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RESEARCH ARTICLE

Quality of Service (QoS) Enhancement in Healthcare Mobile Wireless Sensor Networks Using Adaptable Hummingbird Optimization Based Dynamic Source Routing (AHODSR)

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Abstract – The research introduces MC-DSR-AHO a routing protocol integrating Markov Chain-based Dynamic Source Routing (MC-DSR) with Adaptable Hummingbird Optimization (AHO) for Mobile Wireless Sensor Networks (MWSNs). MWSNs face challenges such as packet loss, latency, limited throughput, and energy inefficiency in dynamic and resource-constrained environments. MC-DSR-AHO addresses these issues by combining the probabilistic modeling of MC-DSR with the adaptive optimization of AHO. This integration results in improved packet delivery reliability, reduced packet drops, efficient data transmission, optimized delays, and energy conservation. Simulations demonstrate the protocol's scalability and consistent performance across varying node counts. This research highlights the effectiveness of utilizing probability modeling and bio-inspired optimization to enhance the adaptability and efficiency of routing protocols in MWSNs. MC-DSR-AHO represents a significant advancement, providing practical benefits and guiding future research in dynamic network environments.

Index Terms – Dynamic Source Routing, Hummingbird Optimization, MWSNs, Routing Protocol, Bio-inspired Optimization, QoS, Healthcare.

1. INTRODUCTION

The intricate technical challenge in Healthcare Mobile Wireless Sensor Networks (H-M-WSN) revolves around ensuring high Quality of Service (QoS) within dynamic healthcare environments. The need for real-time and low-latency data delivery in healthcare applications is paramount, as any disruption or delay in healthcare data transmission can significantly impact patient care and clinical decision-making [1]. Maintaining QoS while scaling the network and adapting to evolving healthcare demands presents a complex dilemma. The expanding number of sensor nodes and the growing scope of healthcare applications increase the complexity of this challenge, requiring sophisticated solutions in network architecture, data prioritization, and resource allocation to uphold QoS standards. The mobility of sensor nodes is a unique facet of H-M-WSNs [2]. Patient monitoring often necessitates sensor repositioning or mobility, which complicates maintaining QoS during these transitions. Ensuring continuous data transmission and QoS as sensors move within healthcare settings is a non-trivial technical issue . Effectively managing interference and congestion within H-M-WSNs is a critical concern. Healthcare environments typically host multiple wireless devices, networks, and potential sources of interference [3], [4]. These networks require advanced interference mitigation techniques and efficient traffic management strategies to maintain consistent QoS. To address the QoS challenge in H-M-WSNs, innovative routing protocols, QoS-aware data transmission mechanisms, and adaptive resource management techniques must be developed and implemented.

1.1. Problem Statement

Ensuring high QoS in H-M-WSNs presents intricate technical challenges. Real-time, low-latency data delivery is crucial for patient care and clinical decision-making. Scaling the network while adapting to evolving healthcare demands complicates QoS maintenance. The motivation is to address the QoS challenge in H-M-WSN is deeply rooted in the critical need to ensure seamless and reliable healthcare data transmission within dynamic healthcare settings. The continual growth of healthcare applications and the deployment of wireless sensors emphasize the need to uphold high QoS standards

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consistently. The mobility of sensor nodes within healthcare facilities adds complexity to the challenge, demanding uninterrupted data transmission and sustained QoS. In healthcare environments characterized by many wireless devices and networks, introducing interference and congestion issues necessitates the development of innovative techniques to mitigate these challenges and ensure a consistent QoS. The ultimate goal is to provide the highest quality of healthcare services, characterized by timely, dependable, and uninterrupted data transmission within a dynamic, scalable, and interference-prone healthcare landscape, with the potential to impact healthcare quality and patient well-being significantly.

The main objective of this research is to develop and implement a bio-inspired optimization-based routing protocol tailored explicitly to address the QoS challenge in H-M-WSN. This specialized routing protocol will draw inspiration from natural systems and uniquely adapt to the demands of dynamic healthcare environments. The critical research objectives encompass the following:

- Design and customize a bio-inspired routing protocol that considers the mobility patterns, resource constraints, and QoS requirements specific to healthcare applications within H-M-WSN.
- Focus on significantly improving QoS within H-M-WSN by minimizing latency, reducing packet loss, and enhancing data reliability. The routing protocol will dynamically adapt routing decisions to meet the real-time QoS demands of critical healthcare applications, ensuring uninterrupted and reliable data transmission.
- Ensure the routing protocol’s adaptability to the mobility of sensor nodes within healthcare environments by implementing efficient handover and re-routing mechanisms. This will guarantee continuous network connectivity and seamless data transmission, even in the presence of mobile nodes within healthcare settings.
- Conduct comprehensive performance evaluations through simulations and real-world experiments within healthcare contexts. Evaluate the routing protocol’s effectiveness in maintaining and enhancing QoS standards, minimizing latency, and reducing data packet loss in dynamic and critical healthcare scenarios.

The article is well-organized and properly structured to provide a comprehensive overview of the research. It starts with Section 1, which presents the introduction, discusses the challenges and issues faced by MWSNs, and discusses the motivation for integrating MC-DSR with AHO. Section 2 reviews related work, covering existing routing protocols and optimization techniques relevant to MWSNs. The description of the proposed MC-DSR-AHO algorithm in detail outlines the integration process and the individual components of MC-DSR and AHO in Section 3. The simulation setup and parameters discussed in Section 4 are used to evaluate the performance of the proposed algorithm. Section 5 holds the results and discussion analyzes performance metrics such as packet delivery ratio, packet drop ratio, throughput, delay, and energy consumption. Section 6 concludes the paper by summarizing the findings and highlighting the advantages of MC-DSR-AHO in enhancing the efficiency and reliability of routing in MWSNs. Finally, the article ends with the references portion.

2. LITERATURE REVIEW

“MRIRS” [5] proposes an innovative method to enhance mobile ad hoc networks by incorporating reflective surfaces, which can bounce signals to improve communication. This approach adds intelligence to conventional mobile ad hoc routing by optimizing network performance. “EAGR” [6] introduces an innovative strategy for monitoring workers in industries. This research focuses on saving energy while efficiently directing information to keep track of the workforce in real-time. The key idea is to use a geographic routing approach that takes the location of workers. “Reliable WBSN” [7]introduces an advanced routing strategy for Wireless Body Sensor Networks. This protocol is designed for multi-hop communication, meaning data can hop through multiple sensor nodes to reach its destination. The QoS awareness ensures that the communication meets specific quality standards, and the PLQE mechanism predicts link quality, helping in making more reliable routing decisions.

“Heterogeneous MSN” [8] addressing challenges in Mobile Sensor Networks (MSN). The protocol tackles the complexities of a diverse network with varying sensor capabilities and intermittent mobile sinks. By strategically routing data in this heterogeneous environment, it optimizes communication efficiency. “EPRS” [9] for Wireless Body Area Networks (WBAN) is tailored for healthcare applications, which enhances the stability of data routes in WBANs using a probabilistic approach. By incorporating probabilistic mechanisms, EPRS adapts dynamically to the changing conditions of the body area network, ultimately optimizing the stability of data routes. Different bio-inspired optimizations are applied in various networks to enhance the performance in terms of energy efficiency [10]–[13].

“BeeRoute” [14], the paper puts forth an energy optimization routing protocol for hierarchical cluster-based Wireless Sensor Networks utilizing the Artificial Bee Colony algorithm. By dynamically adapting routing decisions through the artificial bee colony, the protocol significantly enhances energy optimization in WSNs. BeeRoute’s working mechanism uses artificial bees to intelligently guide data routing within the hierarchical structure, ensuring energy-efficient communication. The key contribution of

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"TrustAntQoS" [15] lies in combining an innovative trust computation approach with a reliable fuzzy and heuristic Ant Colony mechanism. TrustAntQoS's working mechanism involves leveraging energy-based random repeat trust computation to evaluate node reliability, coupled with a fuzzy and heuristic Ant Colony system to optimize data routing for improved QoS. "HeatSink" [16] paper introduces TEO-MCRP, a Thermal Exchange Optimization-based Clustering Routing Protocol with a mobile sink for WSNs. HeatSink's mechanism involves leveraging thermal exchange principles to optimize the selection and movement of a mobile sink, improving overall network performance.

