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Enhancing On-Demand Multicast Routing Protocol (ODMRP) using Mayfly Algorithm and Reference Point Mobility Group Model for Cattle Monitoring

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Abstract
Cattle migration presents significant challenges for wireless network routing due to dynamic and unpredictable movement patterns. This study introduces an innovative framework that enhances the On-Demand Multicast Routing Protocol (ODMRP) using the Mayfly Optimization Algorithm (MOA) and the Reference Point Group Mobility Model (RPGM) for cattle monitoring. A simulation environment using Network Simulator 3 (NS-3) was employed to evaluate routing efficiency, energy consumption, and scalability with varying node counts. Various performance metrics such as throughput, energy efficiency, and packet delivery ratio were analysed to compare the effectiveness of the proposed model against traditional random waypoint models. By leveraging RPGM's group-based mobility approach, the framework adapts to cattle movement while optimizing routing efficiency, energy consumption, and scalability. The proposed solution demonstrates superior performance in IoT-enabled livestock monitoring systems, achieving improved throughput, energy efficiency, and reduced latency compared to traditional random waypoint models. The findings confirm superior performance in IoT-enabled livestock monitoring systems, achieving a 35% increase in throughput, a 27% reduction in energy consumption, and a 40% decrease in latency compared to the baseline model. These results establish the enhanced ODMRPMF RPGM framework as a robust, scalable, and reliable solution for dynamic and resource-constrained applications, particularly in real-time livestock tracking.

***Keywords**: Cattle migration, wireless network routing, IoT-enabled livestock monitoring, mayfly optimization algorithm (MOA), reference point group mobility model.*

1.0 Introduction

The rapid advancement of Internet of Things (IoT) technology has revolutionized various industries, enabling seamless connectivity and real-time data exchange among smart devices (Ye *et al*., 2021). IoT's transformative potential spans numerous domains, including smart cities, healthcare, and agriculture (Kurni, 2024). In agriculture, particularly livestock management, IoT solutions offer unprecedented opportunities to address longstanding challenges such as monitoring (Adanigbo *et al*., 2025), resource allocation (Atiq *et al*., 2023), and conflict mitigation. Wireless Sensor Networks (WSNs) play a crucial role in this integration, enabling efficient data collection and communication in remote and dynamic environments (Chander *et al*, 2024).

Cattle migration, a vital aspect of livestock farming, presents unique challenges for traditional monitoring systems. Nomadic practices and unpredictable movement patterns complicate efficient resource management, leading to issues such as land degradation, grazing disputes, and cattle rustling (Ehiane *et al*., 2024). Existing solutions often fail to meet the demands of scalability, energy efficiency, and reliability in these dynamic scenarios (Yamsani *et al*., 2024). Mobile Ad Hoc Networks (MANETs), characterized by their decentralized architecture and self-organizing capabilities (Asra, 2022)., emerge as a promising alternative. However, their performance is hindered by node mobility, power constraints, and frequent link failures.

This study addresses these challenges by introducing a novel framework that integrates the On-Demand Multicast Routing Protocol (ODMRP) with the Mayfly Optimization Algorithm (MOA) and the Reference Point Group Mobility Model (RPGM). The Mayfly Optimization Algorithm (MOA**)** was selected as the metaheuristic in this study due to its superior characteristics in solving routing and optimization challenges in dynamic, resource-constrained environments (Wang & Li (2024)) such as IoT-based cattle monitoring. By combining MOA's optimization capabilities with RPGM's group-based mobility model, the proposed framework enhances routing efficiency and energy management in IoT-enabled livestock monitoring systems. Through comprehensive simulations, this study demonstrates significant improvements in throughput, energy efficiency, and latency, offering a scalable and adaptable solution for real-world applications.

1.1 Related Work

Kandris *et al*. (2017) introduced the Congestion Alleviation and Avoidance (COALA) protocol to address congestion in WSNs by proactively preventing and reactively mitigating it. Using an accumulative cost function, COALA identifies optimal routing paths, improving adaptability but facing challenges in resource-constrained environments. Gholipour *et al*. (2018) combined Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Response Surface Methodology (RSM) to enhance congestion management in cognitive WSNs, optimizing network performance. However, reliance on accurate input data and RSM complexity limits its use in dynamic settings. Kazmi *et al*. (2019) proposed a methodology for congestion avoidance and fault detection in WSNs by utilizing data science techniques. Their approach analyzes network traffic patterns and node behaviours to detect potential congestion and faults before they affect network performance. However, the computational demand of this method is a limitation for resource-constrained WSN deployments.

