



Invigorated Chameleon Swarm Optimization-Based Ad-Hoc On-Demand Distance Vector (ICSO-AODV) for Minimizing Energy Consumption in Healthcare Mobile Wireless Sensor Networks

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Abstract – This study explores the advancements in Wireless Sensor Networks (WSNs) and their application in Mobile Wireless Sensor Networks (MWSNs), particularly within Healthcare Mobile Wireless Sensor Networks (H-MWSNs). Routing in WSNs poses challenges, including adaptability to dynamic environments and efficient path computation. Addressing these challenges, this research propose the Floyd-Warshall-based Ad-hoc On-Demand Distance Vector (FW-AODV) approach. FW-AODV seamlessly integrates the Floyd-Warshall Algorithm with the AODV protocol, providing optimal path computation and dynamic routing capabilities. This integration is particularly promising for MWSNs, where adaptability and efficiency are crucial, especially in healthcare applications. We elucidate the working mechanism of FW-AODV, detailing its iterative rejuvenation process and dynamic color-based communication. Through simulations, this research evaluate FW-AODV's performance in dynamic and challenging WSN environments. Our results demonstrate FW-AODV's effectiveness in enhancing routing efficacy, resilience, and adaptability, offering a robust solution for modern healthcare-focused WSNs.

Index Terms – FW-AODV, Optimal Path, Dynamic Routing, Chameleon Optimization, MWSN, Healthcare MWSN, Routing.

1. INTRODUCTION

Health is the vital thing in human life. Healthcare is considered as a basement for a thriving society, health maintenance is a primary aspect its impact in not only individual well-being but also economic productivity. Reachable and effective healthcare services ensures the timely disease prevention, identification, diagnosis, and treatment it reduces the burden of illness on individuals and the societies[1]. Beyond the immediate health benefits, a strong healthcare system offers a better way to survive for the overall

society. It enhances productivity, reduces absenteeism, fosters a healthier and more engaged population. Healthcare systems roles and responsibility is vital in addressing public health crises and safeguarding against the spread of infectious diseases. Enriched healthcare system leads a society to the sustainable future where citizens can lead a healthy and happy life with satisfaction.

MWSNs transforms data collection by introducing the feature of mobility to the sensor nodes. Unlike the traditional networks this MWSNs allow sensors to move within their deployed environment, and enable new options for the applications [2]. In surveillance process mobile sensors can dynamically track and monitors objects by enhancing situational awareness. In disaster management MWSNs with mobile nodes enable swift deployment for rapid data collection in the affected areas, assisting in efficient response strategies. The adaptability of MWSNs to dynamic scenarios makes them indispensable in real-time [3].

In the sector of healthcare the MWSNs plays a transformative role by providing dynamic and real-time monitoring capabilities [4]. These networks are equipped with mobile sensors, facilitate patient tracking, enabling healthcare professionals to gather crucial data constantly. MWSNs enhance patient care by allowing healthcare providers to monitor vital signs, medication adherence, and overall patient activity [5]. This technology is particularly beneficial in elder care, where continuous monitoring can provide timely interventions in case of emergencies. The adaptability of MWSNs ensures that the patients are not confined to fixed monitoring stations, promoting freedom of movement while maintaining comprehensive healthcare oversight.

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Deploying MWSNs introduces a set of challenges that claims a careful navigation. The primary among these challenges is the complexity of managing energy consumption. The mobility aspect increases the need for an energy efficient solutions to sustain continuous sensor operations [6]. Coordinating the movement of sensors without interference or collisions are the tedious process, so the requirement of an algorithm is essential to optimize mobility and avoid conflicts. Striking the right balance between sensor movement and data accuracy poses another significant challenge [7]. Excessive mobility may lead to inconsistent or redundant data, affecting the reliability of the MWSNs. Among all the above specified this work deals with energy consumption.

In MWSNs within the healthcare sector, bio-inspired optimization techniques play a pivotal role. These algorithms, drawing inspiration from natural processes, are instrumental in addressing the intricate challenges associated with routing in dynamic healthcare environments. Bio-inspired optimization aids in formulating efficient routing strategies that optimize energy consumption [8]–[11]. By mimicking biological systems, these algorithms contribute to adaptive and energy-efficient routing solutions, ensuring continuous data collection for real-time patient monitoring. The use of bio-inspired optimization in routing algorithms becomes imperative for striking a delicate balance between sensor mobility, data accuracy, and energy efficiency in the context of MWSNs deployed in healthcare scenarios [12].

Energy consumption is a critical challenge in H-MWSNs. These networks involve mobile sensor nodes operating in dynamic healthcare environments. The primary issue revolves around managing energy resources efficiently to extend the network's operational lifetime while ensuring uninterrupted healthcare data transmission and communication. The inherent limitation of mobile sensor nodes' battery capacities and frequent movement and data transmission requirements accelerates energy depletion, reducing network longevity and increasing operational costs. Maintaining a balance between mobility and energy efficiency in H-MWSNs is a complex challenge that demands the development of energy-efficient routing protocols, adaptive power management techniques, and intelligent data acquisition strategies. Efficient energy management is vital to unlock the full potential of these networks in healthcare applications like patient monitoring and disease management.

The motivation for addressing the energy consumption challenge in H-MWSNs is grounded in the complexities these networks face when operating in healthcare environments. H-MWSNs, with their mobile sensors in dynamic healthcare settings, pose intricate technical challenges, particularly concerning energy efficiency. The key concern revolves around the limited energy resources of mobile sensors in healthcare. Frequent movement, continuous data transmission,

and the critical need for data accuracy accelerate energy depletion rates, jeopardizing network longevity and healthcare data continuity. Resolving this challenge necessitates the development of technologically advanced solutions, including energy-efficient routing protocols, adaptive power management algorithms, and intelligent data sampling strategies. The objective is to strike a precise balance between energy consumption, healthcare data precision, and healthcare service quality in H-MWSNs. This research is driven by the need for innovative, technically sophisticated solutions to advance mobile data collection in healthcare, extend network lifespan, and minimize disruptions in ever-changing healthcare environments, ensuring the sustained utility and technical viability of H-MWSNs in healthcare applications.

The research aims to address the energy efficiency challenge in H-MWSN by developing and implementing an innovative bio-inspired optimization-based routing protocol tailored to healthcare settings. This protocol will harness the adaptability and efficiency of biological and ecological systems to overcome the unique constraints and dynamics of H-MWSNs in healthcare. The key research objectives are as follows:

- **Protocol Development:** Create a bio-inspired routing protocol that draws inspiration from natural systems, such as ant colony optimization, genetic algorithms, or particle swarm optimization. The protocol will be tailored to the mobility patterns and energy limitations specific to healthcare applications within H-MWSNs.
- **Energy Efficiency Enhancement:** Focus on significantly improving energy efficiency within H-MWSNs by reducing energy consumption during healthcare data routing and transmission. The protocol will dynamically adapt routing decisions to real-time energy levels and changing network conditions, ensuring uninterrupted patient monitoring and data integrity.
- **Mobility Adaptation:** Ensure the protocol's adaptability to the mobility of sensor nodes in healthcare environments by implementing efficient handover and re-routing mechanisms. This will enable seamless network connectivity and healthcare data transmission, even in the presence of mobile nodes within healthcare settings.
- **Performance Assessment:** Conduct comprehensive performance evaluations through simulations and real-world experiments in healthcare contexts. Assess the protocol's effectiveness in extending the operational lifespan of the H-MWSN, reducing energy consumption, and maintaining the integrity of healthcare data transmission in dynamic and critical healthcare scenarios.

By achieving these research objectives, this study aims to contribute substantially to energy-efficient H-MWSNs in healthcare, enhancing their potential for applications in

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patient monitoring, disease management, and healthcare service improvements, where mobile data collection, network sustainability, and healthcare data accuracy are paramount.

The paper is structured into distinct sections to effectively address the research problem. Section 1 introduces the study's context and objectives, while Section 2 critically examines existing literature, discussing methodologies, algorithms, and their respective merits and demerits. In Section 3, the proposed solution, Invigorated Chameleon Swarm Optimization-Based Ad Hoc On-Demand Distance Vector (ICSO-AODV), is elaborated upon, detailing its integration and operational mechanism. Following this, Section 4 meticulously outlines the simulation settings and parameters, including the experimental setup and metrics for evaluation. Section 5 presents the findings from simulations, offering an in-depth analysis and comparison with existing approaches. Finally, Section 6 summarizes the key contributions, highlights future research directions, and underscores the significance of the proposed methodology.

2. LITERATURE REVIEW

“Heterogeneous routing protocol for balanced energy consumption in mobile wireless sensor network (NMSFRA)” [13] the Heterogeneous Routing Protocol stands out for its pivotal role in achieving balanced energy consumption within ME-WSNs. By integrating heterogeneous sensor nodes, each with varying energy capacities and communication ranges, to ensure a balanced distribution of energy loads. “Energy efficient scheme for better connectivity in sustainable mobile wireless sensor networks (LEACH-RN)” [14] the energy-efficient mobile sink data collection protocol revolutionizes WSNs by leveraging the Low Energy Adaptive Clustering Hierarchy model with the integration of rendezvous nodes. “Residual-Energy Aware Modeling and Analysis of Time-Varying Wireless Sensor Networks (REAMAT)” [15] the paper conveys in the domain of WSNs by introducing a residual-energy aware modeling and analysis framework tailored for the inherent time-varying nature of these networks.

“Delay-Aware Green Routing for Mobile-Sink-Based Wireless Sensor Networks (Delay-Aware Green Routing)” [16] is a revolutionary approach to optimize routing in WSNs employing mobile sinks. Integration of delay-awareness into the routing strategy, stirs the research to enhance the efficiency of data transmission without compromising energy conservation. “Energy-Efficient Mobile Sink-Based Intelligent Data Routing Scheme for Wireless Sensor Networks (EEMI-DS)” [17] the paper introduces a groundbreaking paradigm in WSNs with its Energy-Efficient Mobile Sink-Based Intelligent Data Routing Scheme. By leveraging mobile sinks judiciously, the protocol minimizes communication distances, enhancing energy efficiency without compromising data collection. “Energy-Efficient

Tour Optimization of Wireless Mobile Chargers for Rechargeable Sensor Networks (EETO)” [18] identifies an innovative strategy in WSNs. By introducing a sophisticated optimization framework, the research focuses on enhancing energy sustainability in rechargeable sensor networks. This optimization process aims to minimize energy consumption while ensuring the timely and effective recharging of sensor nodes. “MWCERSF: Mobility-based weighted cluster routing scheme for FANETs (MWCERSF)” [19] the paper presents a Mobility-based Weighted Cluster Routing Scheme for Flying Ad Hoc Networks (FANETs). It optimizes cluster formation by assigning weighted values based on node mobility, facilitating efficient communication.

