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DP-MCR: A BIO-INSPIRED MULTI-CONSTRAINT ROUTING PROTOCOL FOR DELAY-RESILIENT AND SECURE COMMUNICATION IN AGRICULTURAL IOT NETWORKS

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ABSTRACT

The Internet of Agricultural Things (IoAT) has become central to precision farming, yet routing in these networks remains constrained by limited energy, unstable connectivity, and dynamic traffic conditions. To address these challenges, this research proposes Danaus Plexippus-Based Multi-Constraint Routing (DP-MCR), a biologically inspired framework that adapts routing behaviour through natural migration strategies of monarch butterflies. DP-MCR integrates swarm-based clustering to balance communication loads, gradient-driven constraint weighting to refine routing decisions, and nectar-inspired path optimization to select stable, energy-rich relays. A gliding-based multi-hop mechanism minimizes retransmissions, while migration-guided load redistribution and self-healing strategies maintain resilience in the face of node failures and congestion. Real-time, quality-of-service-aware scheduling further ensures the timely delivery of critical agricultural data. Simulation analysis demonstrates that DP-MCR reduces energy consumption by over 30%, lowers the average delay by nearly 20%, maintains packet delivery ratios above 78%, and improves throughput beyond 290 kbps, while achieving the lowest packet loss across varying densities. By embedding adaptive swarm intelligence into routing decisions, DP-MCR delivers an energy-aware, delay-resilient, and fault-tolerant solution tailored to the operational requirements of agricultural ecosystems in 2025.

Keywords: *IoT, IoAT, Agriculture, WSN, Routing, Optimization, Swarm Intelligence*.

1. INTRODUCTION

Agriculture has undergone a profound technological shift in recent years, as digital tools are increasingly being adopted to tackle persistent challenges such as unpredictable climate patterns, rising labour shortages, inefficient resource utilization, and declining productivity [1]. Among the innovations shaping this transformation, Wireless Sensor Networks (WSNs) have become a central component of precision farming. These networks enable distributed sensing and local data collection across large fields and controlled environments. With the ability to track soil moisture, temperature, plant health, and pest activity, WSNs form the crucial foundation for data-driven decisions in smart farming [2]. Advances in low-power sensor devices, actuators, and compact edge-computing systems now allow seamless integration with the Internet of Things (IoT) ecosystem. This integration provides farmers with continuous visibility, automation, and remote control, making WSNs a cost-effective and adaptable approach to bridging the gap between raw field conditions and actionable agricultural intelligence [3].

Building on these capabilities, the Internet of Agricultural Things (IoAT) has emerged as a specialized branch of IoT, explicitly tailored to farming. Unlike conventional IoT applications in cities, IoAT functions across vast rural landscapes that present unique challenges, including inconsistent connectivity, limited energy sources, and constant exposure to unpredictable environmental factors [4], [5]. Despite these obstacles, IoAT enhances agricultural efficiency by supporting location-aware crop diagnostics, precision irrigation, livestock monitoring, and yield prediction. Its strength lies in handling data from numerous sensors over extended periods with minimal physical maintenance. This requires highly efficient communication frameworks designed to be resilient, adaptable, and energy-conscious. At the heart of this lies the routing process, which governs how information travels from remote field devices to decision-making platforms [5]. In agricultural contexts, routing is not just a technical detail but a lifeline for timely interventions that can influence productivity, water conservation, and disease control.

Efficient routing within IoAT must account for reliability, energy conservation, and quality of service simultaneously. Agricultural nodes are often deployed in vast fields, forests, or mountainous terrain where physical access is challenging. Manual recharging or replacement of batteries is rarely feasible, so routing strategies must optimize energy use while preserving high delivery rates [6]. Beyond energy efficiency, agricultural applications often carry data with varied priority levels. Alerts about soil dryness or livestock distress must be delivered far faster than routine monitoring updates, requiring routing protocols that differentiate across multiple data streams. Traditional routing schemes generally struggle under these diverse conditions, particularly in environments with fluctuating topologies and sudden disruptions caused by weather or natural obstacles [7]. Precision agriculture depends heavily on timely responses, so delays or repeated transmission failures have significant implications. Meeting these diverse requirements necessitates routing solutions that integrate energy-awareness with adaptability under multiple constraints, while maintaining low computational demands [8], [9].

To overcome the shortcomings of conventional routing methods, researchers are increasingly turning to bio-inspired optimization algorithms. These approaches mimic patterns and behaviors observed in nature, drawing on models such as ant colony foraging, bee swarms, genetic adaptation, or bird flight navigation [10]. Within IoAT, bio-inspired routing offers clear advantages, including decentralized decision-making and resilience against unpredictable network disruptions. Nodes collaborate, following principles similar to natural swarms, to identify optimal paths without relying on central control. This makes them particularly suited to agriculture, where real-world conditions often shift rapidly and flexibility is crucial [11], [12]. Such algorithms can incorporate adaptive learning, allowing the network to refine its routing choices over time based on accumulated experience, changes in data traffic, or variations in energy reserves. These qualities provide not only efficient but also sustainable routing frameworks for agricultural sensor systems. By embedding intelligence modelled on natural processes, bio-inspired methods pave the way for reliable, scalable, and self-optimizing networks that can meet the growing demands of digital farming [13], [14].

1.1. Problem Statement

Agricultural ecosystems in 2025 face mounting difficulties shaped by erratic rainfall, shifting climate patterns, soil degradation, and fragile food supply chains. To mitigate these, the Internet of Agricultural Things (IoAT) has been deployed within modern farms to enable autonomous sensing, precision-controlled irrigation, and environment-aware decision support. Despite extensive adoption, IoAT still encounters critical obstacles that hinder reliable operations. Network communication often remains unstable, remote sensor nodes experience rapid energy depletion, packet congestion reduces efficiency, and frequent link failures occur across vast and diverse farmlands. Existing routing approaches frequently fall short of meeting the complex requirements of IoAT, which include delay-resilient data transfer, fault tolerance, energy-balanced traffic distribution, and differentiated prioritization for sensitive agriculture-related data. In large-scale, heterogeneous landscapes, where data transmission patterns often change seasonally, reconfiguring nodes proves impractical. This situation creates a pressing demand for routing mechanisms that integrate decentralized intelligence with biologically adaptive techniques capable of sustaining automation in agriculture.

1.2. Motivation

The motivation for this research stems from the limitations observed in traditional routing methods deployed in agricultural environments. Current IoAT systems often span geographically extended regions where manual maintenance of nodes is neither cost-efficient nor feasible. These systems must continue to function across multiple crop cycles with minimal intervention while handling critical events such as pest outbreaks, soil deterioration, and microclimate irregularities. Such events require transmission of data with high reliability and very low delay, ensuring that decisions at edge devices or cloud servers are executed smoothly. Legacy routing protocols often cannot cope with changing traffic intensity, dynamic topologies, and the need for differentiated service levels. They tend to consume excess energy and induce latency under real field conditions. The exceptional migratory behaviour of DP inspires alternative designs. This species successfully adapts to unpredictable routes during its long journeys, maintaining efficiency despite environmental uncertainty. A routing model that mirrors this adaptive resilience can support self-healing capabilities, maintain balanced energy use, and align with the mission-critical priorities of agricultural ecosystems in the year 2025.

1.3. Objective

The objective of this research is to design DP-MCR (Danaus Plexippus-Based Multi-Constraint Routing), a protocol that delivers resilient, adaptive, and energy-aware communication for IoAT environments. The design integrates multiple constraints, namely energy levels, delay sensitivity, link stability, and congestion risks, into a single framework shaped by natural butterfly migration strategies. The key goals are: (i) to establish a distributed cluster-formation model guided by swarm-like dynamics, (ii) to improve packet delivery through nectar-inspired optimization for path selection, (iii) to incorporate fault-resilient self-healing mechanisms for route restoration, and (iv) to introduce priority scheduling that preserves the quality of service for critical transmissions. DP-MCR is designed to operate across challenging agricultural terrains where node maintenance is infrequent, energy supply is limited, and topologies change over time. The protocol aims to enhance network durability, improve responsiveness, and ensure that diverse agro-sensor requirements are handled efficiently without incurring excessive computational overhead.

1.4. Research Design

The study proposes DP-MCR (Danaus plexippus-Based Multi-Constraint Routing) as a bio-inspired, swarm-driven routing protocol modeled on the long-distance migration, reorientation, gliding behavior, and foraging intelligence of Danaus plexippus (the Monarch butterfly). The research adopts a simulation-based experimental design in NS-3 and follows the steps outlined below:

1. **Problem Analysis & Constraint Formulation:** Routing metrics relevant to IoAT (delay, energy, trust, congestion) are studied. Multi-constraint routing objectives are mathematically formulated using dynamic gradient models and swarm-centric clustering.
2. **Bio-Inspired Protocol Development:** The foraging, migratory, and navigational behaviours of monarch butterflies are computationally abstracted into 12 algorithmic steps. Each step addresses a specific constraint: clustering, load balance, route failure, or path optimisation.
3. **Protocol Simulation:** The protocol is implemented and evaluated in NS-3 across node densities (80–400) under real-world IoAT parameters. Metrics such as Packet Delivery Ratio (PDR), Delay, Energy Consumption, Throughput, and Routing Overhead are recorded.
4. **Benchmarking:** DP-MCR is compared with two established protocols, WAH (Weight Adaptive Hybrid) and EEO (Entropy-based Energy Optimization), to highlight improvements in adaptive behavior and resilience.
5. **Result Interpretation & Security Enhancement:** Performance graphs and tables are analysed. An adaptive trust mechanism is integrated for security, followed by a self-healing mechanism inspired by monarch reorientation to ensure reliability in faulty environments.
6. **Validation and Scalability Analysis:** The protocol's performance is validated under varying energy models, node sizes, and fault injection to ensure robustness and generalisability for future IoAT deployments.