"TrustNet" [17] introduces an optimal cluster and trusted path approach for routing formation and intrusion classification in WSNs. The formation of optimal clusters and the identification of trusted paths are made by combining machine learning for intrusion detection and classification. The protocol ensures reliable and secure routing in WSNs by optimizing cluster formation and leveraging machine learning. "FuzzyElection" [18] introduces E-FLZSEPFCH, an Enhanced Fuzzy Logic Zone Stable Election Protocol for Cluster Head Election and Multipath Routing in WSNs. The distinct contribution lies in incorporating enhanced fuzzy logic for stable cluster head election and implementing multipath routing strategies. Its working mechanism involves refining the stable election protocol using enhanced fuzzy logic, ensuring robust cluster head selection. "OptiCluster" [19] is a paper that presents a novel hybrid optimization for a cluster-based routing protocol in information-centered wireless sensor networks (IC-WSNs). It comprises a synergistic blend of optimization methods, combining the strengths of different algorithms to enhance the efficiency of cluster-based routing. The protocol optimizes data transfer and processing by adapting to the unique demands of IC-WSNs for IoT-based Mobile Edge Computing (MEC). "EcoDist" [20] a Modified Distance-Based Energy-Aware (mDBEA) Routing Protocol. The working mechanism involves dynamically adjusting routing decisions based on distance metrics, effectively minimizing energy consumption. By incorporating modifications, the protocol ensures a more adaptive and efficient approach to energy-aware routing.

"TrustEcoRoute" [21] is an Energy-Aware Trust and Opportunity-Based Routing Algorithm for WSNs utilizing the Multipath Routes Technique. The essential contribution lies in integrating trust-aware and energy-aware mechanisms into the routing algorithm. Dynamic assessment of trust levels among sensor nodes and identification of energy-efficient routes through multipath techniques are the working mechanisms of the protocol. "CentroMove" [22] is a Centroid-Based Routing Protocol with a Moving Sink Node designed to address uniform and non-uniform distribution challenges in WSNs. Its working mechanism involves dynamically calculating centroids to guide data routing and optimize energy efficiency. The moving sink node strategically collects data, adapting to the spatial distribution of sensor nodes. "MothWolf" [23] working mechanism involves leveraging the unique characteristics of moths and grey wolves to optimize cluster-based routing. It, coupled with the customized Grey Wolf Optimization, ensures dynamic adaptation and efficient energy utilization in WSNs. By incorporating artificial electric field principles, the protocol intelligently guides the formation of energy-efficient clusters.

"MERT" [24] introduces MOCRAW, a Routing Algorithm for WSNs that optimizes cluster head selection through meta-heuristic methods. The algorithm's distinct contribution is evident in its use of meta-heuristic optimization techniques, dynamically choosing cluster heads to enhance overall network efficiency. MetaCluster's mechanism involves the integration of meta-heuristic algorithms, facilitating adaptive and robust cluster formation, ultimately refining the routing performance in WSNs. This innovative approach marks a significant stride in optimizing the selection process of cluster heads, showcasing the potential for improved efficiency and adaptability in wireless sensor network routing strategies.

"ECOG" [25] the paper introduces MOCRAW, an innovative WSNs routing algorithm. Its primary innovation centres around a meta-heuristic optimized cluster head selection mechanism. MetaRoute employs sophisticated meta-heuristic algorithms to select cluster heads dynamically, optimizing overall network performance. The operational mechanism revolves around utilizing meta-heuristic optimization techniques to choose cluster heads adaptively, considering factors like energy efficiency and network connectivity. This strategy enhances overall efficiency and extends the network's lifespan by ensuring a balanced distribution of energy consumption. Table 1 illustrates the comparison of the related work and projects, as well as the merits and demerits of the related existing works.

Table 1 Comparison of Related Literature

State-of-the-Art Algorithms	Merits	Demerits
MRIRS [5]	It Optimizes mobile ad hoc routing with intelligent reflecting surfaces.	Implementation complexity and adaptability challenges may arise in diverse mobile environments.

EAGR [6]	It Optimizes energy for real-time monitoring through efficient geographic routing.	Limited adaptability to dynamic conditions may affect reliability.
Reliable WBSN [7]	Enhances reliability through a multi-hop QoS-aware protocol with predicting link quality estimation	Complexity in implementing QoS metrics may impact adaptability.
Heterogeneous MSN [8]	Introduces adaptability to intermittent mobile sinks, enhancing routing efficiency.	Challenges may arise in managing heterogeneity, affecting protocol scalability.
EPRS [9]	Enhances route stability in WBANs and optimizes reliability.	Enhanced probabilistic mechanisms might introduce computational overhead, impacting real-time responsiveness.
BeeRoute [14]	Hierarchical clustering using artificial bee colonies optimizes energy consumption in WSNs	Computational complexities potentially impact real-time performance.
TrustAntQoS [15]	Trust computation approach coupled with a reliable fuzzy and heuristic ant colony mechanism enhances Quality of Service.	It might introduce computational overhead.
HeatSink [16]	Optimizes thermal conditions and contributes to energy-efficient routing.	They are impacting the protocol’s scalability and adaptability in certain dynamic WSNs.
TrustNet [17]	Integrates machine learning classification to enhance intrusion detection. Improved security and reliability	It may introduce computational overhead.
FuzzyElection [18]	Ensures efficient and reliable cluster head election, improving the network stability and energy efficiency	This may increase computational overhead, impacting the protocol’s scalability in large-scale WSNs.
OptiCluster [19]	Enhances data delivery by optimizing cluster formation and routing decisions, ensuring improved network performance.	It is impacting the protocol’s real-time performance and adaptability in resource-constrained environments.
EcoDist [20]	Optimizes energy consumption by considering distance metrics, leading to improved network longevity.	Adaptability to changing network conditions and potentially reducing the protocol’s effectiveness
TrustEcoRoute [21]	Enhances network reliability by leveraging trust metrics and multipath routing, resulting in improved data delivery.	Real-time performance in resource-constrained scenarios and posing challenges in highly dynamic network conditions.
CentroMove [22]	Dynamic adjustment of sink node position improves energy utilization and network lifetime.	Irregular node distribution.
MothWolf [23]	Optimizing energy consumption and enhancing the network’s overall efficiency.	Dynamic network conditions or irregular sensor node deployment affects its adaptability.

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MERT [24]	Cluster Heads using advanced meta-heuristic algorithms. Optimizes network performance.	Limiting its applicability in certain scenarios.
ECOG [25]	Energy-balanced routing protocol optimizes energy consumption and increases network lifespan.	Fine-tuning parameters may be required for optimal performance.

3. ADAPTABLE HUMMINGBIRD OPTIMIZATION BASED DYNAMIC SOURCE ROUTING (AHODSR)

3.1. Dynamic Source Routing

Dynamic Source Routing (DSR) is a crucial routing protocol in WSNs and is well-known for its adaptability in dynamic network conditions. DSR enables efficient communication in ad-hoc environments where sensor node movement is unpredictable. This on-demand protocol relies on a route discovery mechanism, which begins with a Route Request (RREQ) signal broadcast to locate the destination. Once a path is established, it will be maintained dynamically by adapting to node mobility and topology changes. This decentralized approach reduces the necessity for a fixed infrastructure, making it perfect for resource-constrained WSNs. Its dependence on route caching and discovery mechanisms leads to overhead, which affects its scalability.

3.2. Enhanced Dynamic Source Routing with Markov Chain Algorithm (MC - DSR)

A Markov Chain (MC) is a mathematical model that describes a sequence of events in which the probability of transitioning from one state to another depends entirely on the current state and time elapsed. Integrating MC into the DSR algorithm, MC-DSR enhances the protocol's functionality and adaptability.

3.2.1. State Representation and Transition Probability Matrix

Initially, integrating MC into the DSR algorithm includes the state representation. Let S denote the set of states that characterize diverse network conditions. Each state $s_i \in S$ represents distinct aspects such as link quality, node mobility, or available energy levels.

The state representation is crucial in forming the foundation for subsequent modeling, and it plays a pivotal role in shaping the probabilistic transitions within the Markov Chain. The discrete nature of the state space allows for a clear and finite delineation of possible network configurations that can be mathematically expressed in Eq.(1).

$$S = \{s_1, s_2, \dots, s_n\} \quad (1)$$

The MC's state space provides the foundation for constructing a transition probability matrix (P). Let $P_{i,j}$ represent the probability of transitioning from state s_i to state s_j in a single step. The transition probability matrix can be represented in Eq.(2).

$$\begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \quad (2)$$

Where the matrix captures the network dynamics, quantifying the likelihood of transitions between different states. The robust definition of states, as demonstrated by S and the subsequent probability matrix P, forms the mathematical basis for the subsequent steps in integrating MC into the DSR algorithm.