“Efficient method to identify hidden node collision and improving Quality-of-Service (QoS) in wireless sensor networks (QoSGuard)” [20] the paper introduces a proficient solution to detect hidden node collisions and enhance Quality-of-Service (QoS) in WSNs. QoSGuard employs advanced techniques to mitigate collisions, improving overall QoS in WSNs. “An optimal cluster-based routing algorithm for lifetime maximization of Internet of Things (LifeMax IoT)” [21] the paper proposes an optimal cluster-based routing algorithm designed to maximize the lifetime of Internet of Things (IoT) devices. The protocol employs intelligent clustering mechanisms that consider factors such as energy levels and communication distances, ensuring an efficient distribution of network load. “Decision fusion for multi-route and multi-hop Wireless Sensor Networks over the Binary Symmetric Channel (BinaryNet Fusion)” [22] the paper introduces a valuable solution for WSNs. BinaryNet Fusion optimizes data transmission by intelligently fusing decisions from multiple routes and hops. This sophisticated decision fusion process that strategically integrates information from diverse routes, mitigating the impact of channel imperfections.

“A high-scalability and low-latency cluster-based routing protocol in time-sensitive WSNs using genetic algorithm (GenRoute)” [23] presents a high-scalability, low-latency cluster-based routing protocol for time-sensitive WSNs using genetic algorithms. By dynamically evolving clusters through genetic algorithms, the protocol significantly improves scalability and reduces latency in WSNs, particularly crucial for time-sensitive applications. “A cluster-tree-based energy-efficient routing protocol for wireless sensor networks with a mobile sink (ClusterFlow)” [24] proposes a cluster-tree-based energy-efficient routing protocol designed for WSNs featuring a mobile sink. ClusterFlow's working mechanism involves organizing sensor nodes into a hierarchical cluster-tree, with each cluster led by a cluster head. The mobile sink strategically traverses these clusters to collect data, minimizing energy consumption by leveraging the organized structure.

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“EARP: An Enhanced ACO-Based Routing Protocol for Wireless Sensor Networks with Multiple Mobile Sinks (AntRoute)” [25] introduces EARP, an Enhanced ACO-Based Routing Protocol designed for WSNs with support for multiple mobile sinks by enhancing the efficiency of ACO in selecting optimal paths, particularly catering to scenarios with multiple mobile sinks. “A review on distributed cluster based routing approaches in mobile wireless sensor networks (ClusterScope)” [26] conducts a comprehensive review of distributed cluster-based routing approaches tailored for MWSNs. The key contribution lies in synthesizing and evaluating various methodologies used in distributed clustering, shedding light on their strengths and weaknesses. “A Competent Ad-hoc Sensor Routing Protocol for Energy Efficiency in Mobile Wireless Sensor Networks (EcoAdapt)” [27] introduces a Competent Ad-hoc Sensor Routing Protocol designed for optimizing energy efficiency in MWSNs. The working mechanism involves real-time assessment of energy levels, allowing nodes to selectively participate in routing to conserve energy.

“Energy balanced routing protocol based on improved particle swarm optimisation and ant colony algorithm for museum environmental monitoring of cultural relics (ECOG)” [28] the protocol introduces an innovative approach to energy-efficient routing tailored for museum environmental monitoring of

cultural relics. The key contribution lies in integrating improved particle swarm optimization and ant colony algorithms, optimizing data paths to balance energy consumption among sensor nodes. Its working mechanism involves leveraging swarm intelligence to find optimal routes, considering both the efficiency of particle swarm optimization and the adaptability of ant colony algorithms. This hybrid approach ensures that the routing protocol adapts dynamically to changing environmental conditions, enhancing the reliability of data collection while preserving energy resources.

“MOCRAW: A Meta-heuristic Optimized Cluster head selection based Routing Algorithm for WSNs (MERT)” [29] the paper details a novel routing algorithm named MOCRAW designed for WSNs. The key contribution lies in its meta-heuristic optimized cluster head selection mechanism. MetaRoute employs advanced meta-heuristic algorithms to dynamically select cluster heads, optimizing network performance. The working mechanism involves the use of meta-heuristic optimization techniques to adaptively choose cluster heads, considering factors such as energy efficiency and network connectivity. This approach enhances the overall efficiency and prolongs the network lifespan by ensuring balanced energy consumption. The comparison of related literature is shown in Table 1.

Table 1 Comparison of Related Literature

State-of-the-Art Algorithms	Merits	Demerits
NMSFRA [13]	Optimizes energy consumption for balanced usage in heterogeneous MWSNs	Possible scalability challenges and dependency on accurate node information may impact effectiveness.
LEACH-RN [14]	Enhances data collection efficiency through strategic use of rendezvous nodes, optimizing network performance.	Increased implementation complexity due to the integration of rendezvous nodes, potential deployment challenges.
REAMAT [15]	Excels in energy optimization through adaptive strategies and introduces dynamic scheduling for efficient data transfer.	Implementation complexity due to adaptive scheduling, potential overhead in certain computational scenarios.
Delay-Aware Green Routing [16]	Prioritizes energy-efficient paths, contributing to prolonged network operation and minimizing environmental impact.	Complex implementation may affect ease of deployment, and prioritizing energy efficiency may lead to potential latency concerns in certain scenarios.
EEMI-DS [17]	Enhances energy efficiency and minimizes latency through optimized design strategies.	Implementation complexity and potential resource overhead may be considerations in specific scenarios.
EETO [18]	Optimizes energy consumption, contributing to prolonged network operation with prioritized energy-efficient routing paths.	Complexity in implementation due to the optimization focus, and challenges in adapting to diverse network conditions may arise.



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MWCRSF [19]	Mobility-based weighted cluster routing for FANETs enhances adaptability.	The mobility-based approach may introduce implementation complexities, and scaling to larger networks might pose challenges.
QoSGuard [20]	Ensures quality of service in WSNs with intelligent monitoring.	Increased computational overhead may be a consideration in resource-constrained environments.
Lifemax IoT [21]	Maximizes the lifetime of IoT devices through optimized energy consumption.	The consideration of potential complexity arises when implementing lifecycle optimization strategies.
Binary Net Fusion [22]	Optimizes information fusion in WSNs for improved decision accuracy.	The possibility of increased computational complexity may influence real-time performance in scenarios with constrained resources.
GenRoute [23]	Improves routing efficiency with a genetic algorithm, improving network performance.	Improved implementation complexity may affect ease of deployment in certain scenarios.
Cluster Flow [24]	Enhances data flow efficiency via optimized clustering in WSNs.	Difficulty in dynamic clustering implementation may pose challenges in certain network scenarios.
Ant Route [25]	Boosts routing efficiency through ant colony optimization for enhanced network performance.	Execution difficulties could affect straightforward deployment in certain network settings.
Cluster Scope [26]	Increases network efficiency by optimizing communication within defined clusters in WSNs.	Consideration may be given to potential challenges in adapting to dynamic network conditions.
EcoAdapt [27]	Excels in energy efficiency through adaptive mechanisms in WSNs.	Challenges in certain deployment scenarios may arise due to intricacies in implementation.
ECOG [28]	Prioritizes environmental conservation and implements energy-efficient protocols for prolonged network life.	Focusing on environmental conservation and adapting to diverse network conditions may introduce implementation challenges, affecting overall efficiency.
MERT [29]	Optimizes routing paths for enhanced network efficiency with dynamic adaptability to changing conditions.	Potential overhead and implementation complexity may be considerations in deployment.

Table 1 depicts the merits and demerits of the existing works, the consolidated table gives a clear vision about the existing work which proposes the solution for the problem that has been engaged.

The existing literature presents several notable contributions to routing optimization in Wireless Sensor Networks (WSNs). However, a critical research gap persists in comprehensively addressing the dynamic nature of energy consumption and routing efficiency in Mobile Wireless Sensor Networks

(MWSNs), particularly within Healthcare Mobile Wireless Sensor Networks (H-MWSNs). While various protocols and schemes have been proposed to optimize energy consumption and enhance routing efficiency, a comprehensive solution integrating adaptive energy management, efficient routing strategies, and real-time monitoring tailored specifically for healthcare applications is lacking.

Thus, there is a clear need for a novel approach that seamlessly integrates these components to ensure balanced energy consumption, efficient data collection, and enhanced network performance in healthcare-focused MWSNs.

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3. INVIGORATED CHAMELEON SWARM OPTIMIZATION-BASED AD HOC ON-DEMAND DISTANCE VECTOR (ICSO-AODV)

3.1. Ad Hoc On Demand Distance Vector (AODV)

Ad Hoc On-Demand Distance Vector (AODV) is a dynamic and decentralized routing protocol specifically designed for wireless ad hoc networks. In AODV, routes between nodes are established on-demand, meaning that they are created only when needed for communication. The protocol operates efficiently in environments characterized by frequent node mobility and changing network topologies, such as mobile ad hoc networks (MANETs) and WSNs. AODV employs a reactive approach where, upon initiation of communication between source and destination nodes, a Route Request (RREQ) is broadcasted through the network.

This RREQ propagates dynamically, seeking a path to the destination. Once the RREQ reaches either the destination or a node with a valid route to the destination, a Route Reply (RREP) is generated, establishing the route. Primarily it combines the mechanisms for route maintenance and error handling. In a wireless network if there is a failure in node or link then AODV sends a Route Error (RERR) message to the source. This triggers a process of new route discovery if it is required. AODV is an effective one because of its adaptability in the dynamic conditions of wireless ad hoc networks, minimising control overhead, and utilising resources efficiently.

3.2. Enhanced Floyd-Warshall Based Ad Hoc On Demand Distance Vector (FW-AODV):

The *Floyd – Warshall* (FW) algorithm is a method for finding the shortest paths between the vertices in a weighted graph, it is for both directed and undirected graphs. To represent the path the matrix will be marked with values and updated. When the FW is combined with AODV protocol then the routing efficiency and resilience in WSNs will be enhanced. This integration results in Floyd-Warshall based AODV (FW-AODV) a new methodology for finding a shortest path.