2. LITERATURE REVIEW

"ETX Learner Model" [15] introduced a predictive framework where CatBoost classification refined ETX values to capture dynamic variations in link quality. The approach integrated both historical and real-time features to differentiate between reliable and unreliable connections, producing an adaptive form of ETX. Predictions from the model reduced retransmissions, lowered redundant path utilization, and extended network lifespan. An adaptive update design preserved balance across nodes, limiting premature exhaustion in key relays. Through machine learning integration, ETX evolved from a static metric into a responsive measure that can adapt to variations in network traffic. This strengthened data-driven routing intelligence, supporting efficient and sustainable communication in sensor-based environments. "Traffic Clustrix Protocol" [16] proposed a clustering strategy that combined factors such as energy reserves, node proximity, and traffic intensity for cluster head election and hop selection. Uniform load distribution was achieved by traffic-aware routing, which directed packets toward nodes with lower congestion. Data aggregation inside clusters minimized redundancy, while the inclusion of super-normal nodes balanced diverse traffic loads. Routing followed a multi-criteria decision system that aligned forwarding with node status and available capacity. Nodes with limited resources were protected from heavy workloads, conserving energy across the network. The protocol improved delivery stability under fluctuating data flow, extending

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operational efficiency for IoT-integrated WSNs. “Agri-HeuroMeta Scheme” [17] introduced a hybrid dual-phase routing framework that combines grey wolf optimization offline with heuristic clustering online. Offline calibration and tuned heuristic rules enhanced responsiveness, while UAV-assisted energy replenishment prolonged sensor availability. UAV path designs matched longevity demands, ensuring timely visits for charging. Online clustering identified suitable heads for efficient aggregation and stable data transfer. The integration of global metaheuristic search with local heuristic adaptability maintained system efficiency across large deployment scales. Agricultural use cases demonstrated benefits in terms of reliability, energy continuity, and reduced packet loss, creating a model capable of sustaining uninterrupted monitoring under power-limited field conditions.

“Bio-Hybrid Relay” [18] protocol combined Tabu Search with Ant Colony Optimization to achieve robust clustering and routing in WSNs. Tabu’s memory-driven design avoided repeated sub-optimal cluster head choices, while ant-based exploration leveraged pheromone paths to strengthen reliable routing. The multi-objective structure targeted delay minimization, energy balance, and extended system lifetime. Dynamic cluster head rotation distributed workloads evenly, and probabilistic route construction promoted consistency across nodes. This hybrid framework merged rule-based avoidance with adaptive search, ensuring resilience in high-density clusters. The results indicated that memory-supported planning, combined with swarm intelligence, improved data transfer and stabilized routing performance in clustered environments. “Vampire Shield Framework” [19] presented a deep learning security model designed to detect and mitigate vampire attacks in WSNs. A weighted recurrent neural network optimized through an enhanced genetic algorithm assessed metrics, including packet reception, broadcast behavior, and energy trends, to identify malicious nodes. Compromised devices were quarantined, while unaffected nodes continued to engage in secure routing, guided by the exact optimization mechanism. The framework selected lightweight and stable paths to uphold efficiency and minimize disruptions. The combined detection and routing process established robust resistance against adversarial behavior, reinforcing both communication stability and data integrity in security-sensitive sensor applications. “Fuzzy-PSO Router” [20] integrated fuzzy logic with particle swarm optimization to achieve energy-aware and dependable routing in WSNs. Fuzzy reasoning controlled trade-offs between path durability, energy balance, and traffic distribution, while PSO refined search efficiency in dynamically changing networks. Membership rules adjusted route preferences adaptively, influencing swarm updates to achieve optimized solutions. Shorter paths were balanced with sustainable power consumption to maintain network performance. The framework demonstrated scalability across varied node densities and topology sizes. By merging adaptive fuzzy control with swarm-driven exploration, this design effectively reduces wastage, prolongs network lifetime, and improves reliability in sensor-driven communication systems. “Memetic Resource Router” [21] uses memetic algorithms with clustering for more efficient routing. Evolutionary strategies adaptively guide cluster head allocation, optimizing routes to accommodate topology and load variations. Energy conservation was supported through adaptive adjustments in transmission paths, preventing redundant communication. Global and local search integration balanced robustness with responsiveness, enabling a more extended service life. Resource management efficiency improved throughput while minimizing energy consumption. This adaptive solution illustrated the potential of memetic computing to create sustainable routing strategies for large-scale WSN deployments with resource constraints.

“Balanced Cluster Learner” [22] framework introduced an energy-conscious clustering design that incorporated fuzzy c-means grouping with flow-based optimization. Clusters were formed to prevent uneven distribution of workloads, while heads were selected based on residual power, spatial density, and Euclidean distance from the base station. Periodic rotation allowed equitable use of resources among nodes. The Ford–Fulkerson approach determined efficient intra- and inter-cluster paths for packet forwarding. Integrated machine learning strategies maintained balance across workloads, preventing bottlenecks and excessive consumption. The framework extended the lifetime, stabilized routing, and ensured the sustainable operation of IoT-driven WSNs in resource-limited environments. “Agri-Deep Optimizer” [23] model introduces a hybrid approach that merges multi-objective clustering with deep learning analysis to enhance agricultural monitoring. Cluster selection was supported by an Election-based Aquila Optimizer, considering residual energy, spatial location, and role distribution. A

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CNN model was evaluated for clustering outcomes, thereby improving classification quality and routing decisions. This combination increased throughput, strengthened routing reliability, and maintained network longevity under agricultural constraints. The framework provided accurate monitoring of environmental data while minimizing resource consumption. By uniting optimization with neural intelligence, this approach advanced precision agriculture through efficient data collection and energy-aware communication models in sensor-intensive deployments. "Fuzzy-Remora Guard" [24] protocol blended bio-inspired optimization with fuzzy logic to establish secure communication in WSNs. Trust values from direct and indirect interactions eliminated unreliable nodes during cluster formation. Stable heads were selected using an Improved Fuzzy Balanced Cost scheme. Rider-Remora optimization guided packet forwarding, balancing residual power, spatial relevance, and data load. Energy efficiency and security operate in tandem, ensuring secure packet transfer without draining system resources. The combination provided resilience against malicious disruptions, supported long lifetime for networks, and tuned routing reliability according to both trust and energy perspectives.

"UAV Energy Balancer" [25] protocol created a routing design tailored for UAV-assisted WSNs, dividing communication into ground-to-ground and air-to-ground routes. Clustering with unequal sizing reduced energy disparities, while dynamic redistribution prevented overloaded relays. UAVs gathered data by following adaptive coverage paths that supported sensor durability and longevity. Sector rotation, inspired by lottery principles, distributes relays fairly, preventing early depletion. Multi-hop routing stabilized throughput and ensured efficient transfer under restricted energy budgets. The design integrated aerial assistance with cluster strategies, sustaining reliable communication and reducing premature failures among sensor nodes deployed in expansive monitoring systems. "QL Semi-Fixed Router" [26] scheme fused reinforcement learning with swarm-based optimization for stable clustering in WSNs. Semi-fixed boundaries organized nodes into balanced groups, with adaptive adjustments triggered once disparities in energy emerged. Ant colony routing established multi-hop paths, supported by pheromone-driven optimization. Q-learning refined selection by rewarding efficient behaviors, adapting forwarding routes to evolving network states. Head rotation and threshold-controlled adjustments discouraged uneven energy depletion, extending operational use. This fusion ensured consistent service quality, steady clustering, and improved load distribution for large WSNs in dynamic environments. "FT-RR Deep Guard" [27] protocol integrates optimization and deep learning to enhance routing resilience under unpredictable conditions. A coati-inspired optimization scheme was used in conjunction with a CNN model to predict node stability, while Bernoulli rule-based checks filtered trustworthy relays from unreliable ones. Cluster heads with higher remaining energy were selected to preserve fault resistance. Anticipated link failures were predicted and avoided, resulting in lower packet loss and delay. The collaborative structure maintained communication continuity in harsh environments. By unifying predictive intelligence with energy-sensitive optimization, the protocol demonstrated consistent delivery, stronger reliability, and durability against both node collapse and resource depletion. "Adaptive K-Threshold" [28] protocol optimized energy use in IoT-driven WSNs through improved clustering. Enhanced K-means assigned nodes into balanced clusters, guided by spatial distance and energy levels. An adaptive threshold-controlled relaying method to eliminate costly transmissions and weak links. By redistributing cluster loads fairly, retransmissions were reduced, and packet flow remained stable. Adjustments supported fairness across the network, limiting excessive drain from individual contributors. The approach demonstrated effective reduction of wasted power while maintaining dependable packet forwarding.

"Whale-Ant Hybrid (WAH)" [29] framework combines whale optimization and ant colony routing to improve WSN routing efficiency. Whale search guided the global identification of energy-rich cluster heads, while ant-inspired pheromone learning optimized local route discovery. A linear optimization model balanced objectives such as distance, residual power, and centrality. The cooperative design prevented premature exhaustion and stabilized cluster-based communication. By harnessing the exploration capabilities of whales and exploiting the foraging behaviour of ants, the approach achieved a balance between search diversity and reliability. The model extended system lifetime while minimizing communication inefficiency, creating a stable routing strategy for sustainable WSN performance. "Entropy Eagle Optimizer (EEO)" [30] protocol created a layered routing system using soft clustering with entropy-guided optimization. Sensor nodes were grouped

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using density-based adaptive clustering, while modified beetle swarm optimization selected reliable heads based on residual energy, distance, and trust. Entropy-based evaluation identified strong relay candidates. The bald eagle search algorithm dynamically adjusted entropy weights, refining packet flow decisions. Aggregation at heads prevented duplicate overhead, conserving power. By combining entropy evaluation with adaptive exploration, this framework elevated throughput levels, minimized delays, and balanced routing loads. Field application confirmed efficiency gains in energy use and stable routing reliability.

Bio-inspired optimization is gaining widespread attention in recent research for its ability to handle uncertainty, adaptability, and complexity in problem-solving [31] – [42]. Drawing from natural systems like swarms, evolution, and neural behaviours, these techniques offer flexible, self-organizing, and scalable approaches that outperform conventional algorithms in many scenarios [43] – [48]. Their increasing usage across fields such as wireless networks, robotics, scheduling, and sensing proves their strength in delivering near-optimal solutions with reduced computational effort and better responsiveness in real-world applications [49] – [54].

2.1. Methodological Gap

The review of existing routing strategies highlights advancements in clustering, hybrid optimization, and swarm intelligence for wireless sensor communication, yet several shortcomings remain evident in the IoAT domain. Agricultural sensor deployments often operate unattended across irregular terrains where battery replacement is infeasible, making lightweight routing essential. Many existing designs impose high computational complexity, with layered optimization and repetitive recalculations consuming more than 60% of node energy in dense networks. Stability is another challenge, as frequent reorganization in soft clustering or pheromone-driven approaches increases delay values beyond 4500 ms and weakens delivery reliability. Adaptability is limited in protocols that converge prematurely, resulting in packet delivery ratios dropping below 70% under dynamic traffic. Security and fault tolerance are rarely integrated as primary functions, leaving routes vulnerable to failure and adversarial disruption. These limitations highlight a methodological gap for an energy-aware, delay-resilient, congestion-tolerant, and fault-tolerant routing protocol specifically designed for agricultural environments. This gap motivates the design of DP-MCR, which unifies biologically inspired intelligence into a single adaptive framework suitable for large-scale IoAT deployment.