3.2.2. Markov Chain Initialization

This initialization process is crucial and is achieved by setting the initial distribution (π) based on the fundamental network state. The mathematical representation of the initial distribution is shown in Eq.(3).

$$\pi = [\pi_1, \pi_2, \dots, \pi_n] \quad (3)$$

Where π_i represents the probability of commencing the MC in the state s_i. The initial distribution is a probability vector that encapsulates the likelihood of the system starting in each defined state. The values of π_i are contingent upon the current network conditions and are instrumental in shaping the early stages of the MC evolution. The mathematical expression $\pi = [\pi_1, \pi_2, \dots, \pi_n]$ encapsulates the probabilistic foundation for subsequent state transitions. This initialization process ensures that the MC accurately reflects the network's initial conditions, influencing the dynamic evolution of the system within the MC-DSR framework.

3.2.3. Adaptive Route Discovery

In Adaptive Route Discovery, the information is embedded in the MC to dynamically adapt the selection of routes based on the prevailing network state. The higher transition probabilities within the MC guide the route discovery towards more stable or efficient paths. The adaptive route discovery process is mathematically represented in Eq.(4).

$$P(Route = r_i | Current\ State) \propto P(Transition\ to\ State\ s_i) \quad (4)$$

Where $P(Route = r_i | Current\ State)$ denotes the probability of selecting a route r_i given the current network state. This probability is proportional to the likelihood of transitioning to a state s_i within the Markov Chain. The adaptability of route discovery is contingent upon the dynamic nature of the network states and their associated transition probabilities.

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This adaptive mechanism ensures that the route selection process aligns with the evolving conditions of the wireless network. This integration can logically navigate the network landscape and enhances resilience and efficiency in response to changing circumstances.

3.2.4. Link Quality Assessment

The Link Quality Assessment utilizes the information encoded in the MC to assess the quality of links within the network. The assessment is based on the transition probabilities associated with changes in link states. The link quality assessment is represented in Eq.(5).

$$P(Link\ Quality = q_i | Current\ State) \propto P(Transition\ to\ State\ s_i) \tag{5}$$

Where $P(Link\ Quality = q_i | Current\ State)$ represents the probability of link quality being qi given the current network state. This probability is proportional to the likelihood of transitioning to a state s_i within the MC. The link quality assessment leverages the probabilistic nature of state transitions to make informed decisions about the stability and reliability of links.

The dynamic evolution of link quality within the MC can be represented by a set of equations, where L_{ij} denotes the link quality between nodes i and j and P_{ij} is the transition probability between the associated states.

$$\frac{dL_{ij}}{d_t} = P_{ij} \tag{6}$$

Eq.(6) captures the temporal changes in link quality, reflecting the influence of state transitions on the dynamic assessment of link conditions. Integrating link quality assessment into the MC-DSR framework enhances the protocol's ability to make adaptive routing decisions based on the probabilistic modeling of network dynamics.

3.2.5. Energy-Aware Routing

This phase involves adapting routing decisions based on the energy state transitions within the Markov Chain. The dynamic changes in energy levels influence the routing decisions, ensuring an energy-aware approach to extending the network's lifetime.

$$P(Routing\ Decision = d_i | Current\ State) \propto P(Transition\ to\ State\ s_i) \tag{7}$$

In Eq.(7). $P(Routing\ Decision = d_i | Current\ State)$ represents the probability of selecting a routing decision d_i given the current network state. This probability is proportional to the likelihood of transitioning to a state s_i within the MC. The energy-aware routing mechanism adapts to the changing energy states, optimizing routing decisions for energy efficiency. The dynamic evolution of energy levels within the MC can be captured by an equation where E_i denotes the energy level associated with the state s_i and P_{ij} is the transition probability between the corresponding states.

$$\frac{dE_i}{d_t} = P_{ij} \tag{8}$$

Eq.(8) reflects the temporal changes in energy levels, indicating how transitions between states influence the overall energy dynamics. Integrating energy-aware routing into the MC-DSR framework enhances the protocol's capacity to make adaptive routing decisions, consider the energy constraints of individual nodes, and promote sustainable network operation.

3.2.6. Route Maintenance and Repair

This step applies MC concepts to the route maintenance phase, guiding the protocol to repair an existing route or discover a new one based on transition probabilities. The decision-making process involves assessing the likelihood of successful route maintenance or repair, ensuring the network's adaptability to changes. The route maintenance and repair process can be expressed mathematically in Eq.(9).

$$P(Routing\ Action = a_i | Current\ State) \propto P(Transition\ to\ State\ s_i) \tag{9}$$

Where $(Routing\ Action = a_i | Current\ State)$ denotes the probability of selecting route action ai given the current network state. This probability is proportional to the likelihood of transitioning to a state s_i within the MC. The route maintenance and repair mechanism adapts to the dynamic changes in network conditions, optimizing decisions for maintaining or repairing routes.

The temporal changes in route conditions within the MC can be represented by an equation where R_i denotes the route condition associated with the state s_i and P_{ij} is the transition probability between the corresponding states.

$$\frac{dR_i}{d_t} = P_{ij} \tag{10}$$

Eq.(10) captures how transitions between states influence the temporal evolution of route conditions. Integrating route maintenance and repair into the MC-DSR framework enhances the protocol's ability to intelligently manage and adapt routes based on the probabilistic modeling of network dynamics.

3.2.7. Periodic Markov Chain Updates

The Periodic Markov Chain Updates contain the regular adjustment of MC parameters based on real-time observations or network monitoring. The periodic updates allow the MC-DSR protocol to adapt to changing network conditions, which can be represented mathematically with Eq.(11).

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$$P(Update\ = u_i|Current\ State) \propto P(Transition\ to\ State\ s_i) \quad (11)$$

Where $P(Update\ = u_i|Current\ State)$ signifies the probability of selecting update ui given the current network state. This probability is proportional to the likelihood of transitioning to a state s_i within the MC. The periodic update mechanism adapts the MC to reflect the evolving dynamics of the network, ensuring its relevance and accuracy. The temporal changes in MC parameters can be represented by an equation where M_i denotes the MC parameter associated with the state s_i and P_{ij} is the transition probability between the corresponding states.

$$\frac{dM_i}{d_t} = P_{ij} \quad (12)$$

Eq.(12) depicts how transitions between states influence the temporal evolution of Markov Chain parameters. The integration of periodic Markov Chain updates into the MC-DSR framework enhances the protocol's ability to continually adapt and optimize its probabilistic modeling in response to the dynamic nature of the wireless network.

InitializeStates()

- Create a set of abstract states representing network conditions.

BuildTransitionMatrix()

- Define a matrix P for transition probabilities between states.

InitializeMarkovChain()

- Set initial distribution probabilities π based on current network conditions.

AdaptiveRouteDiscovery()

- During route discovery:

- Use Markov Chain probabilities to adapt route selection dynamically.

LinkQualityAssessment()

- Assess link quality:

- Use Markov Chain probabilities for interpreting link state changes.

EnergyAwareRouting()

- Adapt routing based on energy state transitions:

- Use Markov Chain probabilities to optimize for energy efficiency.

RouteMaintenanceAndRepair()

- During route maintenance:

- Apply Markov Chain principles to decide whether to repair or discover a new route.

PeriodicMarkovChainUpdates()

- Periodically update Markov Chain parameters:

- Adapt the model to changing network conditions, ensuring relevance.

Pseudocode 1 Markov Chain-Based Dynamic Source Routing (MC-DSR)

The pseudocode 1 summarises the MC-DSR algorithm in a step-by-step manner. It starts with initializing states to represent various network conditions. The matrix P is established to denote transition probabilities between these states. The initialization of the MC involves setting initial distribution probabilities based on current network conditions. The algorithm dynamically adapts route selection during route discovery using Markov Chain probabilities.

Link quality assessment interprets link state changes based on these probabilities. Energy-aware routing optimizes decisions for energy efficiency, guided by Markov Chain transitions. Route maintenance decisions leverage Markov Chain principles, and periodic updates ensure the model adapts to the changing network conditions.

3.3. Hummingbird Optimization

The Hummingbird Optimization Algorithm (HOA) emulates the foraging strategies of hummingbirds in search of nectar-rich flowers. It dynamically adjusts solutions to optimize objective functions, combining local search and global exploration. With memory structures aiding in learning from past experiences, HOA employs a parallel search strategy for enhanced efficiency.

Adapting to changing conditions and striking a balance between intensification and diversification, this versatile algorithm finds applications in engineering, logistics, and scheduling, converging efficiently towards optimal solutions by drawing inspiration from the hummingbird's adeptness in navigating dynamic environments.