3.2.1. Initialization

The integration of the FW Algorithm with the AODV protocol is the initial process, a new mathematical approach is used for calculating the shortest paths between all pair of nodes in a weighted graph. In which it denotes the set of nodes in the MWSNs as V and the set of directed edges as E . Let W_{ij} represent the weight associated with the directed edge from node i to node j . The FW algorithm seeks to construct a matrix $D^{(0)}$ where $d_{ij}^{(0)}$ denotes the initial shortest path distance from node i to node j . This initialization process is expressed with the Eq.(1).

$$D^{(0)} := \begin{bmatrix} d_{11}^{(0)} & \dots & d_{1[V]}^{(0)} \\ \vdots & \ddots & \vdots \\ d_{[V]1}^{(0)} & \dots & d_{[V][V]}^{(0)} \end{bmatrix} \tag{1}$$

This initialization sets the foundation for subsequent iterations and ensures an initial representation of the network's pairwise shortest path distances. The resulting $D^{(0)}$ matrix serves as the starting point for the adaptive routing capabilities of the subsequent AODV protocol, fostering efficient and context-aware route discovery in the dynamic WSNs.

3.2.2. Route Discovery with AODV

The integration of the FW Algorithm with the AODV protocol initiates the route discovery process. A source node s in the network seeks a route to a destination node d . If the precomputed FW matrix $D^{(0)}$ indicates an existing optimal path or the absence of a route, the AODV protocol is triggered to initiate route discovery. This is realized through the broadcast of a Route Request (RREQ) packet. The broadcast of the RREQ packet is described mathematically in Eq.(2).

$$RREQ_{SD} := \{s, d, RREQID, LastHop, NodeSeqNum, BroadcastID\} \tag{2}$$

where $RREQ_{SD}$ represents the RREQ packet from source s to destination d , $RREQID$ is a unique identifier for the RREQ, $LastHop$ is the last node that forwarded the RREQ, $NodeSeqNum$ is the sequence number associated with the source node, and $BroadcastID$ is the broadcast identifier.

3.2.3. Optimal Path Selection

It involves evaluating AODV Route Reply (RREP) packets received by the algorithm to identify the most efficient route from a source node s to a destination node d . When presented with multiple potential paths, the algorithm seeks to determine the route that minimizes the cumulative path cost. This path selection process is mathematically expressed in Eq.(3).

$$Path_{Selected} = Min_{Path_i} \sum_{j=1}^N w_{ij} \tag{3}$$

where, $Path_{Selected}$ signifies the chosen path, and $Path_i$ traverses all possible paths from the source s to destination d . The summation incorporates the weights w_{ij} associated with the edges along each path.

3.2.4. Route Maintenance

Route Maintenance with Floyd-Warshall, the algorithm periodically updates the FW matrix $D^{(t)}$ to adapt to changes in the dynamic WSNs. This maintenance process ensures the accuracy of the matrix in representing all-pairs shortest paths over time. The update equation is expressed in Eq.(4).

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$$D_{ij}^{(t)} = \min(D_{ij}^{(t-1)}, D_{ik}^{(t-1)} + D_{kj}^{(t-1)}) \quad (4)$$

where, $D_{ij}^{(t)}$ denotes the updated shortest path distance from node i to node j at time t . The update involves comparing the existing shortest path $D_{ij}^{(t-1)}$ with the sum of paths through an intermediate node k , represented by $D_{ik}^{(t-1)} + D_{kj}^{(t-1)}$. The minimum of these values is then selected to update the matrix.

3.2.5. Adaptive Path Switching

The algorithm dynamically switches between available paths by assessing their costs and selecting the most optimal route. Let $P = \{P_1, P_2, \dots, P_n\}$ represent the set of potential paths from a source node to a destination node, and $f(P_i)$ denote the cost associated with each path P_i which is shown mathematically in Eq.(5).

$$P_{optimal} = \min_{P_i \in P} f(P_i) \quad (5)$$

The cost function $f(P_i)$ can incorporate various metrics, such as the sum of link weights, available bandwidth, or residual energy. For example, considering the sum of link weights as the cost.

$$f(P_i) = \sum_{j=1}^N w_{ij} \quad (6)$$

where in Eq.(6), w_{ij} represents the weight associated with the link from node i to node j . The algorithm dynamically selects the path $P_{optimal}$ that minimizes the overall cost, which indicates the most efficient route based on the specified criteria. The adaptive switching process may involve monitoring of the real time conditions of the network and updating the cost function dynamically.

$$f(P_i) = \alpha \cdot PathLength(P_i) + \beta \cdot LinkQuality(P_i) \quad (7)$$

In Eq.(7), α and β are the weighting factors, $PathLength(P_i)$, and $LinkQuality(P_i)$ represent the length of the path, and the quality of its links. It adopts more flexible approach by enabling the algorithm to evaluate various factors for the best path selection.

3.2.6. Energy Aware Routing

This step integrates energy considerations into the routing decision process, aiming to minimize energy consumption and prolong the network's operational lifespan. This involves integrating an energy aware costfunction $f(energy(P_i))$ into the path selection mechanism is shown in Eq.(8).

$$f(energy(P_i)) = \sum_{j=1}^N E_{ij} \quad (8)$$

where E_{ij} represents the energy consumption associated with the link from node i to node j . The algorithm aims to select paths that minimize the cumulative energy consumption across the network. A trade-off between energy consumption and path length may be considered by introducing a weighting factor represented mathematically with Eq.(9).

$$trade_off(P_i) = \alpha \cdot PathLength(P_i) + \beta \cdot E(P_i) \quad (9)$$

where α and β are weighting factors, $PathLength(P_i)$ represents the length of the path, and $E(P_i)$ is the energy consumption associated with the path. To balance the considerations of energy efficiency and path length, providing a flexible approach to energy-aware routing. The optimization objective is to select paths that achieve an steadiness between minimizing energy consumption and ensuring effective data transmission within the WSNs.

3.2.7. Dynamic Network Reconfiguration

In the Dynamic Network Reconfiguration the algorithm leverages AODV decisions to adaptively modify the network structure based on real-time changes. This involves updating routing tables RT_{ij} and responding to alterations identified by the AODV protocol which is shown mathematically in Eq.(10).

$$RT_{ij}(t + 1) = RT_{ij}(t) + \Delta RT_{ij} \quad (10)$$

Where $RT_{ij}(t)$ represents the routing table entry between nodes i and j at time t , and ΔRT_{ij} denotes the change in this entry due to AODV decisions. The algorithm dynamically adjusts routing information, ensuring the network remains synchronized with changing conditions. Moreover, adaptive responses to network alterations involve executing functions F_{adapt} .

$$F_{adapt}(t + 1) = F_{adapt}(t) + \Delta F_{adapt} \quad (11)$$

In Eq.(11), $F_{adapt}(t)$ represents the state of adaptive functions at time t , and ΔF_{adapt} signifies the change in function states. These equations encapsulate the continuous process of network reconfiguration, where routing tables and adaptive functions evolve to accommodate the dynamic nature of the WSNs. This adaptability enhances the network's resilience and responsiveness to varying environmental and operational factors.

3.2.8. Cross Layer Optimization

Cross-layer Optimization integrates information and functionality across different layers of the network protocol stack to enhance overall system performance. This involves optimizing a Joint Objective Function (JOF) that incorporates metrics from multiple layers shown mathematically in Eq.(12).

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$$JOF = \alpha.Throughput + \beta.End_to_End_Delay + \gamma.Energy_Efficiency \quad (12)$$

Where α , β , and γ are weighting factors representing the importance assigned to throughput, end-to-end delay, and energy efficiency, respectively. The algorithm seeks to find a configuration that maximizes the joint objective function. Cross-layer optimization exploits inter-layer dependencies, ensuring that decisions made in one layer impact and improve performance metrics in other layers. By considering multiple metrics simultaneously, this approach strives to achieve a balanced and globally optimized network operation, transcending individual layer optimizations and improving the overall efficiency, delay, and energy consumption of the WSNs.

Step 1: Initialization with FW

```
function initialize_network():
network_topology = create_topology()
node_weights = assign_weights()
floyd_warshall_matrix =
initialize_floyd_warshall(network_topology, node_weights)
return floyd_warshall_matrix
End function initialize_network()
```

Step 2: Route Discovery with AODV

```
function route_discovery(source, destination,
floyd_warshall_matrix):
if optimal_path_exists(source, destination,
floyd_warshall_matrix):
return get_optimal_path(source, destination,
floyd_warshall_matrix)
else:
aodv_route = initiate_aodv_route_discovery(source,
destination)
return aodv_route
```

```
End function route_discovery(source, destination,
floyd_warshall_matrix)
```

Step 3: Optimal Path Selection

```
function optimal_path_selection(aodv_routes,
floyd_warshall_matrix):
for route in aodv_routes:
evaluate_criteria(route, floyd_warshall_matrix)
selected_path = select_optimal_path(aodv_routes)
return selected_path
```

```
End function optimal_path_selection(aodv_routes,
floyd_warshall_matrix)
```

Step 4: Route Maintenance with FW

```
function route_maintenance(floyd_warshall_matrix):
updated_matrix =
update_floyd_warshall_matrix(floyd_warshall_matrix)
handle_link_failures(updated_matrix)
End function route_maintenance(floyd_warshall_matrix)
```

Step 5: Adaptive Path Switching

```
function adaptive_path_switching(network_changes,
available_paths):
monitor_network(network_changes)
assessed_paths = assess_paths(available_paths)
optimal_path = select_optimal_path_realtime(assessed_paths)
return optimal_path
End function adaptive_path_switching(network_changes,
available_paths)
```

Step 6: Dynamic Network Reconfiguration

```
function dynamic_network_reconfiguration(aodv_decisions):
update_routing_tables(aodv_decisions)
adapt_to_changes(aodv_decisions)
End function
dynamic_network_reconfiguration(aodv_decisions)
```

Step 7: Energy-Aware Routing

```
function energy_aware_routing(paths, energy_costs):
calculate_energy_costs(paths, energy_costs)
energy_optimal_path = select_energy_optimal_path(paths)
return energy_optimal_path
End function energy_aware_routing(paths, energy_costs)
```

Step 8: Security Enhancement

```
function security_enhancement():
perform_security_analysis()
implement_security_measures()
End function security_enhancement()
```

Step 9: Data Aggregation

```
function data_aggregation():
identify_aggregation_points()
```