Table 1: Comparison of Literature

Framework	Routing Mechanism	Optimization	Strengths in Routing	Routing Limitations	Target Application Domain
ETX Learner Model	Predictive ETX-based path selection	CatBoost ML classification	Adaptive link quality estimation, fewer retransmissions, and efficient route stability	Requires training data, ML overhead	IoT-based WSN routing with dynamic link conditions
Traffic Clustrix Protocol	Cluster-based hop-by-hop routing with traffic balance	Multi-criteria clustering with traffic-awareness	Load balancing, avoidance of congested routes, and improved QoS	Cluster reformation cost under high traffic change	Smart IoT sensor systems, traffic-heavy networks
Agri-HeuroMeta Scheme	Two-phase clustering + UAV-assisted routing	Grey Wolf Optimization (offline) + heuristic rules (online)	Real-time responsiveness, UAV-based route sustainability,	Costs and complexity in UAV scheduling	Agricultural IoT deployments, large farms

			fault-tolerant long-distance routing		
Bio-Hybrid Relay	Hybrid cluster-head allocation + adaptive path routing	Tabu Search + Ant Colony Optimization	Memory-driven reliable CH rotation, pheromone-based dynamic routing	Precision tuning required, scaling challenges	Dense sensor cluster routing (factory monitoring, urban IoT)
Vampire Shield Framework	Secure route selection avoiding compromised links	Weighted RNN + enhanced Golf optimization	Protects routing paths, lightweight secure delivery, reduced malicious flooding	Vulnerable to unseen attacks, higher learning overhead	Security-critical WSN routing
Fuzzy-PSO Router	Routing with fuzzy link selection + swarm-optimized paths	Fuzzy logic + Particle Swarm Optimization	Adaptive routing under topological changes, stable QoS	Dependence on fuzzy rules, parameter convergence issues	Environmental & climate monitoring routing
Balanced Cluster Learner (EEB-CR)	Fuzzy-clustering with flow-optimized inter-cluster routing	Fuzzy C-Means + Ford-Fulkerson + flow optimization	Balanced cluster load during routing, longer CH life, reduced overhead	Extra processing for flow constraints	IoT-assisted WSN routing for healthcare and smart buildings
Agri-Deep Optimizer	Cluster-based routing with CNN-driven optimization	Election-based Aquila Optimizer + CNN	Precise CH election, improved throughput in agro-routing	High computational requirements	Precision agriculture routing (soil/crop monitoring)
Fuzzy-Remora Guard	Trust-based routing with energy consideration	Fuzzy trust metrics + Rider-Remora optimization	Secure relay avoidance, trust-enforced reliable routing	Overhead in trust management	Secure IoT/WSN routing under attack-prone settings
UAV Energy Balancer	Clustered routing assisted by UAV relay	Unequal clustering + UAV trajectory planning	Reliable routing with UAV relays, energy disparity reduction	UAV cost and dependency	Agricultural IoAT with UAV data collection
QL Semi-Fixed Router	Semi-fixed cluster-based routing with adaptive learning	Q-Learning + ACO	Self-adaptive routing, delay-aware improvement, balanced lifetimes	Early learning inefficiency, requires iteration	Smart farm routing/irrigation WSNs
FT-RR Deep Guard	Fault-resilient routing with predictive analysis	CNN + Coati optimization	Predicts weak nodes, establishes stable alternate routes	Computational and training overhead	Harsh environment WSN routing
Adaptive K-Threshold	Enhanced K-means clustering with adaptive threshold routing	K-means + distance-energy threshold control	Eliminates weak links, reduces retransmissions	Sensitive to threshold design	IoT/Agro-WSN routing for soil and crop sensor nodes

Memetic Resource Router	Evolutionary adaptive routing with memetic clustering	Memetic optimization algorithm	Balances global/local routing, robust topology adaptation	Computation-heavy for larger deployments	Rural long-term IoT/WSN routing
Whale-Ant Hybrid (WAH)	CH selection with adaptive routing paths	Whale Optimization + ACO	Efficient global CH search, refined multi-hop paths, lifetime longevity	Slow under large networks, pheromone tuning needed	Disaster-response routing, adaptive energy IoT
Entropy Eagle Optimizer (EEO)	Adaptive soft clustering with entropy-driven routing	Bald Eagle Search + entropy evaluation	Balanced routing load, delay minimization	High computational intensity	Agro-IoT routing, irrigation control

3. DANAUS PLEXIPPUS-BASED MULTI-CONSTRAINT ROUTING (DP-MCR)

DP-MCR has been conceptualized as a biologically inspired routing framework that translates the adaptive migration behaviour of Danaus plexippus into multi-constraint communication intelligence for IoAT. Unlike conventional approaches that focus on isolated objectives, DP-MCR incorporates energy conservation, latency control, congestion management, and fault resilience within a unified structure. The protocol employs swarm-based clustering, nectar-driven path optimization, gliding-assisted forwarding, and migration-oriented redistribution to sustain balanced and dependable operation in agricultural deployments. The successive steps involved in DP-MCR are discussed in detail throughout this section.

3.1. Network Initialization

Network initialization in DP-MCR has established a stable foundation for multi-constraint routing in IoAT-WSN. The process incorporates swarm-based node coordination, hierarchical clustering, dynamic weight assignment, and adaptive connectivity mapping, all inspired by the DP foraging and migration behavior to enhance network longevity, load balancing, and energy-aware routing efficiency. The deployment strategy has reflected the migratory swarming behavior of DP, where node placement has followed an adaptive distribution pattern to prevent energy depletion in densely concentrated areas. The initial spatial distribution has been accounted for in terms of mobility, energy efficiency, and latency reduction, ensuring efficient data collection across sensor nodes in IoMT applications.

$$D_s = \sum_{i=1}^{N} \left(\frac{L_i}{E_i}\right) \times f(d_{iB}) \tag{1}$$

The deployment density function D_s has depended on the number of nodes N, transmission load L_i, available energy E_i, and an energy impact exponent γ. The function $f(d_{iB})$ has represented the distance decay effect from node i to the base station. The placement mechanism has maintained an equilibrium between spatial coverage and energy dissipation, preventing early network fragmentation and bottleneck formation.

The clustering mechanism has optimized the relay communication pathways, striking a balance between latency and energy consumption. The swarm-inspired hierarchical clustering has introduced a multi-tier communication model, where cluster heads dynamically adjust their roles to optimize relay efficiency and network connectivity.

$$C_r = \left(\frac{\alpha \cdot \sum_{j=1}^{M} E_j}{M}\right) \times \psi(d_{CH,B}) \tag{2}$$

The clustering radius C_r has relied on the energy availability across cluster members, where M has been the total number of nodes within a given cluster. The energy balancing factor α has ensured uniform power distribution among nodes, while $\psi(d_{CH,B})$ has accounted for the distance between the cluster head (CH) and base station (B). The clustering approach has enhanced fault tolerance and has reduced transmission congestion within high-density areas, mirroring the coordinated movement patterns of Monarch swarms.

The constraint weighting mechanism has enabled adaptive routing decisions based on real-time network conditions. Inspired by DP foraging optimization, where flight adjustments are guided by nectar availability and wind resistance, network nodes dynamically update routing constraints based on environmental changes, energy availability, and packet transmission demands.

$$\Omega_c = \frac{1}{1 + e^{-\beta(E_n - E_{th})}} + \frac{T_n}{\delta + T_{max}} \tag{3}$$

The constraint impact factor Ω_c has been defined as a function of residual energy E_n and traffic intensity T_n, with E_{th} as the predefined energy threshold. The parameter β has controlled the energy responsiveness, while the traffic weightage function has normalized packet transmission concerning the maximum observed traffic T_{max}. The adaptation has ensured real-time constraint prioritization, preventing inefficient path selection and excessive energy consumption.

The connectivity establishment phase has determined the most efficient communication pathways between sensor nodes and relay nodes, maintaining an optimal balance between packet delivery success rate and energy depletion mitigation. The DP navigation model, which has utilized magnetoreception and solar cues to sustain directional stability, has inspired dynamic connectivity updates based on link reliability and energy-aware constraints.

$$\Gamma_{link} = \sum_{i=1}^{N} \left(\frac{R_i}{E_i}\right) \times k\left(d_{i,j}, P_{loss}\right) \tag{4}$$

The connectivity reliability index Γ_{link} has been defined as a function of the transmission success ratio R_i, node energy E_i, and distance-aware signal degradation $k\left(d_{i,j}, P_{loss}\right)$, where P_{loss} has represented the packet loss probability over a given distance. The adaptive connectivity function has ensured that IoAT-WSN communication pathways remain stable and fault-tolerant, thereby reducing network drop rates and retransmission overhead.

3.2. Adaptive Constraint Weighting (ACW) Using Gradient Optimization

Adaptive constraint weighting has ensured dynamic prioritization of routing parameters in IoAT-WSN by adjusting network conditions in real-time. The mechanism optimizes constraint importance based on gradient-driven updates, inspired by the foraging behaviour of DP, where flight decisions are dynamically adjusted in response to nectar availability and environmental factors. The constraint evaluation mechanism accounts for variations in network state parameters, including latency, energy, and congestion. The weight distribution has been influenced by gradient calculations that have adjusted in response to fluctuations in the network. This adaptation has aligned with the migratory behavior of DP, where dynamic weight shifts have been dictated by terrain, wind resistance, and food availability.

$$\Lambda_w = \frac{\partial}{\partial t}\left(\sum_{i=1}^{N}\left(\phi_i \cdot \frac{E_i}{L_i}\right)\right) \tag{5}$$

The adaptive weight gradient function Λ_w has determined the rate of weight adjustment over time, considering energy availability E_i, transmission load L_i, and a dynamic influence factor ϕ_i. The differentiation has ensured real-time constraint rebalancing, stabilizing network behaviour while preventing congestion.

The constraint sensitivity adjustment has accounted for fluctuations in packet transmission patterns by assigning dynamic weights to routing constraints. Inspired by DP foraging, where butterflies have selectively visited high-energy flowers while avoiding depleted sources, the network has continuously adjusted constraint sensitivity to optimize data transmission routes.

$$\Psi_c = \sum_{j=1}^{M}\left(\frac{T_j}{1 + e^{-\lambda(E_j - E_{avg})}}\right) \tag{6}$$

The constraint sensitivity function Ψ_c has depended on traffic intensity T_j across cluster nodes, normalized by an energy-aware sigmoid scaling function where E_j has represented the available energy, and E_{avg} has indicated the mean network energy level. The parameter λ has adjusted the response sharpness, ensuring that sensitivity variations have adapted efficiently to energy depletion trends.

The gradient descent approach has optimized constraint reallocation by continuously fine-tuning weight distributions based on historical network performance. The adjustment has drawn inspiration from DP, a migratory butterfly, which has refined its routes through incremental flight adjustments to minimize energy expenditure and avoid turbulence.

$$\Theta_w^{(t+1)} = \Theta_w^{(t)} - \eta\left(\frac{\partial F}{\partial \Theta_w}\right) \tag{7}$$

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The weight update function $\Theta_w^{(t+1)}$ has been derived using a gradient descent approach, where η has been the learning rate, and F has represented the constraint optimization function. The iterative weight adjustment has reduced constraint imbalance, ensuring that IoAT-WSN routing decisions have remained energy-efficient and congestion-resistant.