Another notable development is the Weighted Energy and Temperature-Aware Routing Protocol (WETRP) by Bhangwar *et al*. (2019), designed to optimize energy consumption and thermal management in body sensor networks. These innovations reflect the ongoing evolution of routing protocols to meet the complex and dynamic demands of mobile ad hoc networks (MANETs). For energy optimization, several protocols have been proposed. Rajpoot and Dwivedi (2019) introduced a modified Bellman-Ford algorithm, and Kanagasundaram & Kathirvel (2019) developed the Enhanced Improved Multi-Objective Energy-aware and Secure Optimized Link State Routing Protocol (EIMO-ESOLSR) protocol, both of which incorporated energy metrics into routing decisions to achieve significant energy savings. However, issues such as scalability, fault tolerance, and network delays remained prevalent across these studies.

Innovative algorithms for energy-efficient cluster head selection have also been introduced. Mukhedkar and Kolekar (2020) proposed a secure dolphin glowworm optimization, while Kathiroli and Selvadurai (2021) developed the Improved Sparrow Search Algorithm (ISSA). These protocols optimized data handling in large networks but faced challenges such as complex usability and uneven cluster head distribution. Similarly, the Dynamic Range Clustering (DRC) approach by Aroulanandam *et al*. (2020) employed a learning-based routing scheme to manage energy and congestion, but dynamic nature of the network topology changes introduced delays. Recent progress has also emphasized the integration of Artificial Intelligence (AI) into energy enhancement in MANETs. Malar *et al*. (2021) presented an ant colony-inspired technique to enhance energy efficiency in dynamic networks, while Vani *et al*. (2021) focused on AI-based security frameworks for threat detection in MANETs. Despite their potential, these algorithms encountered performance issues in scenarios involving high mobility or complex environments.

Vanarasan *et al*. (2023) introduced a novel meta-heuristic algorithm tailored to dynamic MANET environments. The balance between load and energy efficiency demonstrates adaptability, especially in scenarios with fluctuating network conditions. However, the approach requires high computational overhead, making it less suitable for low-power devices. Additionally, its performance in large-scale MANETs with high node mobility remains to be validated. Tej & Ramana (2023) proposed an approach which integrates the Modified Simulated Annealing (MSA) and Squirrel Flying Optimization (SFO) algorithms to establish secure and energy-efficient routing paths. By leveraging neighbour trust information, the proposed protocol selects the most secure routes for data transmission, achieving higher delivery rates and lower delays compared to existing protocols like Ad hoc On-Demand Distance Vector (AODV) and Ad hoc On-demand Multipath Distance Vector (AOMDV). However, the protocol’s reliance on trust metrics introduces delays in real-time applications. Moreover, the complexity of combining two algorithms increases implementation difficulty in resource-constrained systems.

Zhang (2024) demonstrated improvement in energy conservation by reducing energy usage in routing paths. However, they faced challenges like high computational overhead and extended training times, especially in resource-constrained environments. Deep Reinforcement Learning for Energy-efficient Routing (DRLER) by Wang (2024) and Trust-based Secure Routing Protocol (TSRP) by Kumar *et al*. (2024) introduced novel methods for optimizing energy consumption and ensuring secure routes, but these too were hindered by training overhead and scalability concerns.

Integration with edge computing and software-defined networking (SDN) was explored in protocols by Park and Kim (2024) and Rodriguez *et al*. (2024). These approaches showed promise in reducing latency and improving resource utilization. However, they relied on specialized infrastructure and faced challenges such as single points of failure and the control overhead.

2.0 Materials and Methods

The materials used in this study are presented in the following sub-sections.

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2.1 *Simulation Environment*

The simulation was conducted using Network Simulator 3 (NS-3) version 40 and MATLAB R2015a for algorithm implementation and performance evaluation. The simulation environment consisted of a 200m x 200m terrain, where cattle nodes followed the Reference Point Group Mobility Model (RPGM). The parameters used in setting up the simulation are presented in Table 1. The network defining equations are also presented in the following sub-sections:

2.2 *ODMRP Route Discovery*

The On-Demand Multicast Routing Protocol (ODMRP) (Lee *et al.*, 1999) is a mesh-based multicast routing protocol designed for mobile ad hoc networks. For incorporating Mayfly Optimization Algorithm into the On-Demand Multicast Routing Protocol (ODMRP), its mathematical foundation can be represented as follows:

a) Join Query Propagation

The total number of broadcasts B(t) at time t is:

$$B(t) = \sum_{i=1}^{N} I_{broadcast}(n_i, t) \quad (1)$$

where $I_{broadcast}(n_i, t)$ is the indicator function:

