperformed the existing algorithms by providing higher throughput levels and observing less significant decreases in data transfer rate as the network scale expanded. For example, with 1000 nodes, MOHOA-CRA achieved throughput increases of up to 79.45%, 54.12%, 32.32%, and 19.09% compared to ABC-PSO, MKMPE, ECSO-APRP, and E-MAVMMF, respectively. The cluster formation and cluster head selection based on HOA algorithm simply relocated every node into a cluster for forming more reliable path through inside and between clusters. Thus, HOA enhance the throughput of network than other existing protocols.

4.5. Mean E2D

It signifies the average duration required for data transmission between the originating node and the target destination.

$$Mean\ E2D = \frac{1}{\rho} \sum (t_{RX} - t_{TR}) \quad (38)$$

In Eq. (38), ρ represents the total amount of packets, t_{TR} is the transmission period of a packet, and t_{RX} is reception period of a packet. Figure 6 portrays the E2D results of MOHOA-CRA compared to other algorithms. MOHOA-CRA consistently outperforms existing algorithms by decreasing the mean E2D for different node counts. For instance, with 1000 nodes, MOHOA-CRA reduces the mean E2D by 21.57%, 16.67%, 12.28%, and 6.54% compared to ABC-PSO, MKMPE, ECSO-APRP, and E-MAVMMF, respectively. Because the proposed work uses the HOA algorithm to provide load balanced routing, there is a reduction in end-to-end latency. The end-to-end delay is improved by HOA, which determines the best route with the least delay using the fitness function. The algorithm's consideration of node density, energy, mobility, and hop count in selecting CHs and routes leads to lower E2D values even when network sizes are grown or shrinks.

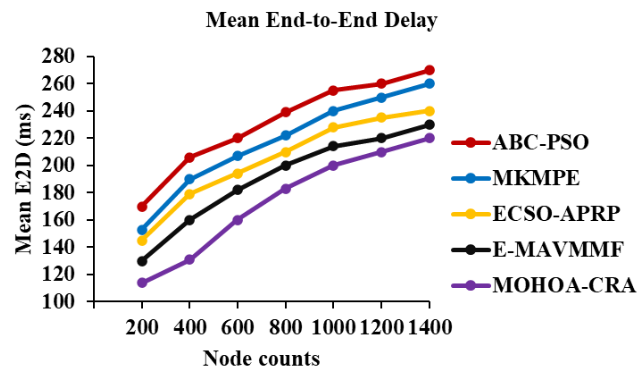

Figure 6 Comparison of Mean E2D for Different Node Counts

4.6. Packet Loss

It is the ratio of data units that were not successfully delivered to the target destinations.

$$Packet\ loss = \frac{\sum Pkt_{TR} - \sum Pkt_{RX}}{\sum Pkt_{TR}} \quad (39)$$

In Eq. (39), Pkt_{TR} and Pkt_{RX} are the number of transmitted and received packets, respectively.

Figure 7 depicts the packet loss results for MOHOA-CRA and existing algorithms across various network sizes. MOHOA-CRA consistently outperforms the existing algorithms for all network sizes. Specifically, in a network with 1000 nodes, MOHOA-CRA reduces packet loss by 26.72%, 20.56%, 15.84%, and 11.46% compared to ABC-PSO, MKMPE, ECSO-APRP, and E-MAVMMF, respectively.

The reduction in redundant broadcast packets leads to significantly fewer lost packets in MOHOA-CRA compared to existing algorithms, with less variation as the network size increases. The HOA algorithm was used for cluster construction and cluster head selection, which merely moved each node into a cluster to create a more dependable path both within and between clusters.

Consequently, HOA outperforms other current protocols in terms of network throughput. Packet loss naturally decreases if throughput increases.

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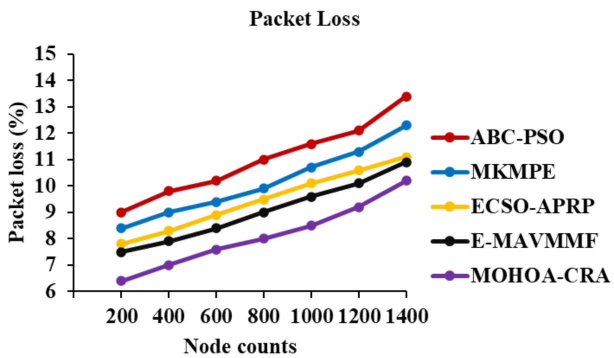

Figure 7 Comparison of Packet Loss for Different Node Counts

5. CONCLUSION

MANETs have various practical examples such as intelligent devices and swarm robotics. The selection of CHs and routing paths are essential for achieving optimal performance in these applications. In this paper, the MOHOA-CRA is developed to address the selection of optimal CHs and paths in MANETs. By considering node density, energy level, mobility, and hop count, the HOA makes informed decisions about optimal CHs and routes. The MOHOA-CRA significantly improves network performance across all metrics. Simulation results illustrate a mean energy consumption of 15.4%, NRL of 60, throughput of 131 Kbps, mean E2D of 200 ms, and packet loss of 8.5% in a network with 1000 nodes compared to existing algorithms. However, the dynamic nature of networks can lead to unpredictable changes in topology and intermittent link failures, resulting in increased packet loss and delay. Future work will focus on developing a link failure prediction algorithm to mitigate these issues. The mathematical molding for the proposed wok will be considered as another future work.

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