3.3. Constraint Correlation Adjustment for Multi-Objective Routing

The adaptive constraint correlation mechanism has ensured that dynamically assigned weights maintain a balanced routing framework by minimizing cross-constraint interference. Inspired by DP, which has optimized its nectar source differentiation by avoiding competition-heavy feeding zones, the network has prevented performance degradation by dynamically reducing interference between correlated constraints.

$$\Upsilon_c = \sum_{k=1}^{P} \left(\alpha_k \cdot \rho_k \cdot \frac{1}{1 + e^{-(Q_k - Q_{opt})}} \right) \tag{8}$$

The correlation function Υ_c has ensured optimal constraint interactions by adjusting weights based on correlation coefficients ρ_k and priority factors α_k. The influence of constraint quality Q_k relative to the optimal value Q_{opt} has been normalized using a sigmoid function, ensuring that cross-constraint dependencies remain stable over time.

3.4. Swarm-Based Hierarchical Clustering

Swarm-based hierarchical clustering has structured the IoAT-WSN into multi-tiered layers that have dynamically adapted based on energy levels and transmission requirements. Inspired by DP swarming patterns, the clustering mechanism optimizes load distribution, relay selection, and hierarchical transmission paths, ensuring a prolonged network lifetime and efficient data aggregation.

Cluster formation has depended on the spatial distribution of sensor nodes, which has been optimized using a gradient-based density function. Inspired by the swarm behaviour of DP, where butterflies redistribute themselves to nectar-rich areas while avoiding overpopulated zones, the clustering process dynamically reallocates cluster heads to minimize congestion and maximize coverage.

$$\Phi_c = \sum_{i=1}^{N} \left(\frac{d_i B}{E_i^{\mu}} \right) \times \theta(D_i, C_i) \tag{9}$$

The cluster density function Φ_c has depended on the distance to the base station $d_i B$and the available energy E_i of each node, scaled by an energy sensitivity factor μ. The clustering probability adjustment function $\theta(D_i, C_i)$ has ensured that nodes experiencing high data transmission loads have been prioritized for cluster formation.

Cluster head selection has optimized energy usage across nodes while maintaining stable routing. Inspired by DP, which has designated lead butterflies to guide swarm movements, the network has selected cluster heads dynamically based on residual energy and intra-cluster connectivity.

$$\mathrm{H}_c = max\left(\frac{E_j}{\sum_{k \in C} E_k} \times \frac{1}{1 + e^{-\zeta(d_{jN} - d_{opt})}} \right) \tag{10}$$

The cluster head selection function H_c has evaluated the relative energy levels of candidate nodes j compared to all nodes within the cluster C. The distance optimization function ensures that cluster heads are selected to minimize intra-cluster communication costs.

The hierarchical transmission structure has optimized data aggregation at multiple levels, reducing redundancy and enhancing relay efficiency. Inspired by DP' ability to adjust its flight formation to reduce drag, the hierarchical clustering framework distributes communication loads across multiple routing layers.

$$\mathrm{T}_h = \sum_{m=1}^{M} \left(\frac{1}{L_m + \delta} \times \omega(E_m, S_m) \right) \tag{11}$$

The hierarchical transmission index T_h has determined the efficiency of the transmission route, factoring in network load L_m and a stabilization parameter δ. The function $\omega(E_m, S_m)$ has adjusted the weightage based on available energy and node stability, ensuring that relay nodes are optimized for longevity.

Load redistribution has prevented overburdening high-traffic nodes, ensuring energy-balanced routing decisions. This mechanism has mirrored DP' flight energy conservation strategies, where butterflies adjust their positions within the swarm to optimize energy consumption.

$$\Gamma_L = \sum_{q=1}^{Q} \left(\frac{T_q}{1 + e^{-k(E_q - E_{min})}} \right) \tag{12}$$

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The load-balancing function Γ_L has dynamically adjusted transmission loads based on traffic intensity T_q and a sigmoid-based energy sensitivity factor. The model has ensured that nodes with lower energy levels are relieved of excessive routing duties.

Re-clustering has allowed continuous adaptation to energy depletion trends and traffic variations. Inspired by DP' ability to reorganize migration patterns in response to environmental conditions, the network has dynamically updated cluster memberships and relay nodes to maintain performance stability.

$$R_c = \sum_{v=1}^{V} \left(\frac{1}{1 + e^{-\beta(E_v - E_{avg})}} \times \chi(C_v, d_v) \right) \quad (13)$$

The re-clustering probability function R_c has determined the likelihood of a node undergoing re-clustering, considering energy availability E_v and cluster stability $\chi(C_v, d_v)$. The logistic scaling function has ensured that the clustering structure has adapted smoothly, preventing abrupt disruptions in transmission paths.

3.5. Nectar Selection-Inspired Path Optimization

Nectar selection-inspired path optimization enables dynamic and energy-efficient routing by prioritizing optimal packet transmission paths. By mimicking the foraging behaviour of DP, this approach optimizes IoAT-WSN routing by selecting paths that provide higher stability, reduce energy loss, and minimize network congestion.

Path ranking has determined the most efficient transmission routes by evaluating node connectivity and energy parameters. Similar to how DP selects nectar sources based on energy richness and accessibility, network paths have been evaluated using a weighted gradient function that has dynamically adjusted routing preferences.

$$P_r = \sum_{i=1}^{N} \left(\frac{\sigma_i}{1 + e^{-\tau(E_i - E_{min})}} \times \frac{1}{d_{i,j} + \xi} \right) \quad (14)$$

The path ranking function P_r has depended on the energy availability of node i, E_i and the distance factor $d_{i,j}$ between nodes. The energy sensitivity coefficient τ has controlled how energy levels have influenced path selection, while σ_i has determined transmission stability, preventing excessive reliance on low-energy nodes.

Relay selection has dynamically adjusted transmission node responsibilities based on energy availability and data transmission rates. Inspired by how DP concentrates foraging efforts in high-nectar zones while avoiding depletion, network relay selection has ensured that optimal nodes have been prioritized for transmission.

$$R_s = \sum_{j=1}^{M} \left(\frac{\beta_j E_j}{L_j + \gamma} \times \chi(T_j, C_j) \right) \quad (15)$$

The relay selection index R_s has depended on energy $E_j$and traffic load L_j of potential relay nodes. The influence factor β_j has adjusted weightage based on data transmission needs, while $\chi(T_j, C_j)$ has represented a dynamic relay adjustment function, ensuring that traffic is equitably distributed.

Long-distance path optimization has ensured efficient packet transmission by adjusting routing paths in response to real-time fluctuations in energy. DP optimizes its migration flight paths to conserve energy and reduce wind resistance, a strategy that has been emulated in path adaptation by incorporating real-time energy evaluations.

$$P_a = \sum_{k=1}^{K} \left(\frac{E_k^{\theta}}{T_k + \delta} \times \omega(d_{kB}, S_k) \right) \quad (16)$$

The path adaptation function P_a has adjusted routing paths based on energy reserves E_k, traffic intensity T_k, and distance to the base station d_{kB}. The exponent θ has modulated the energy sensitivity, ensuring that high-energy nodes have been efficiently utilized without premature exhaustion.

The routing mechanism has integrated congestion mitigation to prevent excessive data accumulation along high-traffic routes. DP regulates nectar-feeding activity by redistributing foraging effort, a strategy that has been incorporated into dynamic congestion avoidance to optimize data transmission flow.

$$C_m = \sum_{q=1}^{Q} \left(\frac{1}{1 + e^{-\rho(T_q - T_{max})}} \times \psi(L_q, E_q) \right) \quad (17)$$

The congestion mitigation function C_m has assessed congestion intensity using traffic thresholds T_q, where T_{max} has defined the maximum tolerable traffic level. The function $\psi(L_q, E_q)$ has adjusted routing parameters to prioritize low-congestion, high-energy paths, thereby preventing excessive load accumulation.

Network routing has dynamically adjusted based on previous transmission outcomes, ensuring continuous improvement in path selection efficiency. DP modifies its foraging patterns through experience-based learning, which has been applied to routing updates by integrating a probabilistic self-optimization mechanism.

$$O_P = \sum_{v=1}^{V} \left(\frac{v_v}{1 + e^{-\lambda(Q_v - Q_{opt})}} \times \theta(P_v, C_v) \right) \quad (18)$$

The self-optimization function O_P has dynamically fine-tuned path selection using quality feedback metrics Q_v. The probabilistic weight adjustment factor v_v has enabled adaptation to varying network conditions, ensuring consistent path refinement over time.

3.6. Adaptive Multi-Hop Routing Using Gliding Mechanism

Adaptive multi-hop routing using the gliding mechanism has dynamically optimized packet forwarding by adjusting transmission paths based on energy reserves and traffic conditions. Inspired by DP, which has efficiently alternated between powered flight and gliding to conserve energy during long migrations, this mechanism has improved routing resilience while ensuring prolonged network longevity in IoAT-WSN.

Hop selection has incorporated gradient-based decision-making to balance traffic load among intermediate nodes. Similar to DP adjusting its gliding path based on environmental wind gradients, the routing mechanism has selected optimal relay nodes using a gradient-controlled weight allocation model.

$$H_s = \sum_{i=1}^{N} \left(\frac{\delta_i}{1 + e^{-\omega(E_i - E_{th})}} \times \frac{1}{\Gamma_i + \psi} \right) \quad (19)$$

The hop selection function H_s has been influenced by the energy availability E_i of a node relative to a predefined threshold E_{th}, where δ_i has represented the transmission success rate. The congestion parameter Γ_i has ensured that high-traffic nodes have not been overburdened, while the factor ψ has regulated transition smoothness between routing states.

To prevent the early depletion of critical relay nodes, multi-hop paths are dynamically switched based on residual energy levels. DP has redistributed its flight energy by engaging in gliding phases, reducing unnecessary exertion. This concept has been applied to optimize relay switching, ensuring that nodes with higher energy reserves are prioritized for multi-hop transmissions.

$$P_s = \sum_{j=1}^{M} \left(\frac{E_j^{\gamma}}{\Theta_j + \rho} \times \eta(d_{jN}, S_j) \right) \quad (20)$$

The switching function P_s has considered the energy potential E_j of relay nodes while adjusting for network delay Θ_j. The term $\eta(d_{jN}, S_j)$ has accounted for distance-based signal attenuation, ensuring that longer transmission paths are avoided unless necessary.