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```
aggregate_data()
transmit_aggregated_data()
End function data_aggregation()
Step 10. Repeat Steps if Required
function repeat_steps():
initialize_network()
route_discovery()
optimal_path_selection()
route_maintenance()
adaptive_path_switching()
dynamic_network_reconfiguration()
energy_aware_routing()
security_enhancement()
data_aggregation()
End function repeat_steps()
```

Algorithm 1 FW-AODV

The Algorithm 1 follows a comprehensive 9-step process for WSNs management and 10th step is progressed only if it is necessary based on network output. It begins with initializing the network topology, assigning weights, and computing initial paths using the FW algorithm. Subsequent steps involve dynamic route discovery, optimal path selection, and real-time adaptive path switching. Network reconfiguration and energy-aware routing adapts to changes, while security enhancements strengthen the system. Data aggregation optimizes information exchange. The process is designed to be repeatable for ongoing adaptability. The technical enhancement ensures the iterative execution of the specified steps, reinforcing the network's responsiveness and efficiency in evolving scenarios.

3.3. Chameleon Swarm Optimization (CSO)

Chameleon Swarm Optimization (CSO) is a nature-inspired optimization algorithm that draws inspiration from the color-changing ability of chameleons and the collaborative behavior of swarms. The algorithm involves a population of agents, each representing a potential solution to an optimization problem. These agents mimic the adaptive color-changing nature of chameleons to communicate and collaborate within the swarm, aiming to collectively find optimal solutions.

The algorithm initiates with an initial population of agents in a randomly distributed solution space. Each agent adjusts its position based on its own experience, and the information obtained from neighboring agents, symbolized by color changes. These color-coded signals convey the quality of

solutions and guide the swarm towards regions of higher fitness. The agents adapt their movement patterns dynamically, balancing exploration and exploitation to navigate the solution space effectively.

CSO incorporates social interactions, allowing agents to share information about promising regions in the solution space through color signals. This collaborative learning enhances the collective intelligence of the swarm. The algorithm continuously evaluates and updates its solutions, iteratively refining the population. CSO leverages the principles of self-organization, emergence, and adaptability to navigate complex optimization landscapes effectively. Through the interplay of color-coded communication and adaptive movement, Chameleon Swarm Optimization showcases its ability to efficiently explore and exploit solution spaces, making it a robust and versatile optimization technique.

3.3.1. Features of CSO

- a) **Initialization:** Chameleon Swarm Optimization (CSO) begins with the initialization of a diverse population of agents in the solution space. These agents represent potential solutions to the optimization problem, and their initial distribution sets the starting point for the algorithm.
- b) **Color-Based Communication:** In CSO the agents communicate by changing colors, inspired by the adaptive color-changing nature of chameleons. This color-based communication serves as a symbolic language, conveying information about the quality of solutions and guiding the swarm towards regions of higher fitness.
- c) **Adaptive Movement:** Agents in the swarm exhibit adaptive movement patterns, adjusting their positions based on their own experiences and the information received from neighboring agents. This dynamic adaptation helps the swarm efficiently explore the solution space, balancing exploration and exploitation.
- d) **Social Interaction:** CSO incorporates social interactions among agents. They share information about promising regions in the solution space through color signals. This collaborative learning enhances the collective intelligence of the swarm, facilitating efficient convergence towards optimal solutions.
- e) **Environmental Sensing:** Agents possess the ability to sense the environment, responding to changes in the problem landscape. Environmental sensing influences the decision-making process of each agent, ensuring adaptability to evolving conditions during the optimization process.
- f) **Dynamic Exploration-Exploitation Trade-off:** The swarm dynamically adjusts its balance between exploration and



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exploitation based on environmental cues and the success of neighboring agents in finding optimal solutions. This trade-off ensures effective navigation through the solution space.

- g) **Temperature Regulation (Inspired by Thermoregulation):** CSO incorporates a temperature-like parameter that influences the exploration rate of the swarm. Higher "temperatures" encourage more exploration, while lower temperatures promote exploitation, providing a mechanism for adaptive and dynamic exploration.
- h) **Dynamic Neighborhoods:** The concept of neighborhoods within the swarm is dynamic, changing based on the current state of the algorithm. Agents selectively interact with others based on their color patterns and success rates, fostering adaptive collaboration.
- i) **Adaptive Memory Mechanism:** Agents maintain an adaptive memory of successful solutions and experiences. This memory is continuously updated based on observed changes in the environment and the success of neighboring agents, ensuring a dynamic learning process.

3.4. Invigorated Chameleon Swarm Optimization

Invigorated Chameleon Swarm Optimization represents a refined and dynamic algorithm, building upon the principles of Chameleon Swarm Optimization (CSO). ICSO introduces a rejuvenating mechanism to enhance the vitality and adaptability of the swarm throughout the optimization process.

- a) **Initialization and Rejuvenation:** ICSO initializes a diverse swarm of agents, each representing a potential solution. Uniquely, the algorithm incorporates periodic rejuvenation events, injecting freshness into the swarm by introducing new individuals or reinitializing certain parameters.
- b) **Dynamic Color-Based Communication:** ICSO relies on dynamic color-based communication among agents, emulating the adaptive color-changing nature of chameleons. This symbolic language conveys not only the quality of solutions but also the recent vitality of information, enriching the adaptability of the swarm.
- c) **Adaptive Movement and Energy Conservation:** Agents within the swarm exhibit adaptive movement patterns, responding to the vitality of neighboring agents. The algorithm introduces energy conservation mechanisms, ensuring dynamic responsiveness while conserving energy for sustained exploration.
- d) **Environmental Sensing and Adaptability:** ICSO endows agents with heightened environmental sensitivity, enabling them to adapt their strategies to changes in the problem landscape. This adaptability ensures swift

responses to environmental shifts, aligning with the overall theme of rejuvenation.

- e) **Dynamic Exploration-Exploitation Trade-off with Revitalization:** ICSO dynamically balances the exploration-exploitation trade-off, introducing periodic revitalization events. These events inject heightened exploration enthusiasm into the swarm, fostering innovation and preventing stagnation in solution space exploration.
- f) **Social Interaction and Collective Revitalization:** Encouraging social interactions among agents, ICSO facilitates the sharing of both solution-related and vitality-related information. The algorithm introduces collective revitalization events, synchronizing renewal processes among agents and fostering synergistic effects.
- g) **Temperature Regulation for Revitalization:** Inspired by the temperature parameter in CSO, ICSO incorporates a similar parameter influencing exploration rates and the frequency of revitalization events. Higher "temperatures" correspond to more frequent revitalization, injecting renewed vigor into the swarm.
- h) **Dynamic Neighborhoods with Regeneration:** ICSO maintains the concept of dynamic neighborhoods, adapting based on the energy levels and vitality of agents. The algorithm introduces regeneration mechanisms, periodically infusing new individuals into neighborhoods, stimulating collaborative rejuvenation.
- i) **Adaptive Memory Mechanism with Memory Regeneration:** Extending the adaptive memory mechanism from CSO, ICSO ensures agents maintain a continuous and evolving memory of successful solutions and vitality experiences. This memory is consistently regenerated, preventing stagnation and fostering a dynamic learning process.

ICSO redefines swarm intelligence by infusing constant vitality. Its dynamic color-based communication, adaptive movement, and periodic rejuvenation foster continuous innovation. ICSO stands as a resilient optimization approach, ensuring adaptability and optimal exploration, propelling it beyond conventional swarm algorithms.

3.4.1. Initialization and Rejuvenation

The optimization process commences with the generation of a diverse population of agents representing potential solutions. This population is denoted as P_t at iteration t . Each agent symbolized as A_i , is defined as a vector in the solution space, $A_i = (x_{i1}, x_{i2}, \dots, x_{in})$ where n is the dimensionality of the solution space. The swarm's initial state is crucial for a robust optimization process and is represented as S_t at iteration t .

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The rejuvenation process involves the introduction of new individuals or the reinitialization of specific parameters in the swarm, promoting continuous adaptability and preventing premature convergence. The rejuvenation term denoted as R_t is dynamically determined based on the overall vitality of the swarm. A rejuvenation factor RF , influences the rate of rejuvenation. The rejuvenation process can be expressed mathematically with Eq.(13).

$$R_t = RF \cdot vitality(S_t) \tag{13}$$

Where $vitality(S_t)$ represents a measure of the swarm's vitality at iteration t . The swarm's vitality is influenced by factors such as the diversity of solutions and the recent success in exploring the solution space. The diversity of the swarm, denoted as D_t is calculated using a diversity measure that considers the Euclidean distances between individual solutions within the population.

$$D_t = \sum_{i=1}^N \sum_{j=i+1}^N \frac{1}{|A_i - A_j|} \tag{14}$$