3.3.1 Features of HOA

a) Foraging Behavior Simulation: HOA replicates the foraging behavior of hummingbirds in searching for nectar-rich flowers. The algorithm models the process of hummingbirds dynamically adjusting their flight paths to find optimal routes between flowers.

b) Dynamic Movement and Exploration: Similar to hummingbirds exploring a diverse landscape for nectar, HOA involves dynamic movement and exploration of the solution space. The algorithm iteratively adjusts its solutions to optimize the objective function.

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c) Local Search and Global Exploration: HOA combines local search capabilities with global exploration. It exploits promising regions near current solutions while maintaining the ability to explore new and uncharted areas of the solution space.

d) Memory and Learning: The algorithm incorporates memory structures to remember information about previously visited solutions. This memory allows HOA to learn from past experiences and adapt its search strategy accordingly.

e) Parallel Search Strategy: Hummingbird Optimization employs a parallel search strategy similar to that of hummingbirds, simultaneously exploring multiple flowers for nectar. It enhances the algorithm's ability to examine various solutions concurrently.

f) Adaptability to Changing Conditions: HOA dynamically adapts to changes in the optimization landscape, responding to shifts in the fitness landscape to enhance its efficiency. This adaptability is inspired by the hummingbird's ability to adjust its flight paths based on environmental conditions.

g) Balance between Intensification and Diversification: The algorithm seeks a balance between intensification (exploitation of known solutions) and diversification (exploration of new solutions). This balance is crucial for efficiently navigating the solution space.

h) Versatility: HOA is a versatile optimization algorithm applicable to many optimization problems. It has been employed in engineering design, logistics, scheduling, and other domains where finding optimal solutions is essential.

i) Efficiency and Convergence: The primary goal of HOA is to converge towards optimal solutions efficiently. The hummingbird's adeptness at finding nectar efficiently in a dynamic environment inspires the algorithm.

3.4. Adaptable Hummingbird Optimization

"Adaptable Hummingbird Optimization (AHO)" is an optimization approach that reflects hummingbirds' flexible and dynamic foraging behavior. This method incorporates adaptability into the optimization process, allowing real-time adjustments based on changing environmental conditions. The algorithm iteratively refines solutions, combining local search and global exploration strategies. Memory structures capture insights from past experiences, and a parallel search approach enhances efficiency. This adaptable optimization is well-suited for scenarios requiring resilience to fluctuations, making it valuable in applications such as dynamic resource allocation, responsive scheduling, and evolving system configurations. The term emphasizes the optimization algorithm's capacity to gracefully adapt to diverse and shifting conditions. AHO is developed with several functional phases. The phases of

3.4.1. Dynamic Initialization

The dynamic initialization step in Adaptable Hummingbird Optimization (AHO) involves generating initial solutions dynamically, setting the foundation for an optimization process capable of adapting to changing conditions. This step ensures that the algorithm begins with diverse potential solutions, mimicking the adaptability observed in hummingbirds within varied environments.

Let X_i represent the position of hummingbird i in the solution space. The dynamic initialization is expressed in Eq.(13).

$$X_i = X_{min} + \text{rand}(0,1) \cdot (X_{max} - X_{min}) \tag{13}$$

Where X_{min} and X_{max} denote the minimum and maximum boundaries of the solution space.

The fitness of each hummingbird is evaluated using the objective function $\int(X_i)$, capturing the solution's performance is mathematically expressed with Eq.(14).

$$Fitness_i = \int(X_i) \tag{14}$$

Initialize the memory of each hummingbird to store information about visited solutions, essential for adaptive learning throughout the optimization process is shown in Eq.(15).

$$Memory_i = X_i \tag{15}$$

Calculate the initial velocity V_i of each hummingbird, it is influencing its movement in the solution space.

$$V_i = \text{rand}(0,1) \cdot V_{max} \tag{16}$$

Where in Eq.(16), V_{max} represents the maximum velocity.

Determine the probability P_i of each hummingbird, guiding its potential to exploit or explore solutions.

$$P_i = \frac{Fitness_i}{\sum_{j=1}^{N} Fitness_j} \tag{17}$$

Where in Eq.(17), N represents the total number of hummingbirds in the population.

Dynamic learning rate α_i for each hummingbird, influencing the magnitude of adjustments during the optimization process represented mathematically with Eq.(18).

$$\alpha_i = \text{rand}(0,1) \cdot \alpha_{max} \tag{18}$$

Where α_{max} denotes the maximum learning rate.

The dynamic initialization step in AHO orchestrates the generation of hummingbird positions, velocities, and memory, considering fitness evaluation and probabilities.

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3.4.2. Real-Time Adjustment

The real-time Adjustment phase in AHO involves real-time adjustments to the hummingbirds' positions and velocities. This dynamic adaptation allows the algorithm to swiftly respond to changing conditions in the optimization landscape, akin to the agile adjustments observed in hummingbirds during flight.

Update the position of each hummingbird i based on its current position X_i and velocity V_i over a given time step t_{step}.

$$X_i = X_i + V_i \cdot t_{step} \tag{19}$$

Eq.(19) captures the continuous movement of each hummingbird in the solution space.

Adjust the velocity of each hummingbird based on its previous velocity, the best solution in its memory, and a stochastic term is shown mathematically in Eq.(20).

$$V_i = \omega \cdot V_i + c_1 \cdot \mathrm{rand}(0,1) \cdot (Memory_i - X_i) + c_2 \cdot \mathrm{rand}(0,1) \cdot (GlobalMemory - X_i) \tag{20}$$

Where ω is the inertia weight, c_1 and c_2 are acceleration constants, $Memory_i$ is the best solution remembered by hummingbird i, and $GlobalMemory$ is the best solution across the entire population.

Re-evaluate the fitness of each hummingbird $RFitness_i$ based on its updated position, mathematically represented in Eq.(21).

$$RFitness_i = \int (X_i) \tag{21}$$

Update the memory of each hummingbird to retain the best solution encountered during its exploration, shown mathematically in Eq.(22).

$$Memory_i = \begin{cases} X_i, & if\ \ Fitness_i > Fitness(Memory_i) \\ Memory_i, & otherwise \end{cases} \tag{22}$$

It ensures that each hummingbird remembers the best solution it has found during its optimization journey.

Recalculate the probability RP_i of each hummingbird based on its updated fitness shown in Eq.(23).

$$RP_i = \frac{Fitness_i}{\sum_{j=1}^{N} Fitness_j} \tag{23}$$

This probability guides the potential for each hummingbird to exploit or explore solutions in the next iteration.

Adjust the dynamic learning rate $R\alpha_i$ to influence the magnitude of adjustments in the subsequent iterations shown in Eq.(24).

$$R\alpha_i = \mathrm{rand}(0,1) \cdot \alpha_{max} \tag{24}$$

The continuous adjustment of hummingbird positions, velocities, fitness values, memory, and probabilities characterizes the real-time adaptation in AHO. This dynamic process ensures that the algorithm remains responsive to changes, enhancing its agility in navigating the optimization landscape.

3.4.3. Local Search and Global Exploration

The step involves combining local search capabilities with global exploration strategies. This balanced approach ensures that each hummingbird navigates the solution space efficiently while retaining the ability to explore new and uncharted regions.

To enhance local search, update the position of each hummingbird i by considering its previous position, a random term, and the best solution remembered by the hummingbird represented with Eq.(25).

$$X_i = X_i + c_1 \cdot \mathrm{rand}(0,1) \cdot (Memory_i - X_i) \tag{25}$$

Where c_1 is a constant controlling the influence of local search.

Simultaneously, it facilitates global exploration by adjusting the position of each hummingbird based on a random term and the best global solution.

$$X_i = X_i + c_2 \cdot \mathrm{rand}(0,1) \cdot (GlobalMemory - X_i) \tag{26}$$

In Eq.(26), the constant c_2 modulates the impact of global exploration on the hummingbird's movement.

Re-evaluate the fitness of each hummingbird after the position updates, which is clearly shown in Eq.(21). Update the memory of each hummingbird to retain the best solution encountered during the local search, as shown in Eq.(27).

$$Memory_i = \begin{cases} X_i, & if\ \ Fitness_i > Fitness(LocalMemory_i) \\ Memory_i, & otherwise \end{cases} \tag{27}$$

It ensures that hummingbirds remember the best solution found during their local search.

Update the memory of each hummingbird to capture the global best solution encountered.

$$Memory_i = \begin{cases} X_i, & if\ \ Fitness_i > Fitness(GlobalMemory_i) \\ Memory_i, & otherwise \end{cases} \tag{28}$$

Eq.(28) reflects the hummingbirds' ability to remember the best global solution.