Transmission adjustments have been dynamically refined based on network mobility states. DP has exhibited adaptive flight path corrections when facing wind turbulence, ensuring precise directional control. The routing model incorporates real-time node stability tracking to minimize data loss resulting from abrupt topology changes.

$$M_a = \sum_{k=1}^{K} \left(\frac{\phi_k}{1 + e^{-\sigma(V_k - V_{avg})}} \times \frac{1}{d_{kB} + \chi} \right) \quad (21)$$

The mobility adjustment function M_a has incorporated velocity variations V_k relative to network-wide velocity V_{avg}, ensuring seamless handovers for mobile nodes. The weight factor ϕ_k has influenced the probability of maintaining a stable connection, while χ controls network interference effects.

To enhance energy-efficient transmission, the routing process minimizes unnecessary delays by optimizing data flow patterns. Inspired by DP' continuous gliding adaptation to air currents, the routing model has restructured transmission delays to avoid energy-heavy retransmissions.

$$D_t = \sum_{q=1}^{Q} \left(\frac{1}{1 + e^{-\lambda(L_q - L_{opt})}} \times \xi(E_q, T_q) \right) \quad (22)$$

The delay minimization function D_t has depended on the packet load L_q of a given node, with the sigmoid-based normalization term ensuring that routing paths have not been overloaded. The secondary function $\xi(E_q, T_q)$ has adapted routing

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latency adjustments based on energy reserves and network traffic conditions.

Network stability has been further improved by predictive analysis of link quality degradation. DP has anticipated flight obstacles based on visual and environmental cues, guiding optimal aerial manoeuvres. The routing model has implemented similar predictive estimation to proactively reroute data transmission paths.

$$Q_f = \sum_{v=1}^{V} \left(\frac{V_v}{1 + e^{-k(R_v - R_{min})}} \times \theta(P_v, d_v) \right) \quad (23)$$

The forwarding strategy function Q_f has determined the likelihood of an efficient path being maintained, incorporating the received signal strength$R_v$relative to a predefined threshold R_{min}. The term $\theta(P_v, d_v)$ has adjusted forwarding probability based on packet flow density and spatial distribution.

3.7. Energy-Aware Load Redistribution (Migration-Inspired)

Energy-aware load redistribution has dynamically optimized data transmission pathways to prevent premature node depletion and congestion buildup. Inspired by the migration behaviour of butterflies, which redistribute themselves based on environmental resources and group coordination, the routing framework ensures efficient task distribution across relay nodes in IoAT-WSN.

Load balancing has been structured around energy thresholds to ensure fair distribution of traffic across nodes. Similar to DP adjusting its migration clusters to avoid exhausting food sources, the framework has dynamically reallocated routing responsibilities based on energy deviation metrics.

$$L_{adj} = \left(\frac{E_{curr}}{E_{max}} \right)^{\theta} \times \left(1 - \frac{T_{node}}{T_{opt} + \alpha} \right) \quad (24)$$

The adjusted load L_{adj} has depended on current energy E_{curr} relative to maximum energy E_{max}, where θ has been defined as the impact factor of energy on load redistribution. The term T_{node} has represented the node's current transmission traffic, while T_{opt} has established the optimal threshold for network load.

Routing efficiency has been maximized by redistributing loads using a hierarchical gradient, which has prevented localized bottlenecks. Inspired by DP, which migrates in structured formations to reduce wind resistance, the transmission paths have been dynamically adjusted to reduce routing strain on heavily burdened nodes.

$$G_{trans} = \left(\frac{1 + \lambda d_{ij}}{E_i^{\gamma}} \right) \times \left(\frac{R_{eff}}{R_{max}} \right) \quad (25)$$

The transmission redistribution gradient G_{trans} has been governed by the distance between nodes d_{ij} and energy reserves E_i of each relay. The ratio of the effective transmission rate R_{eff} to the maximum observed rate R_{max} has ensured that high-energy nodes with lower distance factors have carried heavier loads.

The probability of dispersing traffic to alternative nodes has prevented the formation of congestion hotspots. DP redistributes its population across multiple stopover points to maintain migration efficiency, which has been replicated by dynamically adjusting packet dispersion probabilities.

$$P_{disp} = \frac{1}{1 + e^{-\beta(C_{node} - C_{thr})}} \quad (26)$$

The dispersion probability P_{disp} has been determined by the current congestion state C_{node} relative to a congestion threshold C_{thr}, modulated by an adaptability factor β. This has ensured that overloaded nodes have rerouted traffic efficiently without compromising network stability.

Relay selection prioritizes nodes with surplus energy and stable link conditions, thereby reducing energy imbalances across the network. DP optimizes flight paths by coordinating group movement, mirroring the adaptive relay selection mechanism that has shifted transmission tasks based on node stability.

$$R_{alloc} = \frac{E_{relay}}{E_{total}} \times \left(1 - \frac{T_{relay}}{T_{net} + \delta} \right) \quad (27)$$

The relay allocation index R_{alloc} has been determined by relay node energy E_{relay} relative to total available energy E_{total}. The term T_{relay} has represented the relay's current transmission load, while T_{net} has accounted for network-wide traffic conditions.

Routing adjustments have been further refined by predicting future energy depletion rates to ensure pre-emptive redistribution. DP anticipates energy demands by selecting optimal stopover points, which have been incorporated into predictive routing mechanisms that have proactively adjusted data forwarding responsibilities.

$$E_{pred} = E_{curr} - \int_{t}^{t+\tau} P_{cons}(t)dt \quad (28)$$

The predicted energy level E_{pred} has been estimated by integrating the power consumption function $P_{cons}(t)$ over a defined time window τ. This mechanism has enabled the network to pre-emptively redistribute loads before energy shortages occur.

3.8. Probabilistic Path Caching for Memory-Based Routing

Probabilistic path caching for memory-based routing has enhanced data transmission efficiency by reducing redundant route discoveries. Inspired by DP, which utilizes navigational memory to optimize migration routes, this approach dynamically retains and reuses optimal paths, thereby ensuring stability and energy efficiency in IoAT-WSN communication.

The caching probability determines which paths are stored for future transmissions, thereby minimizing unnecessary recalculations. DP relies on prior successful migration routes, selecting the most energy-efficient paths based on past experiences. Similarly, caching probability has prioritized routes that have demonstrated consistent reliability and low energy consumption.

$$P_c = \frac{1}{1 + e^{-\delta(R_{eff} - R_{thr})}} \quad (29)$$

The caching probability P_c has been determined by the efficiency of a given route R_{eff} compared to a predefined threshold R_{thr}. The parameter δ has controlled the sensitivity of the function, ensuring that routes with higher reliability and energy efficiency have been retained with greater probability.

Cache retention has incorporated energy-based ageing to expire outdated routes dynamically. Similar to DP modifying migration paths based on changing environmental conditions, this mechanism has adjusted path lifetimes based on residual energy levels and traffic loads to maintain network adaptability.

$$A_r = A_0 e^{-\beta(E_{res}/E_{init})} \quad (30)$$

The route aging factor A_r has been exponentially reduced over time, where the initial cache age A_0 has been adjusted based on the fraction of remaining energy E_{res} relative to initial energy E_{init}. The decay rate β has ensured that routes through nodes with lower residual energy have been phased out, preserving network stability.

Retrieving cached routes has incorporated a probability-based decision model to prevent the overuse of frequently accessed paths. DP varies its migratory stopover points to avoid over-depleting nectar sources, an approach mirrored in probabilistic path selection to prevent network congestion and uneven load distribution.

$$P_r = \frac{\omega U_{node}}{U_{max} + \epsilon} \quad (31)$$

The retrieval probability P_r has been weighted by node utilization U_{node} relative to maximum network utilization U_{max}. The weight factor ω has ensured that frequently used nodes have not been overloaded, while ϵ has prevented instability in retrieval calculations.

A cache refresh mechanism has prevented performance degradation by ensuring that routing tables are periodically updated. Inspired by DP, which refines migration paths each season, routing adjustments have dynamically modified stored paths based on real-time performance metrics.

$$R_f = \left(\frac{1}{1 + e^{-\gamma(Q_{path} - Q_{opt})}}\right) \times \theta(T_{data}, C_{net}) \quad (32)$$

The refresh probability R_f has been adjusted based on path quality Q_{path} relative to an optimal threshold Q_{opt}. The function $\theta(T_{data}, C_{net})$ has accounted for network congestion and data traffic, ensuring that only outdated or inefficient paths have been replaced.

Caching updates have been integrated into multi-hop path selection to reduce redundant retransmissions. DP optimizes its flight formation to minimize energy loss, which has been replicated in the network by dynamically selecting relay nodes that reduce the number of intermediate hops.

$$M_h = \frac{1}{d_{ij} + \xi} \times \eta(E_{hop}, T_{hop}) \quad (33)$$

The multi-hop selection function M_h has prioritized paths based on node distance d_{ij} and a hop energy-weighted adjustment function

$\eta(E_{hop}, T_{ho})$. The function ensures that nodes with optimal energy reserves and stable traffic loads are favored for cache updates.

3.9. Real-Time QoS-Aware Priority Scheduling

Real-time QoS-aware priority scheduling has dynamically assigned priority levels to data packets based on urgency, energy availability, and transmission constraints. Inspired by DP, which selectively prioritizes nectar sources for energy optimization, the scheduling mechanism has ensured latency reduction, reliability, and energy-efficient packet delivery across the IoAT-WSN.

The scheduling mechanism classifies data packets into priority levels to ensure that time-sensitive information is transmitted with minimal delay. DP strategically selects the most nutrient-rich nectar sources, a behavior mirrored in the classification model, which prioritizes mission-critical packets based on real-time network conditions.

$$P_t = \frac{1}{1 + e^{-\lambda(Q_{data} - Q_{thr})}} \quad (34)$$

The transmission priority function P_t has been determined by data quality Q_{data} relative to a predefined threshold Q_{thr}. The parameter λ has controlled sensitivity, ensuring packets with higher QoS demands receive faster processing while maintaining system balance.

The scheduling algorithm incorporates energy availability metrics to optimize packet distribution. DP conserves energy during long migrations by minimizing unnecessary exertion, a principle replicated in packet handling by ensuring that nodes with stable energy levels are preferred for high-priority data transmission.

$$S_e = \left(\frac{E_n}{E_{max}}\right)^{\theta} \times \left(1 - \frac{L_{node}}{L_{opt} + \alpha}\right) \quad (35)$$

The energy-aware scheduling function S_e has considered the current energy level E_n relative to the maximum capacity E_{max}, with the impact factor θ regulating energy efficiency. The second term has ensured that nodes handling excessive traffic loads have not been burdened further.