Where in Eq.(14), N is the number of agents in the population. The overall energy $vitality(S_t)$ is a combination of the diversity measure and a success metric that gauges the swarm's recent performance. The success metric, denoted as SM_t can be expressed as a weighted sum of the fitness values of the top-performing agents represented mathematically in Eq.(15).

$$SM_t = \sum_{i=1}^k \omega_i \cdot \int(A_i) \tag{15}$$

Where $\int(A_i)$ represents the fitness of agent A_i , k is the number of top-performing agents, and ω_i is the weight associated with each agent.

The overall $vitality(S_t)$ is then calculated as a combination of diversity and success shown in Eq.(16).

$$vitality(S_t) = \alpha \cdot D_t + (1 - \alpha) \cdot SM_t \tag{16}$$

Where α is a parameter that balances the contribution of diversity and success to the overall vitality.

3.4.2. Dynamic Color-Based Communication

This optimization algorithm introduces a sophisticated communication mechanism among agents inspired by the adaptive color-changing behavior of chameleons. Each agent A_i communicates through a dynamic color variable $C_{i,t}$ which represents the agent's signaling information at iteration t . This color variable dynamically evolves based on the agent's own characteristics and interactions with neighboring agents.

The evolution of the color variable is governed by an adaptive updating mechanism that combines the agent's historical color

information $H_{i,t}$ and the influence from neighboring agents. Mathematically, the dynamic color variable can be expressed in Eq.(17).

$$C_{i,t+1} = \beta \cdot H_{i,t} + \gamma \cdot \sum_{j=1}^N w_{ij} \cdot C_{ij} \tag{17}$$

Where β and γ are parameters controlling the influence of historical color and neighboring color information, respectively. N represents the total number of agents in the population, and w_{ij} is the weight associated with the interaction between agents A_i and A_j .

The historical color information $H_{i,t}$ is updated based on the agent's own success, incorporating a feedback mechanism that emphasizes successful color choices. This update can be formulated in Eq.(18).

$$H_{i,t+1} = (1 - \delta) \cdot H_{i,t} + \delta \cdot \int(A_i) \tag{18}$$

Where δ is a parameter determining the weight of the feedback mechanism, and $\int(A_i)$ is the fitness of agent A_i .

To ensure diversity and prevent color convergence, an entropy term $E_{i,t}$ is introduced, representing the diversity of colors in the neighborhood of agent A_i expressed with Eq.(19).

$$E_{i,t} = - \sum_{j=1}^N w_{ij} \cdot \log(w_{i,j}) \tag{19}$$

The overall color update equation is modified to include the entropy term.

$$C_{i,t+1} = \beta \cdot H_{i,t} + \gamma \cdot \sum_{j=1}^N w_{ij} \cdot C_{j,t} + \alpha \cdot E_{i,t} \tag{20}$$

Where in Eq.(20), α is a parameter controlling the influence of the entropy term on the color update. This dynamic color-based communication mechanism ensures that agents continuously adapt their signaling information based on both individual success and collective interactions, promoting diversity and effective exploration in the optimization process.

3.4.3. Adaptive Movement and Energy Conservation

A dynamic movement strategy for each agent, inspired by the adaptability observed in chameleons. The movement of an agent A_i is influenced by its historical movement vector $M_{i,t}$ the impact of neighboring agents, and an innovative adaptive energy conservation mechanism.

The adaptive movement vector undergoes continuous updates through a combination of historical movement information and the influence from neighboring agents. Mathematically,

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the dynamic movement vector is expressed mathematically in Eq.(21).

$$M_{i,t+1} = \beta \cdot M_{i,t} + \gamma \cdot \sum_{j=1}^N w_{ij} \cdot M_{j,t} \quad (21)$$

Where β and γ are parameters that regulate the influence of historical movement and neighboring movement information, respectively. N signifies the total number of agents in the population, and w_{ij} represents the weight associated with the interaction between agents A_i and A_j .

To incorporate adaptability based on an agent's success, a feedback mechanism is introduced to update the historical movement information

$$M_{i,t+1} = (1 - \delta) \cdot M_{i,t} + \delta \cdot \int(A_i) \quad (22)$$

In Eq.(22), δ is a parameter that determines the weight of the feedback mechanism, and $\int(A_i)$ represents the fitness of agent A_i .

To maintain diversity in the movement strategy and prevent premature convergence, an entropy term $E_{i,t}$ is introduced. This term represents the diversity of movement vectors in the neighborhood of agent A_i expressed mathematically in Eq.(23).

$$E_{i,t} = - \sum_{j=1}^N w_{ij} \cdot \log(w_{ij}) \quad (23)$$

The overall movement update equation is then adjusted to include the entropy term

$$M_{i,t+1} = \beta \cdot M_{i,t} + \gamma \cdot \sum_{j=1}^N w_{ij} \cdot M_{j,t} + \alpha \cdot E_{i,t} \quad (24)$$

In Eq.(24), where α is a parameter determining the influence of the entropy term on the movement update.

The ICSO introduces an energy conservation mechanism to regulate the movement of agents. Each agent possesses an energy level $E_{i,t}$ influencing its movement. The energy level undergoes updates based on the agent's historical success and the effort expended in the current iteration.

$$E_{i,t+1} = (1 - \eta) \cdot E_{i,t} - \lambda \cdot \|M_{i,t}\| \cdot \int(A_i) \quad (25)$$

In Eq.(25), the symbol η is a parameter controlling the decay of energy over time, λ influences the energy consumption during movement, and $\|M_{i,t}\|$ represents the magnitude of the movement vector.

3.4.4. Environmental Sensing and Adaptability

Environmental Sensing and Adaptability intention is to enhance the swarm's responsiveness to variations in the

optimization landscape. The environmental sensing process involves agents gathering information about the local environment, enabling them to adapt their behaviors accordingly. Let $S_{i,t}$ represent the sensing information of agent A_i at iteration t . This information is accumulated through interactions with the environment and neighboring agents. The sensing information is updated based on the fitness of the agent and the historical sensing information is expressed in mathematical form with Eq.(26).

$$S_{i,t+1} = (1 - \phi) \cdot S_{i,t} + \phi \cdot \int(A_i) \quad (26)$$

Where ϕ is a parameter controlling the weight of the fitness information in the sensing update, and $\int(A_i)$ is the fitness of agent A_i .

To ensure diversity in the sensing information and prevent convergence, an entropy term $E_{i,t}$ is introduced, similar to previous steps. This term represents the diversity of sensing information in the neighborhood of agent A_i shown in Eq.(27).

$$E_{i,t} = - \sum_{j=1}^N w_{ij} \cdot \log(w_{ij}) \quad (27)$$

The overall sensing update equation is then adjusted to include the entropy term.

$$S_{i,t+1} = (1 - \phi) \cdot S_{i,t} + \phi \cdot \int(A_i) + \alpha \cdot E_{i,t} \quad (28)$$

In Eq.(28), α is a parameter determining the influence of the entropy term on the sensing update.

The adaptability of agents is further enhanced by incorporating the sensing information into the movement strategy. The movement vector $M_{i,t+1}$ is updated based on the sensing information.

$$M_{i,t+1} = \beta \cdot M_{i,t} + \gamma \cdot \sum_{j=1}^N w_{ij} \cdot M_{j,t} + \alpha \cdot S_{i,t} \quad (29)$$

In Eq.(29), where α represents the weight of the sensing information in the movement update. The algorithm also introduces a mechanism to adjust the energy conservation process based on the sensing information. The energy level $E_{i,t+1}$ is updated which is expressed in Eq.(30).

$$E_{i,t+1} = (1 - \eta) \cdot E_{i,t} - \lambda \cdot \|M_{i,t}\| \cdot \int(A_i) + \beta \cdot S_{i,t} \quad (30)$$

Where β is a parameter controlling the influence of sensing information on the energy update.

These mathematical expressions jointly ensures that the agents in ISCO not only sense changes in the environment but also adapt their movement and energy conservation strategies based on this sensed information.

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3.4.5. Dynamic Exploration-Exploitation Trade-off with Revitalization

A dynamic mechanism to balance exploration and exploitation, emphasizing the significance of a well-tuned trade-off in different phases of the optimization process. The exploration-exploitation trade-off is governed by a dynamic parameter λ_t representing the balance between exploration and exploitation at iteration t . This parameter is updated based on the historical success of the swarm.

$$\lambda_t = (1 - \rho) \cdot \lambda_{t-1} + \rho \cdot \int(S_{t-1}) \quad (31)$$

In Eq.(31), where ρ is a parameter controlling the weight of the historical success in the update, and $\int(S_{t-1})$ is the overall fitness of the swarm at the previous iteration. The dynamic exploration-exploitation parameter is then utilized to adjust the movement vector update equation.

$$M_{i,t+1} = \beta \cdot M_{i,t} + \gamma \cdot \sum_{j=1}^N w_{ij} \cdot M_{j,t} + \alpha \cdot S_{i,t} + \lambda_t \cdot \sigma_t \quad (32)$$

In Eq.(32), $\lambda_t \cdot \sigma_t$ introduces a dynamic component in the movement update influenced by the exploration-exploitation trade-off. σ_t represents a random term that contributes to exploration, and its magnitude is dynamically adjusted based on λ_t .

To prevent premature convergence and introduce periodic exploration revitalization, a revitalization factor R_t is introduced. The revitalization factor is influenced by the diversity of the sensing information and the overall vitality of the swarm.

$$R_t = \omega \cdot E_{sense,t} + (1 - \omega) \cdot vitality(S_t) \quad (33)$$

Where in Eq.(33), $E_{sense,t}$ represents the diversity of the sensing information, and $vitality(S_t)$ is a measure of the overall vitality of the swarm. ω is a parameter controlling the weight of diversity in the revitalization factor.

The exploration-exploitation trade-off parameter is then utilized to adjust the overall vitality of the swarm, ensuring a dynamic interplay between exploration and exploitation, which is clearly depicted in Eq.(34).

$$vitality(S_t) = \alpha \cdot D_t + (1 - \alpha) \cdot SM_t + \beta \cdot R_t \quad (34)$$

Where α controls the influence of diversity and success in the overall vitality measure. The overall movement update equation, considering both exploration-exploitation dynamics and periodic revitalization is