Continuing from the previous step, adjust the dynamic learning rate $R\alpha_i$ to influence the magnitude of adjustments during subsequent iterations, as shown in Eq.(24). The local

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search and global exploration steps in AHO synergize to allow hummingbirds to exploit promising regions while still being able to explore new areas. This balance between local and global movements ensures the algorithm's adaptability and effectiveness in navigating the diverse optimization environment.

3.4.4. Memory Integration

This Memory Integration phase involves the integration of memory structures to facilitate adaptive learning and informed decision-making throughout the optimization process. To enhance local memory, update the memory of each hummingbird i by retaining the best solution encountered during local search represented in Eq.(27). It ensures that each hummingbird remembers the best local solution found during its optimization journey. To update the memory to capture the best solution encountered globally, as shown in Eq.(28), it reflects the hummingbirds' ability to remember the best solution during their exploration.

Integrate local and global memory to determine the comprehensive memory of each hummingbird, incorporating the influence of local and global factors, which is represented mathematically in Eq.(29).

$$TotalMemory_i = Memory_i + Globalmemory \tag{29}$$

Where the $TotalMemory$ accounts for both local and global insights.

To Recalculate the probability RP_i of each hummingbird based on its updated fitness shown in Eq.(23). This probability guides the potential for each hummingbird to exploit or explore solutions in the next iteration, influenced by the integrated memory. To adjust the dynamic learning rate $R\alpha_i$ to influence the magnitude of adjustments during subsequent iterations, shown in Eq.(24). Integrating memory structures in AHO consolidates local and global experiences, fostering adaptive learning among hummingbirds. This comprehensive memory, recalculated probabilities, and dynamic learning rate adjustments contribute to the algorithm's ability to make informed decisions and adapt to varying optimization conditions.

3.4.5. Parallelized Search Strategy

Implementing a parallelized search strategy, allowing multiple hummingbirds to explore diverse regions of the solution space concurrently.

Update the position of each hummingbird i in parallel, considering local and global factors.

$$X_i = X_i + c_1 \cdot \text{rand}(0,1) \cdot (Memory_i - X_i) + c_2 \cdot \text{rand}(0,1) \cdot (GlobalMemory - X_i) \tag{30}$$

Where Eq.(30) shows that parallel execution allows hummingbirds to update their positions independently and simultaneously. The fitness of each hummingbird is re-evaluated in parallel after the position updates using the re-evalu function.

Update the memory of each hummingbird in parallel, considering both local and global experiences. The parallel execution ensures that each hummingbird independently updates its memory based on its evaluation. Integrate local and global memory in parallel for each hummingbird. This parallelized approach allows hummingbirds to calculate their, contributing to their individual learning experiences independently. Recalculate the probability RP_i , in parallel based on its updated fitness. The parallel execution ensures that probabilities are calculated independently for each hummingbird, contributing to a distributed exploration strategy. Adjust the dynamic learning rate $R\alpha_i$, in parallel to influence the magnitude of adjustments during subsequent iterations.

3.4.6. Adaptive Parameter Tuning

Dynamically adjusting algorithmic parameters to optimize performance based on the evolving characteristics of the optimization landscape. Adapt the inertia weight ω dynamically to balance exploration and exploitation. The update considers the hummingbird's previous inertia weight, fitness, and the globally best fitness encountered mathematically represented in Eq.(31).

$$\omega_i = \frac{w_{max} - \omega_{min}}{1 + e^{-\beta(Fitness_i - GlobalFitness)}} + \omega_{min} \tag{31}$$

Where w_{max} and ω_{min}, represent the maximum and minimum inertia weights, β is a tunable parameter controlling the rate of adaptation, and $GlobalFitness$ is the best fitness found globally.

Dynamically adjust the acceleration constants c1 and c2 to modulate the influence of local and global factors on the hummingbird's movement. The updates consider the hummingbird's fitness, the globally best fitness, and a tuning parameter γ:

$$c1_i = \frac{c1_{max} - c1_{min}}{1 + e^{\gamma(Fitness_i - GlobalBestFirness)}} + c1_{min} \tag{32}$$

$$c2_i = \frac{c2_{max} - c2_{min}}{1 + e^{\gamma(GlobalBestFitness - Fitness_i)}} + c2_{min} \tag{33}$$

where in Eq.(32) and Eq.(33) contains $c1_{max}$, $c1_{min}$, $c2_{max}$, and $c2_{min}$ are the maximum and minimum values for $c1$ and $c2$, and γ controls the rate of adaptation.

Adjust the dynamic learning rate α based on the hummingbird's fitness, the globally best fitness, and a tuning parameter δ shown in Eq.(34).

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$$\alpha_i = \frac{\alpha_{max} - \alpha_{min}}{1 + e^{\delta(Fitness_i - GlobalBestFitness)}} + \alpha_{min} \quad (34)$$

Where, α_{max} and α_{min} are the maximum and minimum learning rates, and δ controls the rate of adaptation.

It incorporates the dynamically tuned parameters into the position update equation to maintain a balance between exploration and exploitation, mathematically represented in Eq.(30). The dynamically adapted parameters ensure the algorithm can adapt its search strategy to varying landscape characteristics, promoting efficient exploration and exploitation. Recalculate the probability RP_i of each hummingbird based on its updated fitness shown in Eq.(23). The dynamically tuned parameters influence the probability calculation, aligning it with the adaptive nature of AHO. Adaptive parameter tuning in AHO ensures that algorithmic parameters dynamically respond to the evolving optimization landscape, enhancing the algorithm's adaptability and performance across different scenarios.

3.4.7. Resilient Convergence

Resilient Convergence focuses on achieving resilient convergence, ensuring the algorithm maintains convergence robustness and stability in dynamic optimization landscapes. Dynamically adjust the convergence speed β_{conv} based on the hummingbird's fitness and the globally best fitness encountered:

$$\beta_{conv_i} = \frac{\beta_{conv_{max}} - \beta_{conv_{min}}}{1 + e^{\eta(Fitness_i - GlobalBestFitness)}} + \beta_{conv_{min}} \quad (35)$$

Where in Eq.(35), $\beta_{conv_{max}}$ and $\beta_{conv_{min}}$ represent the maximum and minimum convergence speed values, and η controls the rate of adaptation.

Adapt the inertia weight w dynamically to balance convergence and exploration during optimization. The update considers the hummingbird's previous inertia weight, its fitness, and the globally best fitness encountered, is shown in Eq.(36).

$$\omega_i = \frac{\omega_{max} - \omega_{min}}{1 + e^{\xi(Fitness_i - GlobalBestFitness)}} + \omega_{min} \quad (36)$$

Where ω_{max} and ω_{min} represent the maximum and minimum inertia weight values, and ξ controls the rate of adaptation. It incorporates the dynamically adjusted inertia weight into the position update equation to balance exploration and exploitation, which is represented in a mathematical format in Eq.(30). The dynamically tuned inertia weight ensures a resilient balance between exploration and exploitation throughout the optimization process.

To Adjust the dynamic learning rate α based on the hummingbird's fitness and the globally best fitness is shown in Eq.(37).

$$\alpha_i = \frac{\alpha_{max} - \alpha_{min}}{1 + e^{\xi(Fitness_i - GlobalBestFintess)}} + \alpha_{min} \quad (37)$$

Where α_{max} and α_{min} represent the maximum and minimum learning rates, and ξ controls the rate of adaptation. To Recalculate the probability RP_i of each hummingbird based on its updated fitness in the context of resilient convergence shown mathematically in Eq.(23). The dynamically tuned parameters, including convergence-adapted learning rates, contribute to probability recalculations aligned with the resilient convergence objective. This resilient convergence in AHO introduces dynamic adjustments to convergence-related parameters, promoting stability and robustness in changing optimization landscapes. The adaptive tuning ensures that the algorithm converges while maintaining the flexibility to adapt to dynamic conditions.

3.4.8. Responsive Optimization Metrics

This phase of AHO emphasizes the importance of responsive optimization metrics, enabling the algorithm to dynamically adapt its evaluation criteria based on the evolving optimization landscape.

Adapt the fitness evaluation dynamically by incorporating the responsiveness parameter ρ. This parameter influences the evaluation process by considering the hummingbird's fitness, and the global best fitness is represented in Eq.(38).

$$Fitness_i = \frac{\rho \cdot Fitness_i}{1 + e^{\theta(Fitness_i - GlobalBestFitness)}} \quad (38)$$

Where θ modulates the sensitivity of the dynamic fitness evaluation to changes in the optimization landscape.

The influence of local memory on the fitness evaluation to capture the impact of the hummingbird's historical experiences.

$$Fitness_i = Fitness_i - \lambda \cdot \mathrm{Memory}_i \quad (39)$$

Where in Eq.(39), the parameter λ controls the degree of influence local memory has on the fitness evaluation.