Table 1: Simulation setup

S/N	Parameter	Value
1.	Simulator	NS 3.40, MATLAB R2015a
2.	Node Type	Heterogeneous
3.	Simulation Landscape	200 m x 200 m
4.	Simulation time	600 s
5.	Node Energy	1000 J
6.	Routing Protocol(s)	ODMRP-RWP, ODMRPMF-RPGM
7.	Background Traffic	Constant bit rate
8.	MAC Protocol(s)	IEEE 802.11, TCP
9.	Packet Size	512 bits
10.	Packet Interval	0.01

$$I_{broadcast}(n_i, t) = \begin{cases} 1 & \text{if node } n_i \text{ broadcasts at time t,} \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

b) Path Length

The path length $L_{s,d}$ between a source s and a destination d is:

$$L_{s,d} = \sum_{k=1}^{H_{s,d}} h_k \quad (3)$$

where $H_{s,d}$ is the number of hops, and h_k is the length of hop k.

c) Route Refresh Interval

Route refreshes occur periodically with interval $T_{refresh}$:

$$R(t) = \mathbf{I}_{refresh}(t).B(t) \quad (4)$$

d) Multicast Group Definition

A multicast group G is a subset of nodes which is defined as:

$$G = \{n_i \in N : n_i \text{ is a group member}\} \quad (5)$$

where **G** is a set of nodes n_i that belong to a larger set N and the condition after the colon (:) indicates that only nodes that are group members belong to G.

2.3 *The Mayfly Optimization Algorithm (MOA)*

The Mayfly Optimization Algorithm (MOA) (Zervoudakis & Tsafarakis (2020)) is an optimization technique inspired by the behaviour of mayflies, combining swarm intelligence and evolutionary algorithms. It models the mating and flight behaviours of male and female mayflies to optimize problems.

a) Initialization

Mayflies are initialised randomly in the search space. This process is defined by equation

$$x_i \sim U(x_{\mathbf{min}}, x_{\mathbf{max}}) \quad 6$$

and velocities are initialised as Equation 7.

$$v_i \sim U(v_{\mathbf{min}}, v_{\mathbf{max}}) \quad 7$$

b) Mayfly Position and Velocity

Each mayfly m_i has a position x_i and velocity v_i where:

$$X_i = [x_{i1}, x_{i2}, \dots, x_{id}] \quad 8$$

$$v_i = [v_{i1}, v_{i2}, \dots, v_{id}] \quad 9$$

where d is the dimension of the problem.

2.4 Reference Point Group Mobility (RPGM)

The Reference Point Group Mobility (RPGM) model (Bai and Helmy, 2004) simulates group-based movement in wireless networks, where nodes move dynamically around a central reference point that dictates the group's direction and speed. It is widely used to evaluate protocols in scenarios like disaster recovery (Gupta & Jain, (2023)) and livestock monitoring (Patel & Singh (2024)). The model organizes nodes into groups, where each group has a reference point that dictates the group's overall movement. Individual nodes exhibit random movements around this reference point.

2.5 Integration of Mayfly Optimization Algorithm (MOA) with ODMRP

The Mayfly Optimization Algorithm (MOA) was applied to optimize the On-Demand Multicast Routing Protocol (ODMRP) by refining route selection and energy efficiency. The MOA was initialized with a population of mayflies representing potential routing paths. The following steps were executed:

a. Initialization: Nodes were randomly assigned positions within the network.
b. Fitness Evaluation: The fitness of each mayfly (routing path) was evaluated based on energy consumption, hop count, and network stability.
c. Selection and Mutation: The algorithm selected the most efficient paths and applied perturbation techniques to improve routing stability.
d. Final Route Assignment: The optimized route with the lowest energy consumption and highest throughput was selected for multicast communication.

In this study, MOA is integrated with ODMRP for optimizing route discovery and maintenance. The equations for applying MOA to the Reference Point Group Mobility (RPGM) model, and the equations specifying how node positions are generated and updated are described in the following sub-sections:

i. Fitness Evaluation

The fitness function includes the effects of mobility and its route cost (C_{route}) is described by:

$$C_{\text{route}} = \alpha.\sum_{i=1}^{N} E_{\text{i}} + \beta.\frac{\sum_{i=1}^{N} D_{\text{i}}}{N}\gamma.\text{H} \quad 10$$

where: E_{i} is the Energy consumption of node i, D_{i} is the Distance travelled by node i, H is the total number of hops and α, β, γ are weighting coefficients.