$$M_{i,t+1} = \beta \cdot M_{i,t} + \gamma \cdot \sum_{j=1}^N w_{ij} \cdot M_{j,t} + \alpha \cdot S_{i,t} + \lambda_t \cdot \sigma_t + \beta \cdot R_t \quad (35)$$

The Eq.(35), collectively ensure that the exploration-exploitation trade-off in ISCO is dynamically adjusted based on historical success, and periodic revitalization events inject exploration enthusiasm, preventing premature convergence.

3.4.6. Social Interaction and Collective Revitalization

By Integrating social interaction and collective revitalization the swarm's exploration and convergence capabilities will be enhanced. These mechanisms draw inspiration from social behaviors observed in nature, fostering collaboration among agents and periodically injecting vitality into the entire swarm.

3.4.6.1. Social Interaction

Social interaction in ISCO involves the exchange of information among agents to facilitate collective learning and adaptation. $I_{i,t}$ denote the information held by agent A_i at iteration t . The information is updated based on the agent's historical information and the shared information from neighboring agents.

$$I_{i,t+1} = (1 - \theta) \cdot I_{i,t} + \theta \cdot \sum_{j=1}^N w_{ij} \cdot I_{j,t} \quad (36)$$

In Eq.(36), where θ is a parameter controlling the influence of neighboring information on the update, N represents the total number of agents, and $w_{i,j}$ signifies the weight associated with the interaction between agents A_i and A_j .

3.4.6.2. Collective Revitalization

It introduces periodic events to rejuvenate the entire swarm aiming to prevent premature convergence and maintain diversity.

The revitalization factor R_t is determined by combining the diversity of the information within the swarm $E_{info,t}$ and the overall vitality of the swarm $vitality(S_t)$ which is mathematically represented in Eq.(37).

$$R_t = \omega \cdot E_{info,t} + (1 - \omega) \cdot vitality(S_t) \quad (37)$$

The diversity of information $E_{info,t}$ is calculated based on the entropy of the information shared among agents shown in Eq.(38).

$$E_{info,t} = - \sum_{i=1}^N \sum_{j=1}^N w_{i,j} \cdot \log(w_{i,j}) \quad (38)$$

The overall vitality of the swarm is a combination of diversity, success metrics, and the revitalization factor

$$vitality(S_t) = \alpha \cdot D_t + (1 - \alpha) \cdot SM_t + \beta \cdot R_t \quad (39)$$

In Eq.(39), where α controls the influence of diversity on vitality D_t represents the diversity of the swarm, and SM_t is a success metric based on the fitness values of top-performing agents.

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3.4.6.3. Integration of Social Interaction and Revitalization

The social interaction information $I_{i,t+1}$ is incorporated into the overall movement update equation to enhance adaptability and convergence

$$M_{i,t+1} = \beta \cdot M_t + \gamma \cdot \sum_{j=1}^N w_{i,j} \cdot M_{j,t} + \alpha \cdot I_{i,t+1} + \lambda_t \cdot \sigma_t + \beta \cdot R_t \quad (40)$$

In Eq.(40), α represents the weight of social interaction information in the movement update, and $\lambda_t \cdot \sigma_t$ introduces a dynamic component influenced by the exploration-exploitation trade-off.

Step 1: Initialize Parameters

- Set thresholds and conditions for interaction and revitalization.

Step 2: For each Chameleon in the swarm

- ExchangeInformationWithPeers():
- Share information with nearby chameleons.
- AssessRevitalizationConditions():
- Evaluate if conditions for collective revitalization are met.
- If collective revitalization conditions are met:
- InitiateCollectiveRevitalizationEvent():
- Trigger a collective revitalization event.
- ParticipateInCollectiveRevitalization():
- Engage in the collective revitalization process.

Step 3: End Algorithm

Algorithm 2 Social Interaction and Collective Revitalization

Algorithm 2 depicts the process of chameleon interactions by exchanging information. When conditions for collective revitalization are met, chameleons trigger a joint revitalization event, enhancing collaboration and overall swarm adaptability in response to environmental changes.

3.4.7. Temperature Regulation for Revitalization:

In Temperature Regulation for Revitalization the algorithm presents a temperature-based mechanism to control the frequency and intensity of the revitalization process. The concept of temperature regulation draws inspiration from simulated annealing where the temperature parameter influences the exploration-exploitation trade-off. The temperature is utilized to dynamically modulate the revitalization strategy, ensuring a balanced and controlled rejuvenation of the swarm.

3.4.7.1. Temperature Regulation:

The temperature parameter is denoted as T_t , represents the current temperature of the swarm at iteration t . The

temperature is dynamically updated based on the overall success of the swarm and a cooling schedule

$$T_{t+1} = \alpha \cdot T_t + (1 - \alpha) \cdot \int(S_t) \quad (41)$$

In Eq.(41), α is a parameter controlling the influence of the current temperature on the update and $\int(S_t)$ is a success metric based on the fitness values of top-performing agents in the swarm.

3.4.7.2. Revitalization Factor

The revitalization factor R_t is determined by combining the diversity of the swarm D_t and the overall vitality of the swarm $vitality(S_t)$ is expressed with Eq.(42).

$$R_t = \omega \cdot D_t + (1 - \omega) \cdot vitality(S_t) \quad (42)$$

The diversity of the swarm D_t is calculated based on the entropy of the information shared among agents is shown in Eq.(43).

$$D_t = - \sum_{i=1}^N \sum_{j=1}^N w_{i,j} \cdot \log(w_{i,j}) \quad (43)$$

3.4.7.3. Integration of Temperature Regulation and Revitalization

The overall revitalization factor R_t is modulated by the temperature parameter T_t to control the magnitude of the revitalization process

$$\text{Revitalization Magnitude} = R_t \cdot e^{-\frac{1}{T_t}} \quad (44)$$

In Eq.(44), where the exponential term $e^{-\frac{1}{T_t}}$ acts as a cooling schedule, ensuring that as the temperature decreases, the magnitude of revitalization diminishes, creating a controlled and gradual revitalization process.

3.4.7.4. Overall Movement Update:

The temperature-regulated revitalization magnitude is incorporated into the movement update equation to influence the exploration-exploitation dynamics

$$M_{i,t+1} = \beta \cdot M_{i,t} + \gamma \cdot \sum_{j=1}^N w_{i,j} \cdot M_{j,t} + \alpha \cdot I_{i,t+1} + \lambda_t \cdot \sigma_t + \beta \cdot \text{Revitalization Magnitude} \quad (45)$$

In Eq.(45), where β represents the weight of the revitalization magnitude in the movement update, and $\lambda_t \cdot \sigma_t$ introduces a dynamic component influenced by the exploration-exploitation trade-off.

Step 1 : Initialize Parameters:

- Set performance thresholds and temperature limits.

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Step 2: For each Chameleon in the swarm (Iterate):

- AssessChameleonPerformance():
 - Evaluate the individual chameleon's performance.

If performance is below a threshold:

- IncreaseSwarmTemperature():
 - Raise the overall temperature of the swarm.

If temperature exceeds a limit:

- InitiateRevitalizationEvent():
 - Trigger a collective revitalization event.

Else if performance is above a threshold:

- DecreaseSwarmTemperature():
 - Lower the overall temperature of the swarm.

End Algorithm

Algorithm 3 Temperature Regulation for Revitalization

The Algorithm 3 depicts the temperature regulation for revitalization process in which dynamically adjusts a swarm's temperature based on individual chameleon performance. If a chameleon's performance falls below a threshold, the swarm temperature increases, triggering revitalization. Else if performance is high, the temperature decreases, ensuring adaptive optimization in varying conditions.

3.4.8. Dynamic Neighborhoods with Regeneration

In Dynamic Neighborhoods with Regeneration the algorithm introduces a dynamic neighborhood mechanism coupled with regeneration to enhance the collaborative and adaptive nature of the swarm. The concept of dynamic neighborhoods involves agents adjusting their interaction patterns, promoting collaboration with different subsets of the swarm over time. Regeneration complements this by periodically refreshing the neighborhood structure to foster exploration and prevent stagnation.

3.4.8.1. Dynamic Neighborhood Formation

The dynamic neighborhood formation is governed by the interaction weight $w_{i,j,t}$ between agents A_i and A_j at iteration t . This weight is modulated by a dynamic factor $D_{i,j,t}$ representing the diversity of the information exchanged between the agents are mathematically expressed in Eq.(46).

$$w_{i,j,t+1} = (1 - \rho) \cdot w_{i,j,t+\rho} \cdot D_{i,j,t} \tag{46}$$

Where ρ is a parameter controlling the influence of diversity on the interaction weight, and $D_{i,j,t}$ is calculated based on the entropy of the information shared between agents are expressed with Eq.(47).

$$D_{i,j,t} = - \sum_{k=1}^N \log(w_{i,k,t}) \cdot \log(w_{j,k,t}) \tag{47}$$

3.4.8.2. Dynamic Neighborhood Update

The dynamic neighborhood update influences the overall movement vector $M_{i,t+1}$. Agents adjust their movement based on the dynamically changing interaction weights within their neighborhoods.

$$M_{i,t+1} = \beta \cdot M_{i,t} + \gamma \cdot \sum_{j=1}^N w_{i,j,t} \cdot M_{j,t} + \alpha \cdot I_{i,t+1} + \lambda_t \cdot \sigma_t + \beta \cdot Revitalization_Magnitude \tag{48}$$

In Eq.(48), where γ represents the weight of the dynamic neighborhood in the movement update and $\lambda_t \cdot \sigma_t$ introduces a dynamic component influenced by the exploration-exploitation trade-off.

3.4.8.3. Regeneration of Dynamic Neighborhoods

Regeneration involves periodically refreshing the dynamic neighborhood structure to introduce novelty and exploration enthusiasm. The regeneration factor $R_{neighbour,t}$ is influenced by the success metrics and the diversity of the current dynamic neighborhood configuration is shown in Eq.(49).

$$R_{neighbour,t} = \omega \cdot vitality(S_t) + (1 - \omega) \cdot E_{neighbour,t} \tag{49}$$

The diversity of the dynamic neighborhood configuration $E_{neighbour,t}$ is calculated based on the entropy of the interaction weights shown in Eq.(50).

$$E_{neighbour,t} = - \sum_{i=1}^N \sum_{j=1}^N w_{i,j,t} \cdot \log(w_{i,j,t}) \tag{50}$$

3.4.8.4. Integration of Dynamic Neighborhoods and Regeneration

The overall movement update is adjusted based on the regeneration factor, ensuring that regeneration events influence the exploration-exploitation dynamics

$$M_{i,t+1} = \beta \cdot M_{i,t} + \gamma \cdot \sum_{j=1}^N w_{i,j,t} \cdot M_{j,t} + \alpha \cdot I_{i,t+1} + \lambda_t \cdot \sigma_t + \beta \cdot Revitalization_Magnitude + \delta \cdot R_{neighbour,t} \tag{51}$$