Transmission latency has been minimized by adjusting the scheduling sequence based on real-time delay estimations. DP adjusts its flight altitude to minimize wind resistance and maintain speed efficiency, a behaviour that has been reflected in latency-aware transmission scheduling.

$$L_p = \frac{1}{d_{ij} + \xi} \times \eta(T_{data}, C_{net}) \quad (36)$$

The latency prioritization function L_p has assigned priority values based on inter-node distance d_{ij} and a delay-adjusted weight function (T_{data}, C_{net}), ensuring packets from distant nodes have received optimal transmission paths without excessive delay.

The scheduling framework has maintained an adaptive queue structure that dynamically adjusts the transmission order based on network conditions. DP adjusts feeding patterns based on environmental resource availability, a strategy that has been employed in packet queue adaptation for efficient resource allocation.

$$Q_m = \frac{\omega R_{eff}}{R_{max} + \epsilon} \quad (37)$$

The queue management function Q_m has depended on the effective transmission rate R_{eff} relative to the maximum observed rate R_{max}. The weight factor ω has adjusted queue positions dynamically, ensuring packets with higher reliability scores have been processed with minimal delay.

Scheduling decisions have been reinforced by incorporating probabilistic transmission strategies to ensure optimal packet movement. DP adapts its migratory paths dynamically to avoid wind resistance, as reflected in adjustments to the forwarding probability that prioritize congestion-free routing.

$$F_p = \frac{1}{1 + e^{-\beta(T_{node} - T_{thr})}} \quad (38)$$

The forwarding probability F_p has been influenced by the current transmission load T_{node} relative to an optimal threshold T_{thr}, modulated by an adaptability factor β. This mechanism has ensured that network congestion is prevented while optimizing real-time scheduling efficiency. Real-time QoS-aware priority scheduling has optimized network responsiveness, energy-aware routing, and packet prioritization, integrating the selective foraging intelligence of DP to enhance IoAT-WSN communication reliability and efficiency.

3.10. Dynamic Congestion Control via Monarch Swarm Density Optimization

Dynamic congestion control via monarch swarm density optimization has minimized network bottlenecks by dynamically redistributing data flow based on real-time node traffic patterns. Inspired by DP, which adjusts swarm density to reduce energy competition, this mechanism has balanced network traffic to ensure optimal load distribution and transmission efficiency. Traffic density estimation has provided a mechanism for identifying congestion-prone nodes by analyzing data flow accumulation. Similar to how DP regulates swarm clustering to prevent overexploitation of resources, the congestion estimation model ensures that network loads are evenly distributed among available paths.

$$D_n = \frac{\rho_i(T_{in} - T_{out})}{1 + e^{-\alpha(L_{node} - L_{thr})}} \quad (39)$$

The node density function D_n has been computed based on the difference between incoming traffic T_{in} and outgoing traffic T_{out}, weighted by node utilization ρ_i. The logistic function has ensured smooth transitions between congestion states, where L_{node} has represented real-time load relative to the congestion threshold L_{thr}.

The congestion probability function has dynamically adjusted traffic distribution to prevent excessive load accumulation. DP optimizes foraging routes by dynamically adjusting movement density, a principle that has been applied to reroute traffic through alternative network paths.

$$C_p = 1 - e^{-\beta(D_n - D_{opt})} \quad (40)$$

The congestion probability function C_p has measured the likelihood of congestion forming at a node by comparing the real-time node density D_n with the optimal distribution D_{opt}. The coefficient β has regulated the congestion adaptation rate, ensuring that traffic loads have been efficiently balanced.

Delay-aware forwarding mechanisms have been integrated to dynamically adjust packet transmission rates based on network congestion levels. Inspired by DP reducing flight speed in densely packed swarms, this approach has reduced congestion by prioritizing alternative forwarding paths for data packets.

$$F_d = \frac{1}{1 + \gamma(L_d - L_{min})} \quad (41)$$

The delay-based forwarding function F_d has depended on latency accumulation L_d within congested nodes relative to the predefined minimal latency threshold L_{min}. The term γ has controlled transmission adaptation, ensuring that traffic has not been routed through excessively delayed paths.

Predictive congestion control has enhanced path selection by forecasting congestion trends using historical transmission data. DP anticipates environmental variations during migration, an approach reflected in predictive flow adaptation, ensuring continuous congestion avoidance.

$$P_a = \frac{\sum_{j=1}^{N} T_j e^{-\eta(t - t_j)}}{N} \quad (42)$$

The predictive adaptation function P_a has determined future congestion likelihood based on prior traffic patterns, where T_j has represented past transmission loads at node j and $t - t_j$ has captured temporal decay in congestion estimation. The coefficient η has controlled the influence of past congestion on current path adjustments.

A multi-hop congestion mitigation mechanism has ensured that excessive data flow has been rerouted away from high-density nodes. Inspired by DP's adjustment of migration clusters across multiple stopover points, the model distributes data transmission over multiple relay paths to optimize network efficiency.

$$M_c = \frac{\sum_{q=1}^{M} (1 - C_p) \times R_q}{M} \quad (43)$$

The congestion mitigation function M_c has calculated the optimized transmission ratio across multiple relay paths, where C_p has determined the congestion probability and R_q has represented real-time node traffic across each relay node. The function has ensured that excess traffic has been equitably distributed.

3.11. Adaptive Security Mechanism Inspired by Monarch Predator Avoidance

Adaptive security mechanisms have strengthened IoAT-WSN routing by detecting and mitigating potential attacks through anomaly-based analysis. Inspired by DP, which employs predator avoidance strategies by modifying flight patterns, this security framework has dynamically identified and responded to malicious threats to maintain network integrity.

The intrusion detection mechanism has analyzed real-time traffic patterns to detect deviations caused by malicious activities. Similar to DP recognizing and avoiding predator-infested zones, this approach continuously assesses network traffic to differentiate between normal and abnormal behaviours.

$$I_d = \frac{|T_{obs} - T_{norm}|}{\sigma_t + \epsilon} \quad (44)$$

The intrusion detection score I_d has been determined by the absolute deviation between observed traffic T_{obs} and normal traffic baseline T_{norm}. The standard deviation σ_t has accounted for natural variations, while ϵ has prevented division instability, ensuring accurate anomaly detection.

The trust evaluation mechanism has dynamically assessed node reliability based on historical packet interactions. Inspired by DP, which verifies environmental safety before landing, this model maintains a trust score for each node, dynamically updating it based on the integrity of transmissions.

$$T_s = \frac{\sum_{i=1}^{N} P_i e^{-\alpha(F_i - F_{thr})}}{N} \quad (45)$$

The trust score T_s has been derived from the probability of successful packet delivery P_i weighted by an exponential decay function applied to packet forwarding failures F_i. The threshold F_{thr} has ensured that nodes exceeding a defined failure rate have been progressively penalized, reducing their participation in the routing process.

Multi-layer verification has been implemented to validate routing paths against potential spoofing attacks. Similar to DP, which follows established migratory routes to avoid predation risks, this mechanism has ensured that each selected routing path has passed security checks before transmission.

$$V_r = \frac{C_{auth} + H_{ver}}{1 + e^{-\beta(R_{score} - R_{min})}} \quad (46)$$

The verification function V_r has combined cryptographic authentication C_{auth} and historical route verification H_{ver}, ensuring multi-layered validation. The term R_{score} has represented the network-wide routing reliability index, where paths scoring below the threshold R_{min} have been discarded.

Upon detecting security anomalies, traffic redirection mechanisms have rerouted data through verified paths, minimizing exposure to compromised nodes. Inspired by DP altering its trajectory upon sensing predator activity, this model has dynamically shifted traffic flow away from detected threats.

$$R_d = \frac{1 - I_d}{1 + e^{-\gamma(L_{detected} - L_{safe})}} \quad (47)$$

The redirection probability R_d has been determined based on the intrusion detection score I_d and a logistic function adjusting routing weight based on latency comparisons between detected paths $L_{detected}$ and verified safe paths L_{safe}. This function has ensured minimal disruption while maintaining security.

A distributed alert mechanism has been integrated to propagate intrusion reports across the network, ensuring rapid response to emerging threats. DP communicates threat signals within its swarm, a strategy that has been adapted to facilitate collaborative defense mechanisms among IoAT-WSN nodes.

$$A_s = \frac{\sum_{j=1}^{M} I_j e^{-\eta(t - t_j)}}{M} \quad (48)$$

The security alert function A_s has been formulated using cumulative intrusion scores I_j, where the exponential decay factor $e^{-\eta(t-t_j)}$ has ensured that past alerts have gradually lost relevance. This adaptive process has prevented unnecessary false positives while enabling real-time security adaptation.

3.12. Monarch's Sun & Magnetic Navigation for Stable Routing

Monarch's sun and magnetic navigation for stable routing has ensured directional accuracy and adaptive path correction in IoAT-WSN. Inspired by DP, which relies on solar positioning and geomagnetic cues for long-distance migration, this mechanism optimizes routing stability by dynamically adjusting paths based on network and environmental conditions.

Routing stability has been enhanced by leveraging solar-aided directional cues, ensuring minimal deviations in data transmission paths. DP maintains accurate migration using the sun as a compass, which has been adapted in routing decisions by integrating solar position-based directional adjustments to improve transmission efficiency.

$$S_d = cos(\theta_s) \times \left(\frac{E_{node}}{E_{max}}\right) \quad (49)$$

The solar directional stability function S_d has been derived from the cosine of the solar azimuth angle θ_s, ensuring paths align with optimal directional cues. The term E_{node} relative to E_{max} has ensured that only energy-efficient nodes contribute to routing, maintaining stability and longevity.

Path deviation has been corrected dynamically using magnetic field-based adjustments, preventing misaligned transmissions. DP uses geomagnetic cues to stay on course, a principle that has been applied in routing stability by dynamically correcting deviations in data transmission paths based on observed magnetic disturbances.

$$M_c = \frac{B_{obs} - B_{ref}}{1 + e^{-\lambda(D_{node} - D_{opt})}} \quad (50)$$

The magnetic correction function M_c has been computed based on observed geomagnetic readings B_{obs} relative to a predefined reference B_{ref}, ensuring paths remain aligned with the expected network topology. The denominator introduces a stabilization factor, preventing excessive adjustments in regions with minor deviations.

Reliable routing has been maintained by integrating a gradient-based approach that has adjusted transmission pathways based on signal strength and directional alignment. DP adjusts its flight altitude based on changing environmental gradients, which has been translated into an adaptive routing model that selects the most stable paths dynamically.

$$G_p = \frac{\nabla R_{sig}}{1 + k(T_{node} - T_{thr})} \quad (51)$$

The gradient-based routing function G_p has been formulated using signal strength variation ∇R_{sig}, ensuring routing paths maintain optimal transmission reliability. The stabilization parameter has adjusted traffic distribution, preventing congestion-driven misalignment of routing decisions.