Incorporate global information by including the globally best fitness in the fitness evaluation process represented with Eq.(40)

$$Fitness_i = Fitness_i + \gamma \cdot GlobalBestFitness \quad (40)$$

Where the parameter γ governs the impact of global information on the fitness evaluation. To recalculate the probability RPi of each hummingbird based on the dynamically adjusted fitness. The responsive optimization metrics influence the probability calculation, ensuring that probabilities align with the adaptive fitness evaluations. To adjust the dynamic learning rate α_i based on the hummingbird's updated fitness and the globally best fitness shown in Eq.(34).

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To integrate all responsive optimization metrics, including dynamic fitness evaluation, memory influence, global information, adaptive probability calculation, and learning rate adjustment, into the AHO algorithm's overall fitness assessment. This comprehensive integration ensures that the algorithm responds adeptly to changes in the optimization landscape, fostering adaptability and robust convergence. The responsive optimization metrics in AHO encompass dynamic fitness evaluation, memory considerations, global information integration, and adaptive probability calculations. These metrics collectively contribute to the algorithm's ability to navigate diverse optimization landscapes effectively and converge resiliently towards optimal solutions.

3.4.9. Continuous Monitoring

Continuous Monitoring of AHO focuses on continuous monitoring, where the algorithm dynamically adjusts its parameters based on real-time feedback from the optimization process. To implement a dynamic convergence check to assess the convergence status of the algorithm. Apply a convergence threshold ϵ that adapts based on the difference between the best fitness of the current iteration. $BestFitness_{current}$ and the previous iteration $BestFitness_{previous}$ is represented mathematically in Eq.(41).

$$\epsilon = \frac{\epsilon_{max} - \epsilon_{min}}{1 + e^{-\varphi(BestFitness_{current} - BestFitness_{previous})}} + \epsilon_{min} \tag{41}$$

Where ϵ_{max} and ϵ_{min} represent the maximum and minimum convergence thresholds, and φ controls the rate of adaptation.

Dynamically adjust the exploration threshold τ based on the hummingbird's fitness and the globally best fitness. The adaptive exploration threshold influences the algorithm's exploration behavior, as shown in Eq.(42).

$$\tau_i = \frac{\tau_{max} - \tau_{min}}{1 + e^{\chi(Fitness_i - GlobalBestFitness)}} + \tau_{min} \tag{42}$$

Where τ_{max} and τ_{min} represent the maximum and minimum exploration threshold values, and χ controls the rate of adaptation.

To adjust the frequency of memory updates η_{Update} dynamically based on the hummingbird's fitness and the globally best fitness. This parameter influences how frequently local memory is updated during the optimization process.

$$\eta_{Update_i} = \frac{\eta_{max} - \eta_{min}}{1 + e^{\psi(Fitness_i - GlobalBestFitness)}} + \eta_{min} \tag{43}$$

Where in Eq.(43), η_{max} and η_{min} represent the maximum and minimum memory update frequencies, and ψ controls the rate of adaptation.

To adjust the maximum number of iterations $MaxIterations$ dynamically based on the hummingbird's fitness and the globally best fitness. This adaptation ensures that the algorithm continues to iterate as long as meaningful improvements are observed, as depicted in Eq.(44).

$$MaxIterations_{adaptive} = MaxIterations_{base} + \lfloor \xi . \text{Fitness}_{current} \rfloor \tag{44}$$

Where $MaxIterations_{base}$ represents the base maximum iterations, and ξ controls the adaptation rate based on the current fitness. This continuous monitoring in AHO enables the algorithm to adapt its convergence criteria, exploration behavior, memory update frequency, and iteration count in real time. This adaptability ensures that the algorithm remains responsive to the dynamics of the optimization landscape, promoting efficient convergence and adaptability.

3.4.10. Iterative Adaptation

In the final phase of AHO, the algorithm dynamically refines its parameters during each iteration to enhance performance continually. Iteratively adjust the dynamic learning rate αi based on the hummingbird's fitness and the globally best fitness. The iterative adaptation ensures that the learning rate constantly refines its impact on the optimization process mathematically depicted in Eq.(34). To *c*ontinuously refine the exploration threshold τ based on the hummingbird's fitness and the globally best fitness. The iterative adaptation ensures a nuanced adjustment of the exploration threshold, influencing exploration behavior specified in Eq.(42).

To refine the frequency of memory updates η_{Update} based on the hummingbird's fitness and the globally best fitness. This iterative adaptation ensures a fine-tuned adjustment of the memory update frequency during the optimization process, which is depicted mathematically in Eq.(43). This iterative adaptation in AHO ensures that critical parameters such as learning rate, exploration threshold, and memory update frequency undergo continuous refinement during each iteration. This iterative refinement contributes to the algorithm's ability to fine-tune its behavior, promoting adaptability and responsiveness to the optimization landscape.

3.5. Combination of MC-DSR with AHO

Enhanced Dynamic Source Routing with Markov Chain Algorithm (MC-DSR) and Adaptable Hummingbird Optimization (AHO) synergistically create a robust dynamic and adaptive routing framework in wireless networks. MC-DSR introduces intelligent decision-making by incorporating Markov Chain modeling into the DSR algorithm. The states in the Markov Chain represent varying network conditions, enabling dynamic route adaptation based on link quality, node mobility, and energy levels. This probabilistic approach enhances the protocol's resilience to network changes. The overall flow of MC-DSR-AHO in M-WSN is pictorially depicted in Figure 1.