In Eq.(51), where δ represents the weight of the regeneration factor in the movement update.

3.4.9. Adaptive Memory Mechanism with Memory Regeneration

An adaptive memory mechanism to enhance the retention and utilization of valuable information acquired during the

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optimization process. The adaptive memory is coupled with a memory regeneration process, ensuring that the stored information remains relevant and diverse.

3.4.9.1. Adaptive Memory Mechanism

The adaptive memory for each agent A_i at iteration t is denoted as $M_{adapt,i,t}$. This memory is updated based on the current information $I_{i,t}$ and the historical memory $M_{adapt,i,t-1}$.

$$M_{adapt,i,t} = (1 - \eta) \cdot M_{adapt,i,t-1} + \eta \cdot I_{i,t} \quad (52)$$

In Eq.(52), where η is a parameter controlling the influence of the current information on the memory update. The adaptive memory mechanism allows agents to gradually accumulate valuable information over time.

3.4.9.2. Memory Regeneration

To refresh the adaptive memory and to ensure that stored information remains diverse and relevant. The regeneration factor $R_{memory,t}$ is determined based on the success metrics and the diversity of the current adaptive memory are represented mathematically with Eq.(53).

$$R_{memory,t} = \omega \cdot vitality(S_t) + (1 - \omega) \cdot E_{memory,t} \quad (53)$$

The diversity of the adaptive memory configuration $E_{memory,t}$ is calculated using the entropy of the memory entries are shown in Eq.(54).

$$E_{memory,t} = \sum_{i=1}^N \log(M_{adapt,i,t}) \quad (54)$$

3.4.9.3. Integration of Adaptive Memory and Memory Regeneration

The overall movement update incorporates the adaptive memory with a regeneration term, ensuring that the stored information influences the exploration-exploitation dynamics while undergoing periodic revitalization.

$$M_{i,t+1} = \beta \cdot M_{i,t} + \gamma \cdot \sum_{j=1}^N w_{i,j,t} \cdot M_{j,t} + \alpha \cdot M_{adapt,i,t} + \lambda_t \cdot \sigma_t + \beta \cdot Revitalization_Magnitude + \delta \cdot R_{neighbour} + \epsilon \cdot R_{memory,t} \quad (55)$$

In Eq.(55), where α represents the weight of the adaptive memory in the movement update, and ϵ represents the weight of the memory regeneration factor.

Step 1: Initialization and Rejuvenation

- Initialize the swarm with Chameleon agents.
- Set the initial temperature for the swarm.

Step 2: Dynamic Color-Based Communication

For each Chameleon in the swarm:

- Update the color of the Chameleon.
- Communicate with neighboring Chameleons based on color.

Step 3: Adaptive Movement and Energy Conservation

For each Chameleon in the swarm:

- Adapt the movement strategy based on the current environment.
- Conserve energy during movement.

Step 4: Environmental Sensing and Adaptability

For each Chameleon in the swarm:

- Sense the environment and adapt to changes.

Step 5: Dynamic Exploration-Exploitation Trade-off with Revitalization

- Update the exploration-exploitation strategy of the swarm.
- Revitalize the swarm periodically.

Step 6: Social Interaction and Collective Revitalization

For each Chameleon in the swarm:

- Exchange information with nearby Chameleons.
- Participate in collective revitalization events.

Step 7: Temperature Regulation for Revitalization

- Regulate the swarm temperature based on performance.
- Control the frequency and intensity of revitalization.

Step 8: Dynamic Neighborhoods with Regeneration

For each Chameleon in the swarm:

- Adjust the dynamic neighborhood based on information exchange.
- Periodically regenerate the neighborhood structure.

Step 9: Adaptive Memory Mechanism with Memory Regeneration

For each Chameleon in the swarm:

- Update adaptive memory based on learned information.
- b. Periodically regenerate the adaptive memory to maintain diversity.

Algorithm 4 Invigorated Chameleon Swarm Optimization (ICSO)

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The Algorithm 4 depicts the Invigorated Chameleon Swarm Optimization (ICSO) algorithm emulates chameleon behavior in a collective optimization process. Chameleons adaptively communicate, move, and revitalize, fostering a dynamic and collaborative swarm with temperature regulation, social interaction, and memory adaptation, the algorithm achieves robust and effective optimization in complex environments.

3.5. Union of FW-AODV and ICSO

The merging of the FW based AODV (FW-AODV) and Invigorated Chameleon Swarm Optimization (ICSO) creates a broad paradigm for adaptive and efficient routing. At first FW-AODV the network undergoes meticulous initialization, computing all-pairs shortest paths. During Route Discovery with AODV optimal paths are sought using the precomputed FW matrix, dynamically invoking AODV when necessary. The Optimal Path Selection phase strategically amalgamates AODV Route Reply (RREP) assessments with FW paths, ensuring the selection of the most efficient route. This cooperative integration extends to Route Maintenance with FW, where periodic matrix updates accommodate dynamic shifts in network topology. Adaptive Path Switching, influenced by both AODV and FW, enables nodes to dynamically transition to alternative optimal paths in response to link failures or network alterations. Energy-Aware Routing introduces energy considerations into path selection, accounting for node energy levels and enhancing the network's endurance.

In ICSO the focus pivots to swarm-based optimization. Initialization and Rejuvenation instill diversity and periodic infusion of new entities into the swarm. Dynamic Color-Based Communication, analogous to data exchange, conveys not only the solution quality but also the vitality of the solution. Adaptive Movement and Energy Conservation ensure responsiveness, vital in the context of mobile sensors. Environmental Sensing and Adaptability resonate with adaptability, with strategies evolving based on environmental shifts.

The dynamic Exploration-Exploitation Trade-off with Revitalization amplifies innovation enthusiasm, mirroring the vigor required in dynamic scenarios. Social Interaction and Collective Revitalization embody collaborative synergy, aligning with collective rejuvenation events. The incorporation of Temperature Regulation for Revitalization introduces a parameter influencing exploration and revitalization frequencies. Dynamic Neighborhoods with Regeneration adapts neighborhoods based on energy and stimulates collaboration. The Adaptive Memory Mechanism with Memory Regeneration maintains an adaptive memory, preventing stagnation and ensuring continuous learning. This amalgamation of FW-AODV and ICSO underscores adaptability, resilience, and efficiency, offering a promising paradigm for dynamic environments.

Step 1: Initialization and Adaptive Formation:

- ICSO: Initializes a diverse swarm of agents, injecting diversity into the network.
- FW-AODV: Concurrently computes optimal paths using the FW algorithm during the network initialization.

Step 2: Dynamic Communication and Collective Decision-Making:

- FW-AODV: Leverages precomputed paths for efficient route discovery and optimal path selection.
- ICSO: Facilitates dynamic color-based communication among swarm agents, exchanging information on solution quality and vitality.

Step 3: Adaptation and Maintenance Synergy:

- FW-AODV: Periodically updates the FW matrix, accommodating changes in network topology.
- ICSO: Adapts swarm movement patterns based on agent vitality, ensuring continuous dynamic responsiveness.

Step 4: Energy-Aware Routing with Sustainability:

- ICSO and FW-AODV: Collaboratively integrate energy considerations into path selection, optimizing routing decisions based on node energy levels.
- ICSO: Introduces energy conservation mechanisms, ensuring the swarm's dynamism while conserving energy resources.

Step 5: Collective Exploration and Path Switching:

- ICSO and FW-AODV: Collaboratively contribute to collective revitalization events, injecting increased exploration enthusiasm into both the swarm and the network.
- FW-AODV: Utilizes revitalization triggers for intensified exploration, fostering innovation in optimal path discovery.

Step 6: Environmental Sensing and Adaptability:

- ICSO: Enhances adaptability by sensing changes in the environment, dynamically adjusting swarm strategies.
- FW-AODV: Contributes to dynamic network reconfiguration based on AODV decisions, aligning the network with changing environmental conditions.

Algorithm 5 ICSO based FW-AODV in MWSN

Thus the above Algorithm 5 depicts the overall functionality of the ICSO based FW-AODV protocol in the MWSNs. This refined approach emphasizes the shared responsibilities and collaboration between ICSO and FW-AODV, ensuring that each contributes to the overall efficiency and resilience of the

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network. The roles are distributed, with FW-AODV handling routing-centric tasks and ICSO providing swarm-based adaptability and diversity. Together, they create a symbiotic relationship, leveraging the strengths of both approaches for enhanced performance in WSNs.

3.6. Advantages of ICSO based FW-AODV

The fusion of Invigorated Chameleon Swarm Optimization (ICSO) and FW based Ad-hoc On-Demand Distance Vector (FW-AODV) in Mobile Wireless Sensor Networks (MWSNs) offers several advantages:

- **Adaptive Resilience:** The combination provides adaptive resilience to dynamic changes in the network. FW-AODV's path-centric approach aligns with ICSO's swarm-based adaptability, ensuring robustness in challenging environments.
- **Optimal Path Exploration:** ICSO injects increased exploration enthusiasm into the swarm, complementing FW-AODV's route discovery. This synergy fosters innovation in optimal path exploration and selection.
- **Energy-Efficient Routing:** FW-AODV integrates energy considerations into routing decisions, while ICSO introduces energy conservation mechanisms for the swarm. This shared focus ensures energy-efficient routing, extending the network's operational lifetime.
- **Collective Decision-Making:** It promotes collective decision-making. FW-AODV and ICSO collaboratively contribute to revitalization events, enhancing exploration enthusiasm both at the node and swarm levels.
- **Dynamic Network Reconfiguration:** The combined approach enables dynamic network reconfiguration based on both AODV decisions and swarm intelligence. This ensures that the network can quickly adapt to changes in topology and environmental conditions.