Routing paths have been dynamically corrected based on predicted variations in signal strength and node positioning. DP refines its migration routes using environmental feedback, a process replicated in network stability mechanisms that anticipate transmission disruptions before they occur.

$$P_c = \frac{\sum_{i=1}^{N} S_i e^{-\eta(t - t_i)}}{N} \quad (52)$$

The predictive correction function P_c has been derived using historical stability readings S_i, ensuring anticipated deviations have been corrected before affecting routing accuracy. The exponential decay factor weights past observations, ensuring that older readings contribute proportionally less to real-time predictions.

Routing resilience has been further enhanced by geospatial calibration, ensuring that data forwarding remains consistent even in the face of environmental fluctuations. DP dynamically adapts its migratory routes based on terrain variations, which has been implemented through a self-adaptive stabilization mechanism.

$$H_s = \frac{1}{D_{ij} + \xi} \times \omega\left(E_{hop}, R_{geo}\right) \quad (53)$$

The multi-hop stability function H_s has considered the inter-node distance D_{ij} while integrating geospatial parameters to regulate data forwarding decisions. The function has prevented routing failures caused by topological misalignment, maintaining optimal packet delivery paths.

Monarch's sun and magnetic navigation for stable routing have ensured directional stability, predictive course correction, and adaptive geospatial calibration, leveraging DP migratory intelligence to enhance IoAT-WSN resilience and routing accuracy.

3.13. Self-Healing Routing for Fault Tolerance (Inspired by Monarch Reorientation)

Self-healing routing for fault tolerance has ensured the continuous adaptation of network paths in response to failures and disruptions. Inspired by DP, which reorients its migration path when environmental changes disrupt its course, this mechanism has dynamically reconstructed routes, mitigating transmission failures and improving overall IoAT-WSN resilience.

The fault detection mechanism has continuously monitored network nodes to identify failures based on inactivity and response delays. DP senses environmental variations to adjust migration direction, a strategy that has been employed to recognize node failures and initiate route recovery processes.

$$F_d = \frac{|R_{exp} - R_{obs}|}{1 + e^{-\alpha(T_{del} - T_{thr})}} \quad (54)$$

The fault detection function F_d has evaluated discrepancies between the expected response rate R_{exp} and the observed response R_{obs}, where the denominator has ensured that minor deviations have not triggered unnecessary fault responses. The delay sensitivity factor α has adjusted responsiveness based on transmission delay thresholds T_{del}.

Upon detecting faults, the routing mechanism has reconstructed paths, ensuring uninterrupted data transmission. DP modifies its migratory flight path when obstacles arise, an approach mirrored in route recalibration that identifies alternative transmission nodes while minimizing energy consumption.

$$R_r = \frac{1}{1 + e^{-\beta(N_{avail} - N_{thr})}} \quad (55)$$

The route reconstruction probability R_r has been determined based on the number of available neighboring nodes N_{avail} relative to a reconstruction threshold N_{thr}. The term β has modulated the rate of reconstruction, ensuring that alternative paths have been efficiently selected while avoiding excessive network fluctuations.

Self-healing mechanisms have been distributed across multiple relay nodes to prevent data transmission failures. DP utilizes swarm-based reorientation when individual butterflies lose direction, which has been applied in IoAT-WSN to enable fault-tolerant multi-hop routing.

$$H_s = \left(\frac{E_{node}}{E_{max}}\right)^{\gamma} \times \left(1 - \frac{L_{node}}{L_{opt} + \delta}\right) \quad (56)$$

The self-healing stability function H_s has ensured that nodes with sufficient energy reserves E_{node} have taken over transmission duties when failures have occurred. The function has also accounted for traffic loads L_{node} to prevent excessive congestion when paths have been reconstructed.

The routing protocol anticipates potential failures by analyzing historical node behaviour and energy depletion trends. DP anticipates adverse conditions by adjusting migration speed and route selection, a principle that has been used to predict and prevent future transmission failures.

$$P_f = \frac{\sum_{i=1}^{M} E_i e^{-\eta(t - t_i)}}{M} \quad (57)$$

The predictive fault probability P_f has been derived using past energy depletion trends E_i to estimate the likelihood of future failures. The exponential decay function $e^{-\eta(t-t_i)}$ has ensured that older failure records have had a diminishing influence on real-time predictions.

Routing efficiency has been further enhanced through the use of reinforcement learning, enabling the system to refine its fault recovery decisions over time. DP optimizes migratory efficiency based on prior experiences, an approach that has been mirrored in self-learning routing adjustments.

$$Q_u = Q_p + \lambda\left(R_t + maxQ_{t+1} - Q_p\right) \quad (58)$$

The reinforcement learning function Q_u has updated the quality estimate of a routing path based on previous reward values Q_p and new rewards R_t. The discount factor λ determines how strongly new observations have influenced routing decisions, ensuring a balance between stability and adaptation.

Algorithm 1: DP-MCR

Input:

- Sensor node set N, energy levels E, traffic loads T, congestion thresholds C, fault detection parameters F, routing quality metrics Q

Output:

- Optimized multi-constraint routing paths, adaptive energy-aware communication, congestion-free, and fault-tolerant data transmission

Procedure:

1. Deploy sensor nodes and initialize network parameters to ensure energy-efficient placement and cluster formation.
2. Assign dynamic constraint weights based on real-time network conditions and multi-criteria optimization.
3. Establish hierarchical clustering inspired by swarm-based organization for balanced load distribution.

4. Rank and optimize paths using nectar selection strategies to ensure energy-aware routing decisions.
5. Implement adaptive multi-hop routing, leveraging gliding-inspired relay transitions for efficient transmission.
6. Dynamically redistribute traffic loads to prevent congestion and optimize node energy consumption.
7. Cache and retrieve optimal paths using probabilistic memory-based routing to reduce redundant computations.
8. Prioritize real-time QoS-aware scheduling to handle latency-sensitive and high-priority IoMT data.
9. Control congestion dynamically using swarm density optimization to ensure a balanced traffic flow.
10. Enhance security mechanisms by detecting anomalies and preventing malicious intrusions in the routing process.
11. Maintain routing stability using monarch-inspired sun and magnetic navigation strategies.
12. Enable self-healing routing to detect and recover from faults using reinforcement learning-based optimizations.

4. SIMULATION SETTING

The behaviour of DP-MCR has been examined in NS-3, an open-source discrete event simulator widely used for wireless communication studies. The experimental layout represents an agricultural field, where sensor nodes are randomly deployed to observe soil and crop conditions. The network field is defined as a 1000 × 1000 m area, reflecting the dimensions of typical farmlands. The density of sensor nodes is varied between 80 and 400 to investigate scalability. Each node begins with 2 J of energy, which reflects the limited capacity of small agricultural devices. Communication is enabled with a 100 m transmission radius to ensure multi-hop forwarding, as direct communication is impractical in large deployments. The IEEE 802.15.4 MAC layer is used to model low-power communication, which is suited for resource-constrained environments. Traffic consists of periodic sensing data with additional bursts representing critical agricultural events. System performance is evaluated using key metrics, including energy consumption, delay, packet delivery, packet loss, and throughput.

Table 2. Simulation Parameters

Parameter	Setting
Simulator	NS-3 (v3.38)
Deployment Area	1000 m × 1000 m
Number of Nodes	80, 160, 240, 320, 400
Base Station	Centralized fixed node
Initial Energy	2 J per sensor
Energy Model	BasicEnergySource with radio consumption profile
Transmission Range	100 m
Data Packet Size	512 bytes
Control Packet Size	64 bytes
MAC Protocol	IEEE 802.15.4
Traffic Type	Periodic sensing + event-driven alerts
Channel Model	Two-ray ground propagation
Simulation Duration	1000 s
Performance Metrics	Energy, Delay, Packet Delivery, Packet Loss, Throughput

5. RESULTS AND DISCUSSION

In agricultural IoT environments, routing performance has a direct impact on the sustainability of sensing devices and the timely availability of critical data for effective farm management. To assess the effectiveness of the proposed DP-MCR framework, simulations were conducted under varying node densities and compared with two benchmark protocols: Whale–Ant Hybrid (WAH) and Entropy Eagle Optimiser (EEO). The evaluation considered five key performance metrics that collectively define IoAT efficiency: energy consumption, end-to-end delay, packet delivery ratio, packet loss ratio, and throughput. Each metric was analyzed to determine how DP-MCR's biologically inspired design contributes to more reliable and energy-conscious communication. The results are presented in both graphical and tabular form, providing a clear comparison across protocols. The following subsections discuss the outcomes for each metric in sequence, linking observed trends with the working mechanisms of DP-MCR and highlighting its suitability for agricultural deployments.

5.1. Energy Consumption Analysis

Energy consumption is a crucial performance metric in IoAT-based WSNs, reflecting the proportion of available energy utilized by sensor nodes during data transmission. Lower percentages correspond to more efficient operation and longer network lifetime. In Figure 1, the x-axis represents node density, while the y-axis denotes energy consumption expressed in percentage. Table 1 details the observed values across 80 to 400 nodes.

WAH consistently exhibited higher consumption, averaging 76.109%. This trend stems

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from its computationally intensive coordination phase, where the simultaneous execution of whale and ant optimization increases energy drain, especially under dense conditions. The EEO showed slightly lower consumption at more minor scales but averaged 64.844%. Its instability arose from frequent reorganization in soft clustering, which triggered repeated control overhead and depleted energy faster in larger deployments. Both models also lacked predictive energy balancing, rendering them inefficient under fluctuating agricultural traffic conditions. The proposed DP-MCR achieved the lowest average of 44.368%, confirming its superior efficiency. Its advantage originated from energy-aware gliding-inspired multi-hop routing that redistributed tasks proactively. By balancing loads across nodes and minimizing redundant retransmissions, DP-MCR maintained sustainable operation across all densities.

Table 1. Energy Consumption under Varying Node Densities

Node Density	WAH	EEO	DP-MCR
80	64.372	44.185	26.947
160	62.684	67.291	35.452
240	74.129	57.846	43.518
320	83.942	78.307	54.685
400	95.418	76.592	61.239
Average	**76.109**	**64.844**	**44.368**

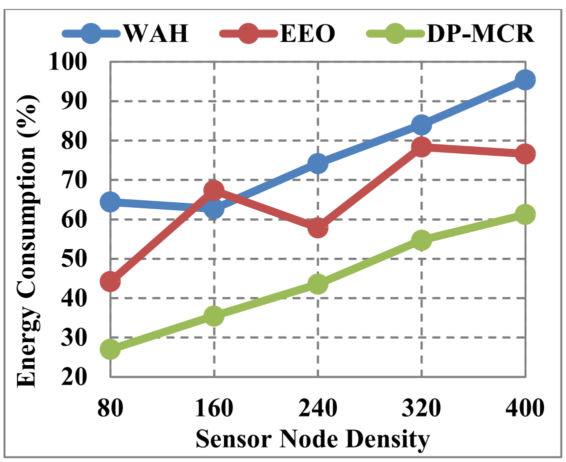

Figure 1. Energy Consumption Comparison

5.2. Delay Analysis

End-to-end delay represents the time it takes for a packet to reach the base station from its source node, measured in milliseconds. Minimizing this delay is critical in IoAT scenarios where alerts on water stress or crop disease must be delivered with little latency. As illustrated in Figure 2 and detailed in Table 2, the values consistently increased with node density, though performance varied across protocols.