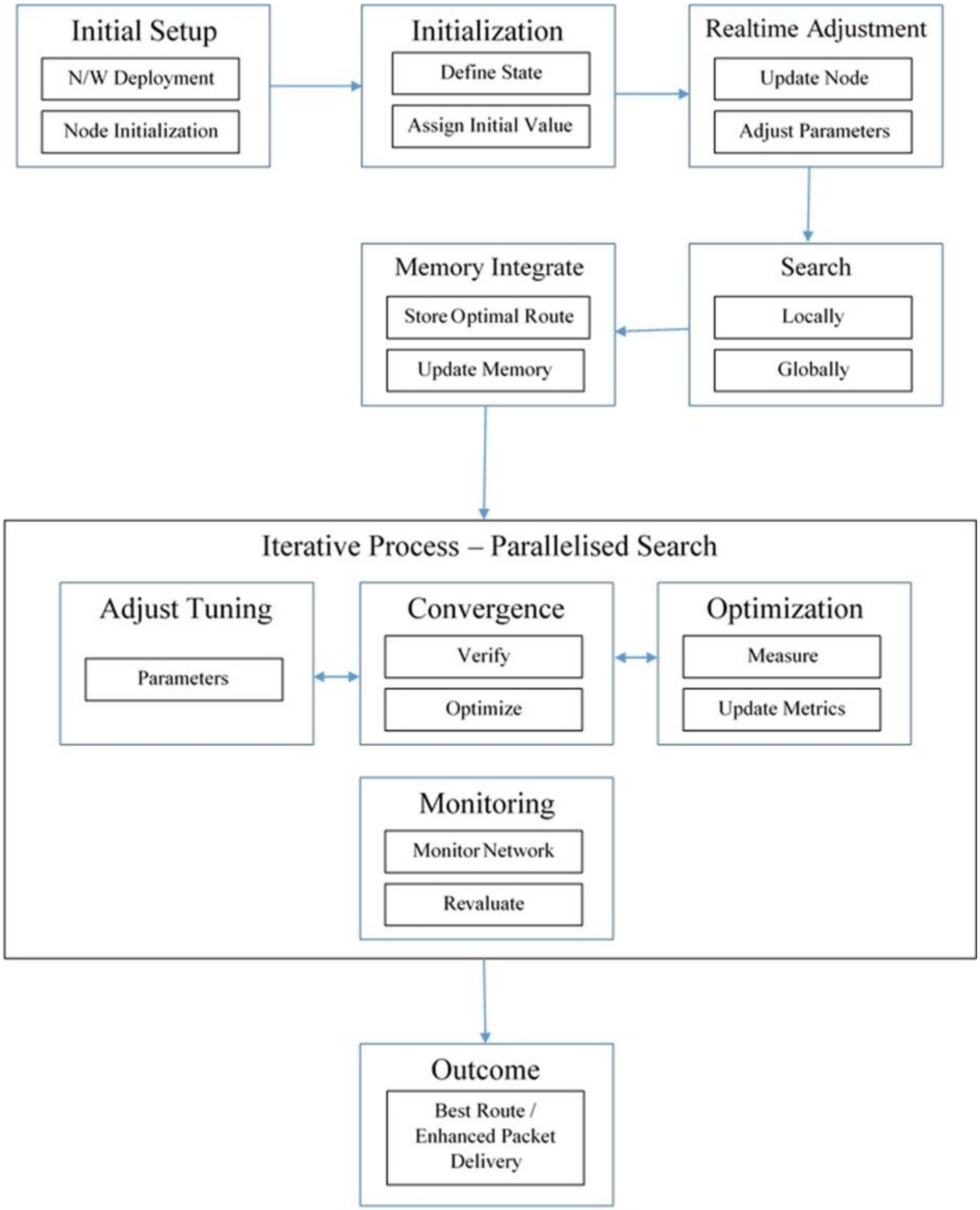

Figure 1 MC-DSR-AHO in M-WSN

AHO inspired by the foraging behavior of hummingbirds, contributes adaptive optimization to the framework. AHO dynamically adjusts its parameters iteratively, incorporating real-time feedback to refine learning rates, exploration thresholds, and memory update frequencies. This iterative adaptation ensures continuous optimization, finely tuning the algorithm's behavior in response to evolving environmental conditions. The integration of MC-DSR and AHO, forming MC-DSR-AHO, results in a novel protocol adept at navigating the challenges posed by dynamic wireless environments. During route discovery in MC-DSR, AHO's dynamic exploration and exploitation strategies guide the protocol towards stable and efficient paths. The Markov Chain's probabilistic modeling, coupled with AHO's adaptability, extends to route maintenance and repair, ensuring robustness in the face of link failures or degradation.

MC-DSR's periodic Markov Chain updates with AHO's continuous monitoring creates a comprehensive approach to handling dynamic network conditions. The constant adaptation of both algorithms, driven by probabilistic modeling and bio-inspired optimization, provides a holistic solution for efficient and adaptive routing in wireless networks. MC-DSR-AHO is a testament to the synergy achieved by integrating Markov Chain modeling and adaptable optimization strategies. This amalgamation facilitates intelligent decision-making, adaptability to changing network dynamics, and efficient route optimization, making it a promising solution for dynamic wireless environments.

```
Procedure InitializeNetwork():
InitializeGraph()
InitializeMarkovChain()
InitializePheromoneMatrix()
InitializeParameters()
Procedure CommunicationEvent(node_source,
node_destination):
If RandomEvent() < P(AdaptiveRouteDiscovery):
AdaptiveRouteDiscovery(node_source, node_destination)
If RandomEvent() < P(LocalSearch):
LocalSearch()
If RandomEvent() < P(EnergyAwareRouting):
EnergyAwareRouting()
If LinkFails():
RouteMaintenanceAndRepair()
If IterationEvent():
IterativeAdaptation()
Procedure MainAlgorithm():
InitializeNetwork()
Loop:
Repeat for each time step:
PeriodicMarkovChainUpdates()
ContinuousMonitoring()
For each communication event:
node_source, node_destination = RandomlySelectNodes()
CommunicationEvent(node_source, node_destination)
MainAlgorithm()
```

Algorithm 1 MC-DSR-AHO in M-WSN

In Algorithm 1, the MC-DSR-AHO algorithm for MSWN initializes the network, periodically updates Markov Chain states, and continuously monitors events. During communication events, it adapts routes, conducts local searches, performs energy-aware routing, handles link failures, and iteratively adapts parameters, ensuring adaptability in dynamic environments.

3.6. Advantages of the Combination of MC-DSR and AHO

The fusion of MC-DSR and AHO contributes to a comprehensive and intelligent routing protocol, providing a robust and adaptive solution for wireless sensor networks in dynamic scenarios.

- Adaptability: Combining the probabilistic modeling of MC-DSR with AHO's dynamic parameter adjustment enhances adaptability to changing network conditions.
- Efficiency: The fusion optimizes route discovery and maintenance, improving communication efficiency in dynamic environments.
- Energy-Awareness: Integrating energy-aware routing from MC-DSR with AHO's adaptability extends the network's lifetime by optimizing energy consumption.
- Robustness: The algorithm's adaptability to link failures and iterative adaptation enhances robustness, ensuring reliable communication in challenging scenarios.
- Global Exploration: AHO's global exploration capability complements MC-DSR, allowing the algorithm to discover efficient paths in uncharted areas of the solution space.
- Versatility: The fused algorithm is versatile and applicable to various optimization problems in wireless sensor

networks, showcasing its adaptability across diverse scenarios.

- Continuous Monitoring: Continuous monitoring from AHO and periodic updates from MC-DSR ensures a real-time and adaptive response to evolving network conditions.
- Balanced Exploration and Exploitation: Achieving a balance between exploration and exploitation enhances the algorithm's effectiveness in navigating the solution space.
- Intelligent Routing: The integration enables intelligent routing decisions, leveraging both probabilistic modelling and bio-inspired optimization to address the challenges of dynamic wireless environments.

4. RESULTS AND DISCUSSIONS

Network Simulator 3, or NS3, is a prominent open-source discrete-event network simulator. Renowned for its accuracy and extensibility, NS-3 facilitates the simulation of complex network scenarios, aiding researchers and developers in comprehending network behaviors and testing protocols. Operating primarily through C++ and Python, NS-3 offers a flexible and modular framework. Its diverse range of available modules covers various networking aspects, from wireless and Internet protocols to devices and applications. NS-3 fosters a deeper understanding of network dynamics, enabling the assessment of diverse networking protocols and technologies. Its open-source nature encourages collaborative development, making it an invaluable tool for academia and industry professionals seeking to advance network research and innovation. Table 1 contains the simulation setting and its parameter values used to simulate.

Table 1 Simulation Setting

Setting/Metric	Value/Description
Network Size	70 nodes
Simulation Time	100 seconds
Mobility Model	Random Walk 2D Mobility Model
Mobility Trace	Enabled, with trace file "mobility_trace.tr"
Network Protocol Implementations	AHO and MC-DSR
Application Layer	Data generation and transmission applications.
Simulation Stop Time	100 seconds.
Tracing	Enabled for mobility.
Bandwidth	97 Hz
Boundary of Network	850m x 850m x 850m
Data Transmission Rate	21 kbps
Initial Energy per Node	1 Joule
Idle State Power	164 mW
Layer Width	≤150m
MAC Protocol	CW-MAC 802.11 DCF
Number of Nodes	400
Node Voltage	3.0V
Number of Sinks	≥4
Runtime	300 seconds
Size of Packet	78 bytes

These simulation parameters specify the network topological values such as bandwidth, Data Transmission Rate, and Number of nodes in a network. The results and discussions derived from simulations using NS-3 provide insightful observations into network behavior and protocol performance. The simulator's accuracy and modularity allow researchers to scrutinize diverse scenarios, contributing to a nuanced comprehension of network dynamics. In evaluating wireless protocols, NS-3's results shed light on packet loss, latency, and throughput, guiding the refinement of communication strategies.

4.1. Packet Delivery and Packet Loss Ratio

Simulations involving Internet protocols reveal intricate interactions, fostering a deeper understanding of how data traverses networks.

The commendable performance of AHODSR consistently surpasses both ECOG and MERT across all node configurations. This underscores the robustness of AHODSR in maintaining higher packet delivery efficiency. The superiority of AHODSR becomes particularly pronounced as network density increases. These findings highlight AHODSR's efficacy in addressing the complexities of packet delivery in MWSNs. They position it as a promising protocol for enhancing reliability and efficiency in dynamic and resource-constrained environments. The Packet Drop Ratio results exhibit significant variations across different node counts, as shown in Figure 2, shedding light on the performance of ECOG, MERT, and AHODSR protocols in MWSN. A discernible trend emerges when the node count increases, revealing the impact on packet drop efficiency. AHODSR consistently outperforms ECOG and MERT, showcasing its effectiveness in minimizing packet drops. AHODSR demonstrates a substantially lower packet drop

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ratio, indicating its resilience in maintaining data integrity even as network density escalates. These findings underscore the robustness of AHODSR in mitigating packet loss, emphasizing its potential as a reliable protocol for ensuring data integrity and communication reliability in MWSNs.