- **Enhanced Synergy:** It capitalizes on the strengths of both algorithms, creating a symbiotic relationship. FW-AODV handles node-centric routing tasks, while ICSO contributes swarm-based adaptability and diversity, resulting in an enhanced overall performance.

The collaborative fusion of ICSO and FW-AODV creates a comprehensive solution that combines the strengths of individual approaches, resulting in a more adaptive, efficient, and resilient WSNs.

4. SIMULATION SETTINGS AND PARAMETERS

Simulation process helps to replicate real-world processes in a controlled environment, this simulation performs testing, analysis, and prediction without physical implementation. It makes complex systems simpler for easy understanding, performance improvement, and informed decision-making

without real-world consequences. This is especially valuable in situations where actual testing is difficult, expensive, or time-consuming. NS-3 which is also known as Network Simulator 3 plays a crucial role in academia and research for simulating network scenarios. As an open-source tool it provides a platform for modeling various networks, including wired and wireless setups. NS-3's modular structure allows for tailored simulations, aiding researchers in analyzing and refining network protocols and algorithms. The Simulation Setting table 2 contains the simulation settings and potential metrics for an ns-3 simulation involving the integrated ICSO and FW-AODV in a MWSN.

Table 2 Simulation Setting

Setting/Metric	Value/Description
Network Size	50 nodes
Simulation Time	100 seconds
Mobility Model	Random Walk 2D Mobility Model
Mobility Trace	Enabled, with trace file "mobility_trace.tr"
Network Protocol Implementations	ICSO and FW-AODV
Application Layer	Data generation and transmission applications.
Simulation Stop Time	100 seconds.
Tracing	Enabled for mobility.
Bandwidth	94 Hz
Boundary of Network	750m x 750m x 750m
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



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Runtime	300 seconds
Size of Packet	78 bytes

These values represent specific settings for the simulation parameters such as bandwidth, network size, energy, and other relevant details.

5. RESULTS AND DISCUSSION

The integration of the FW with the AODV protocol, resulting in the FW-AODV, was undertaken to a severe evaluation in MWSNs. The fusion successfully demonstrated enhanced routing efficiency and adaptability in dynamic and challenging WSNs environment. The incorporation of ICSD into FW-AODV particularly within H-MWSNs has showcased remarkable attributes such as resilience, adaptability, and operational efficiency. The results indicate that the adaptive paradigm introduced by FW-AODV contributes to the optimization of path computation and dynamic routing.

5.1. Packet Delivery and Drop Analysis

The Figure 1, depicts the Packet Delivery in ICSOP signifies a robust mechanism for ensuring that data packets are efficiently transmitted and reach their intended destination with a high success rate. It is very crucial for applications demanding reliable communication in MWSNs. Packet Loss, in the context of ICSOP, is minimal, indicating the protocol's ability to effectively manage and transmit a significant majority of packets without disruptions.

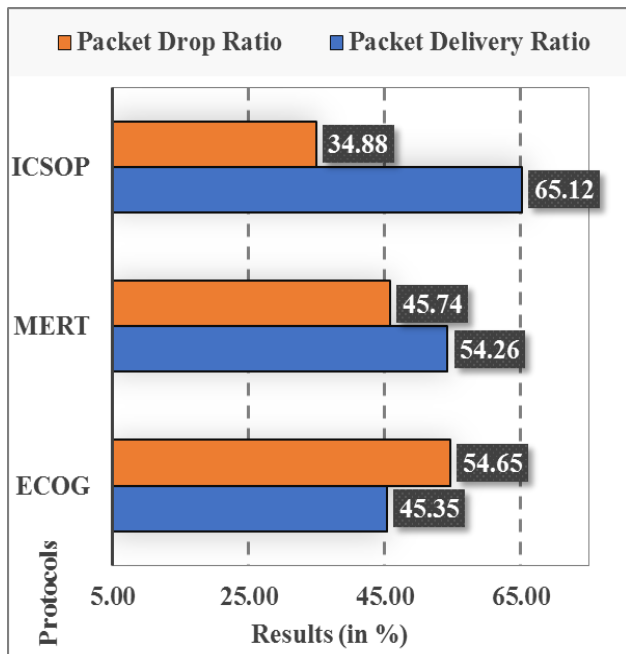


Figure 1 Packet Delivery & Drop Ratio

The Packet Delivery Ratio in ICSOP, standing at an impressive 65.12%, highlights its superior performance in successfully delivering a substantial portion of transmitted packets. This high PDR showcases ICSOP's reliability, making it a favorable choice for scenarios where data integrity and delivery are dominant. The Packet Drop Ratio for ICSOP is the lowest among the compared protocols at 34.88%. This low PDR emphasizes the protocol's efficiency in minimizing packet loss, showcasing its robustness in maintaining data integrity throughout the transmission process. ICSOP's proficiency in minimizing packet drop ensures a dependable communication channel, crucial for applications sensitive to data loss. ICSOP excels in both Packet Delivery Ratio and Packet Drop Ratio, making it a highly reliable routing protocol for WSNs. Its superior performance underscores its suitability for applications where data accuracy, efficiency, and minimal packet loss are critical considerations. ICSOP's robustness positions it as a promising choice for scenarios demanding dependable and efficient communication within the WSN infrastructure.

5.2. Throughput Analysis

In Figure 2, it depicts the throughput which refers to the rate of successful data transmission over the network. It is a critical metric that quantifies the efficiency and capacity of the network to deliver data accurately within a given time frame. The performance of the ICSOP is evaluated based on the number of nodes involved in the network. As the number of nodes increases from 50 to 500, the throughput for ICSOP shows a consistent upward trend. This indicates that ICSOP effectively manages larger networks, showcasing its scalability and capacity to handle increased data transmission demands.

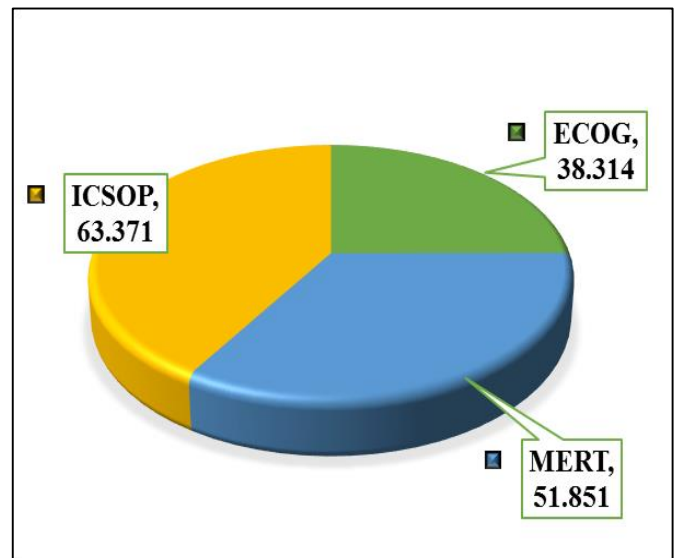


Figure 2 Throughput

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Comparing the average throughput values across the specified protocols ECOG, MERT, and ICSOP. While compares with the existing protocols the ICSOP stands out with the highest throughput of 63.371. This signifies its efficiency in facilitating data transmission within the WSNs. ICSOP's notable performance in throughput underlines its effectiveness in optimizing data transmission and network efficiency. The protocol demonstrates the capability to handle larger networks, ensuring that data is efficiently and reliably transmitted, contributing to a higher overall throughput. This is particularly crucial in scenarios where real-time data delivery is essential, such as in industrial applications, environmental monitoring, or healthcare. The performance of ICSOP, as indicated by its throughput values, positions it as a promising routing protocol for WSN. Its superior average throughput compared to ECOG and MERT suggests its efficacy in managing and optimizing data transmission which demands high-performance communication in large-scale sensor networks.

5.3. Delay Analysis

Figure 3, depicts delay refers to the time it takes for a packet of data to travel from the source to the destination. It is an important metric that directly impacts the responsiveness and efficiency of the network in delivering information. Analyzing the performance of ICSOP based on the delay values across different numbers of nodes reveals noteworthy insights. As the number of nodes increases from 50 to 500, ICSOP consistently maintains lower delay values compared to ECOG and MERT. This suggests that ICSOP excels in minimizing the time it takes for data to traverse the network, ensuring prompt communication even in larger-scale deployments.

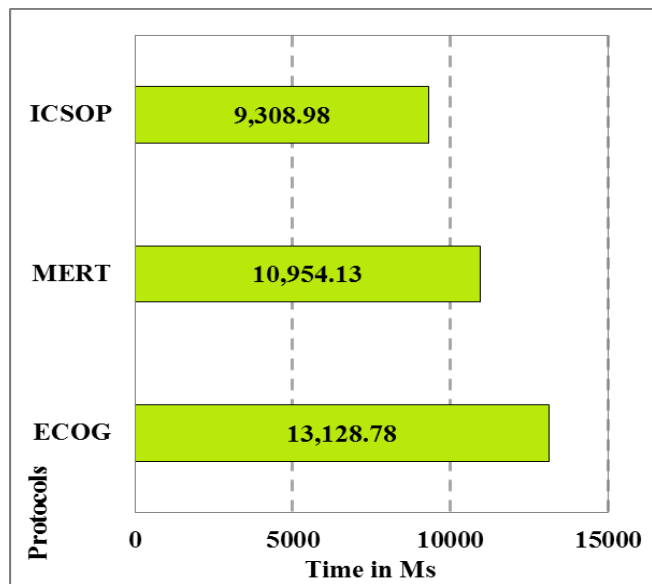


Figure 3 Delay

Comparing the average delay values across the specified protocols ECOG, MERT, and ICSOP. The proposed protocol ICSOP stands out with the lowest average delay of 9308.978. This indicates its effectiveness in reducing packet travel time, resulting in improved real-time responsiveness. ICSOP's impressive delay reduction, particularly as the number of nodes increases, positions it as a robust routing protocol for WSNs. Its ability to minimize communication latency is crucial in applications where real-time data is essential, such as in monitoring critical infrastructure, healthcare, or disaster response. ICSOP's outstanding performance in reducing delay values showcases its efficiency in ensuring swift and responsive communication within MWSNs. Its superior delay management, especially in larger-scale deployments, highlights its potential for applications demanding low-latency and real-time data delivery.

5.4. Energy Consumption Analysis

Figure 4, shows the rate of energy consumption a critical metric in WSNs, directly influencing the operational longevity of sensor nodes and overall network sustainability. Examining the performance of the ICSOP in terms of energy consumption across different numbers of nodes provides valuable insights. As the number of nodes increases from 50 to 500, ICSOP consistently exhibits lower energy consumption values compared to ECOG and MERT. This trend emphasizes ICSOP's efficiency in managing energy resources, contributing to prolonged network operation and reduced environmental impact.

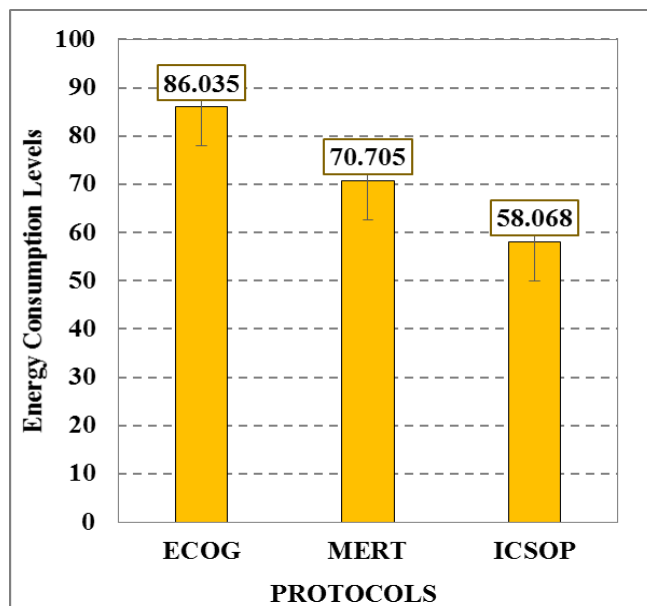


Figure 4 Energy Consumption

Analyzing the average energy consumption values across the specified protocols ECOG, MERT, and ICSOP. The proposed protocol ICSOP stands out with the lowest average

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consumption of 58.0676352. This underscores ICSOP's effectiveness in optimizing energy utilization, making it an environmentally friendly and sustainable choice for WSNs. ICSOP's notable performance in minimizing energy consumption aligns with the growing demand for sustainable and energy-efficient solutions in MWSNs. Its ability to maintain lower energy consumption even as the network scales makes it particularly suitable for applications where battery-powered sensor nodes are deployed in remote or challenging environments. ICSOP's. Its ability to optimize energy utilization aligns with the increasing emphasis on green technologies and positions ICSOP as a promising routing protocol for energy-efficient and environmentally conscious applications.

6. CONCLUSION

The integration of Invigorated Chameleon Swarm Optimization (ICSO) with the Floyd-Warshall-based Ad-hoc On-Demand Distance Vector (FW-AODV) in Mobile Wireless Sensor Networks (MWSNs) marks an innovative advancement in routing efficiency. The collaborative paradigm introduces a resilient and adaptive protocol, optimizing path computation and enhancing network efficacy. FW-AODV's dynamic computation of optimal paths synergizes with ICSO's rejuvenating dynamics, fostering adaptability to network changes. The fusion, particularly in H-MWSNs, demonstrates reliability, minimal packet loss, and efficient data transmission. Results reveal exemplary Packet Delivery Ratios, minimal Packet Drop Ratios, impressive Throughput, reduced Delays, and sustainable Energy Consumption, affirming ICSO's efficiency in managing larger networks. The collaborative protocol emerges as a compelling choice for applications requiring reliable communication, minimal latency, and sustainable energy consumption in diverse scenarios.

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