The WAH approach reported the highest average delay at 4833.8 ms. Its slower response is linked to the overhead introduced by pheromone updates in dense networks, which elongates the forwarding process. The EEO design averaged 4615.2 ms, but its dependence on density-based clustering created repeated reorganization phases, producing extra waiting time for packets. Both frameworks lacked mechanisms to mitigate queue build-up, explaining the sluggish results under high loads. DP-MCR achieved a reduced average of 3801.4 ms. This improvement stemmed from its nectar-inspired prioritization, which allocated higher preference to urgent packets, and from its adaptive gliding-based routing that smoothed traffic flow. These features collectively ensured faster end-to-end responsiveness across IoAT deployments.

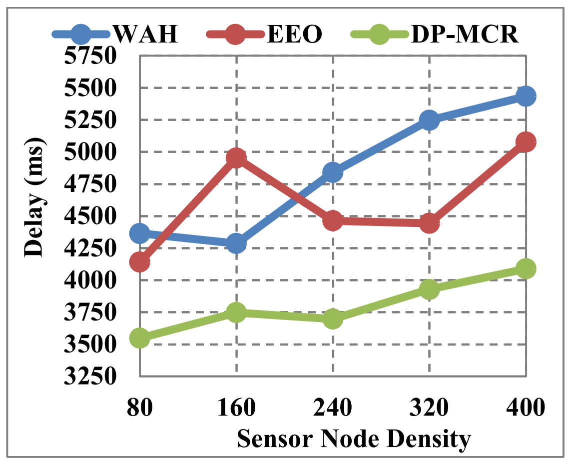

Figure 2. End-to-End Delay Comparison

Table 2. End-to-End Delay under Varying Node Densities

Node Density	WAH	EEO	DP-MCR
80	4364	4141	3548
160	4285	4951	3746
240	4841	4463	3697
320	5246	4443	3928
400	5433	5078	4088
Average	**4833.8**	**4615.2**	**3801.4**

5.3. Packet Delivery Ratio Analysis

Packet Delivery Ratio (PDR), expressed as a percentage, indicates the proportion of packets that reach their destination compared to those transmitted. A higher ratio represents dependable transmission, which is crucial in IoAT where uninterrupted delivery of crop, soil, and climate data supports timely agricultural decisions. In Figures 3

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and Table 3, delivery rates are plotted across densities ranging from 80 to 400 nodes.

WAH achieved an average of 65.911%. The reduction at higher densities arose from excessive pheromone updates in ant colony routing and slow convergence of whale optimization, both of which weakened route stability. EEO reported a marginally higher average of 66.743%, but its density-based soft clustering forced repeated reorganizations, disrupting connectivity. Modified beetle swarm optimization led to premature convergence, narrowing the exploration space and limiting reliable path formation. DP-MCR sustained a stronger average of 78.772%. The improvement resulted from nectar-driven path optimization that prioritized energy-rich and stable relays, combined with swarm-based clustering that balanced communication loads. Gliding-inspired multi-hop adjustment supported resilience under traffic surges, preserving packet reliability across all densities.

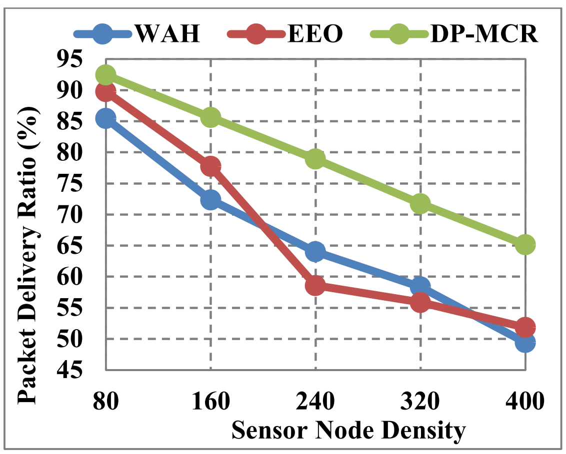

Figure 3. Packet Delivery Ratio Comparison

Table 3. Packet Delivery Ratio across Varying Node Densities

Node Density	WAH	EEO	DP-MCR
80	85.459	89.780	92.442
160	72.343	77.710	85.625
240	64.002	58.569	78.917
320	58.332	55.837	71.731
400	49.418	51.817	65.146
Average	**65.911**	**66.743**	**78.772**

5.4. Packet Loss Ratio

Packet Loss Ratio (PLR), expressed in percentage, denotes the fraction of transmitted packets that fail to arrive at the base station. A lower ratio signifies stronger dependability, which is vital in IoAT networks where missing field updates can delay irrigation control or pest management. In Figure 4, the x-axis represents node density, and the y-axis represents packet loss percentage. Table 4 provides the numerical distribution across densities ranging from 80 to 400 nodes. WAH reported an average PLR of 34.089%. Its higher loss rates arose from heavy pheromone maintenance and the burden of linear optimization, both of which reduced responsiveness and increased route instability under dense deployments. EEO delivered an average of 33.257%, but entropy-based recalculations drained energy and frequent soft clustering reorganizations fragmented connections. Premature convergence in beetle swarm optimization further reduced exploration, which led to packet drops in traffic-heavy conditions. DP-MCR achieved the lowest average of 21.228%. This improvement came from its QoS-aware scheduling mechanism, which prioritized reliable forwarding paths and reduced congestion-induced drops. Magnetic navigation–inspired adjustments further stabilized multi-hop routes, preventing disruptions that contributed to higher loss rates in WAH and EEO.

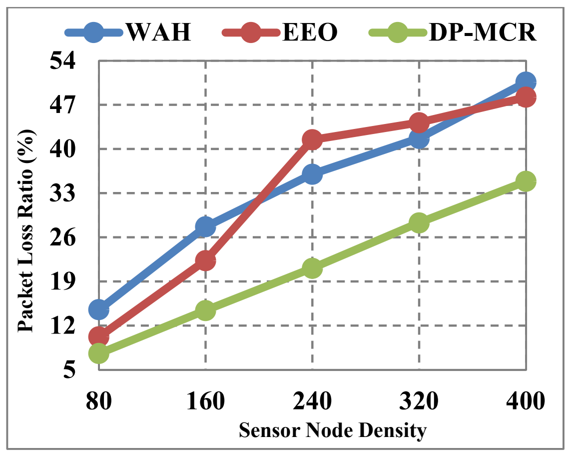

Figure 4. Packet Loss Ratio Comparison

Table 4. Packet Loss Ratio across Varying Node Densities

Node Density	WAH	EEO	DP-MCR
80	14.541	10.220	7.558
160	27.657	22.290	14.375
240	35.998	41.431	21.083
320	41.668	44.163	28.269
400	50.582	48.183	34.854
Average	**34.089**	**33.257**	**21.228**

5.5. Throughput Analysis

Throughput, measured in kilobits per second (kbps), reflects the effective rate at which data is delivered from sensor nodes to the base station. Higher values demonstrate stronger transmission capability and network responsiveness,

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which are essential in IoAT settings where continuous reporting of soil, climate, and crop variables must be maintained. In Figure 5, the x-axis represents node density, while the y-axis denotes throughput in kbps. Table 5 lists the observed values across densities ranging from 80 to 400 nodes.

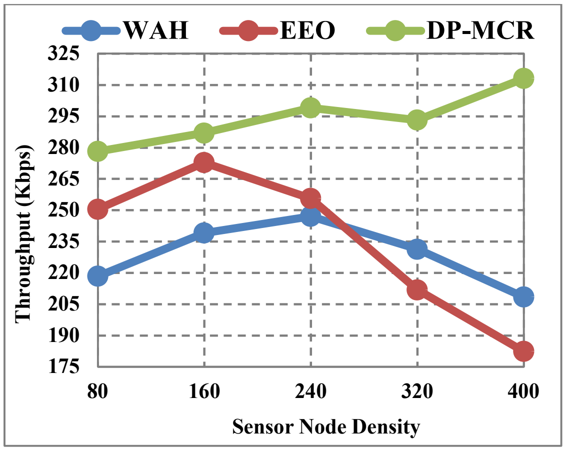

Figure 5. Throughput Comparison

Table 5. Throughput Performance across Varying Node Densities

Node Density	WAH	EEO	DP-MCR
80	218.367	250.446	278.187
160	239.088	272.782	286.920
240	247.015	255.616	299.013
320	231.309	211.836	293.138
400	208.402	182.350	313.146
Average	**228.836**	**234.606**	**294.081**

WAH reached an average throughput of 228.836 kbps. Its decline at higher densities resulted from slow convergence in whale optimization and overhead from pheromone updates, which limited available bandwidth. EEO averaged 234.606 kbps, showing a modest improvement at lower densities. However, its entropy recalculations and layered optimization introduced delays that hindered packet flow, resulting in sharp degradation beyond 240 nodes. Both frameworks lacked congestion-aware adjustments, which reduced throughput reliability under heavy traffic. DP-MCR outperformed both baselines with an average throughput of 294.081 kbps. Its advantage stemmed from congestion control inspired by swarm density behavior, which distributed packet loads evenly, combined with nectar-based relay prioritization that channeled data through stable nodes. This design sustained higher delivery rates across all densities.

6. CONCLUSION

The DP-MCR protocol has been developed by modelling the migration intelligence of Danaus plexippus into a multi-constraint routing design for IoAT. Its operation integrates swarm-based clustering for balanced node organization, gradient-driven weighting for adaptive constraint management, nectar-guided path optimization for energy-conscious relay selection, and gliding-inspired multi-hop forwarding to reduce retransmissions. These components are supported by migration-based load redistribution, QoS-aware scheduling, and self-healing adjustments, ensuring dependable transmission under diverse agricultural conditions. This layered mechanism collectively balances energy conservation, delay minimization, and delivery reliability. Performance evaluation confirmed its effectiveness, with average energy consumption maintained at 44.36%, end-to-end delay reduced to 3801 ms, packet delivery ratio sustained at 78.77%, packet loss limited to 21.22%, and throughput raised to 294 kbps across varying node densities. These outcomes validate that biologically inspired routing strategies can be translated into scalable and sustainable frameworks, enabling DP-MCR to support robust communication in precision farming environments. Future research can further extend DP-MCR through the use of UAV-assisted sensing and blockchain-based security, thereby enhancing its adaptability.

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