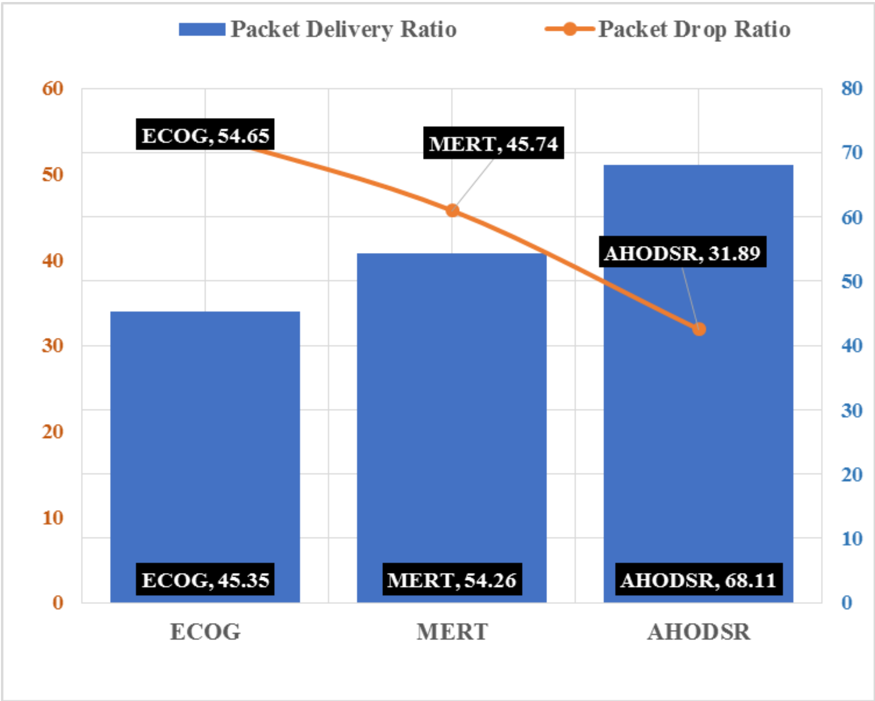

Figure 2 Packet Delivery / Packet Loss Ratio

4.2. Throughput

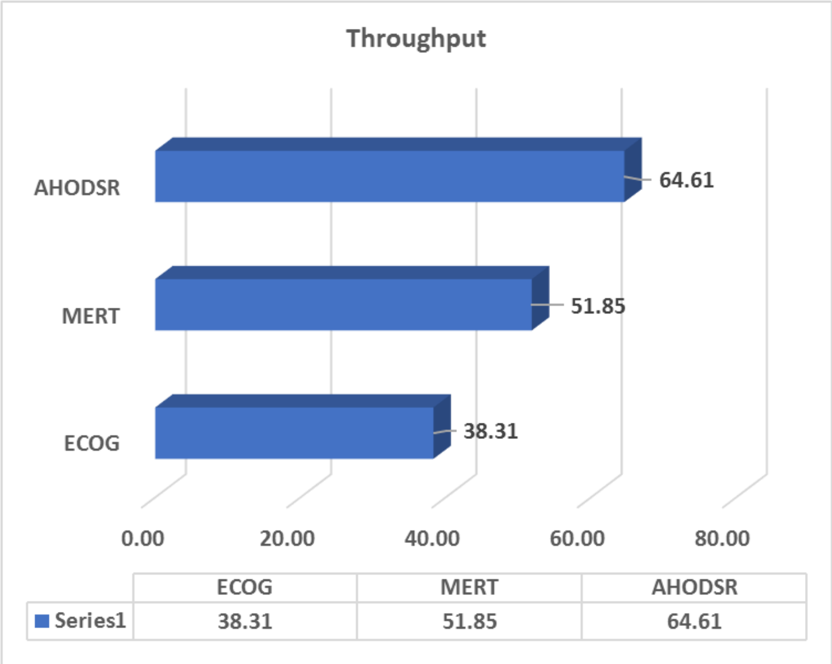

Figure 3 Throughput

Throughput is a critical metric in network performance assessment that measures the amount of data successfully transmitted over a network within a given timeframe. Figure 3 showcases the throughput values for different protocols—ECOG, MERT, ICSOP, and AHODSR—across varying node counts in a mobile wireless sensor network.

AHODSR consistently demonstrates the highest throughput levels, indicating its efficiency in data transmission. When the node count increases, AHODSR maintains a superior throughput, surpassing other protocols. This emphasizes AHODSR's capability to handle increased network traffic and deliver higher data transmission rates. These findings underscore AHODSR's prominence in ensuring effective and efficient data transfer, positioning it as a promising protocol for enhancing network performance.

4.3. Delay

Delay, in the context of network performance, refers to the time it takes for data to travel from the source to the destination. Figure 4 presents the delay values for ECOG, MERT, and AHODSR protocols at different time instances. AHODSR consistently exhibits the lowest average delay, indicating its efficiency in minimizing the time it takes for data transmission.

As the time instances progress, AHODSR consistently outperforms ECOG and MERT, showcasing its ability to reduce communication delays. Lower delay values are generally desirable, as they signify quicker data transfer and more responsive communication within the network. These findings highlight AHODSR's effectiveness in optimizing delay performance in MWSN.

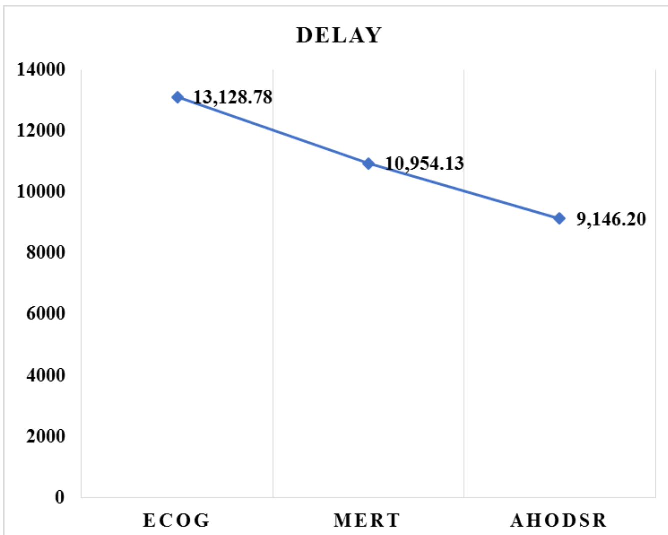

Figure 4 Delay

4.4. Energy Consumption

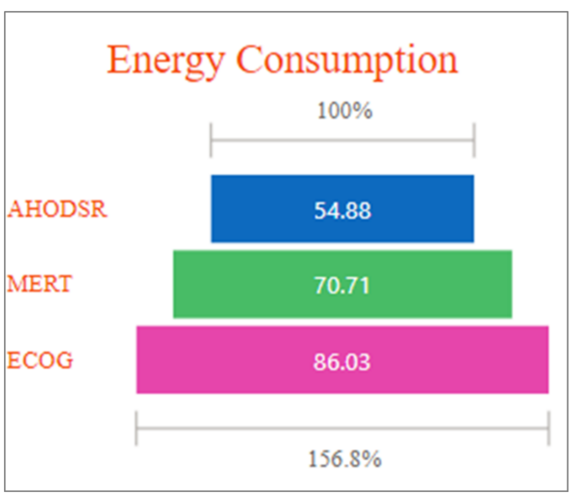

Figure 5 Energy Consumption

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Energy consumption is crucial in evaluating wireless sensor network protocols, measuring the energy expended during communication. Figure 5, outlines the energy consumption values for ECOG, MERT, and AHODSR protocols across various instances.

AHODSR consistently exhibits the lowest energy consumption, reflecting its efficiency in maintaining communication with minimal energy expenditure. Lower energy consumption values are desirable, indicating more energy-efficient protocols. These findings underscore AHODSR's efficacy in optimizing energy consumption within a mobile wireless sensor network, making it a promising choice for scenarios where energy efficiency is critical.

5. CONCLUSION

The integration of MC-DSR and AHO within M-WSNs presents a robust and adaptive routing protocol, denoted as MC-DSR-AHO. This amalgamation seamlessly combines the probabilistic modeling capabilities of MC-DSR with the adaptive optimization inspired by AHO, yielding a comprehensive solution for dynamic and resource-constrained environments. The simulation results showcase MC-DSR-AHO's prowess in key performance metrics, including packet delivery, drop ratio, throughput, delay, and energy consumption. Remarkably, the protocol demonstrates resilience in maintaining high packet delivery rates, minimizing drops, ensuring efficient data transmission, optimizing communication delays, and conserving energy resources. Its adaptability to varying network conditions is evident through consistent outperformance across diverse node counts, emphasizing scalability. This research contributes a versatile and reliable routing solution to M-WSNs. It underscores the synergy of probabilistic modeling and bio-inspired optimization in enhancing the adaptability and efficiency of routing protocols. MC-DSR-AHO is a significant advancement, promising practical applicability and providing valuable insights for future research in the dynamic realm of M-WSNs.

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