2.6 Application of Reference Point Group Mobility Model (RPGM)

The RPGM was employed to model the movement of cattle in a herd-based fashion. Each cattle node moved within a certain radius around a reference point, allowing group-based mobility. The model was configured as follows:

a. Reference Point Update: The central reference point was dynamically updated every 5 seconds.
b. Node Mobility Constraints: Individual nodes had random velocity variations to simulate realistic cattle movement.
c. Routing Impact Assessment: The impact of RPGM on ODMRP's performance was assessed in terms of network overhead, data packet delivery, and end-to-end delay.

2.7 Performance Metrics

a) The energy $E_i(t)$ of node i at time t is:

$$E_i(t) = E_i(t-1) - E_{tx} . P(t) \quad 11$$

Where E_{tx} is the energy cost per transmission, and P(t) is the number of packets transmitted.
Energy Consumed = Initial Energy - Remaining Energy 12
Total Energy Consumed is the sum of energy consumed for all nodes
The packet delivery ratio(PDR) is given as:

$$\text{PDR} = \left(\frac{\sum_{j=1}^{t} r_j}{\sum_{i=1}^{t} s_i}\right) \times 100 \quad 13$$

$$Delay_{avg} = \left(\frac{\sum_{i=1}^{N} T_{recv,i} - T_{send,i}}{\text{N}}\right) \quad 14$$

where N is the total number of received packets, $T_{recv,i}$ is the receive time of packet i, and $T_{send,i}$ is the send time of packet i. If there are multiple packets, it is defined by equation 16. The algorithm for ODMRP and MOA with RPGM is presented in Algorithm 1.

$$\text{Throughput} = \left(\frac{\text{Total Time (in seconds)}}{\text{Total Data Delivered (in bits)}}\right) \quad 15$$

$$\text{Throughput} = \left(\frac{\sum_{i=1}^{N} \text{Packet Size}_i}{\text{Total Time}}\right) \quad 16$$

Algorithm 1: Optimized ODMRP with RPGM and Mayfly Algorithm

1: Update Reference Point Position: RP = (RPx + velocity × cos(θ), RPy + velocity × sin(θ));
2: Determine Group Member Position: GMpos = RP + displacement;
3: Compute Fitness Score: fitness = (W1 × hopCount + W2 × energyUsage + W3 × groupStability);
4: Data Transmission Check: If node possesses data to send:
5: Initialize Mayfly Algorithm: Generate initial mayfly population P;
6: Iterate Until Convergence: While iteration count < maxIterations:
7: Update Mobility Parameters: Adjust reference point and group member locations;
8: Compute fitness score for each mayfly candidate;
9: Optimize Route Selection: Update global best (gbest) and personal best (pbest) values;
10: Select the Most Efficient Routing Path: - Identify the optimal communication route within the group;
11: End Iteration Loop.
12: Multicast Group Formation: - Disseminate Join Request to group members;
13: Acknowledge Responses: - Receive Join Reply confirmations;
14: Establish Routing Path: - Forward data through the optimized multicast route;
15: End Conditional Check.
16: Maintain Group-Based Communication: - Continuously refine and uphold the multicast mesh network.

Where throughput is measured in bits per second (bps), it represents the effective rate of successful data delivery in a network. Total Data Delivered is the amount of data successfully received by the destination(s), usually measured in bits. Total Time is the total duration of the communication session, measured in seconds. Packet Delivery Ratio (PDR) is defined as the ratio of packets successfully received to those transmitted (Kumar *et al*., 2024), Energy Consumption is the total energy used by nodes in transmission and routing (Wang, 2024) and end-to-end delay is the average time taken for a packet to reach its destination.

3.0 Results and Discussion

This sub-section discusses the results and findings from this study. Figure 1 compares the average end-to-end delay for ODMRP RWP and ODMRPMF RPGM as the number of nodes increases. ODMRPMF RPGM maintains a consistently lower delay across all node counts, reflecting its efficiency in handling group-based mobility and maintaining stable communication. In contrast, ODMRP RWP exhibits a significant increase in delay, likely due to frequent link breakages and less efficient routing in dynamic environments. This highlights ODMRPMF RPGM's suitability for low-latency applications in dense or dynamic networks. Figure 2 shows that ODMRPMF RPGM consistently outperforms ODMRP RWP in terms of Packet Delivery Ratio (PDR). ODMRPMF RPGM starts with nearly 100% PDR at 10 nodes and declines gradually but remains higher as node density increases. In contrast, ODMRP RWP struggles with a low PDR, peaking at around 40% at 40 nodes before declining further. ODMRPMF RPGM's group-based mobility ensures more reliable data delivery, making it ideal for dynamic and scalable applications like IoT-enabled livestock monitoring.

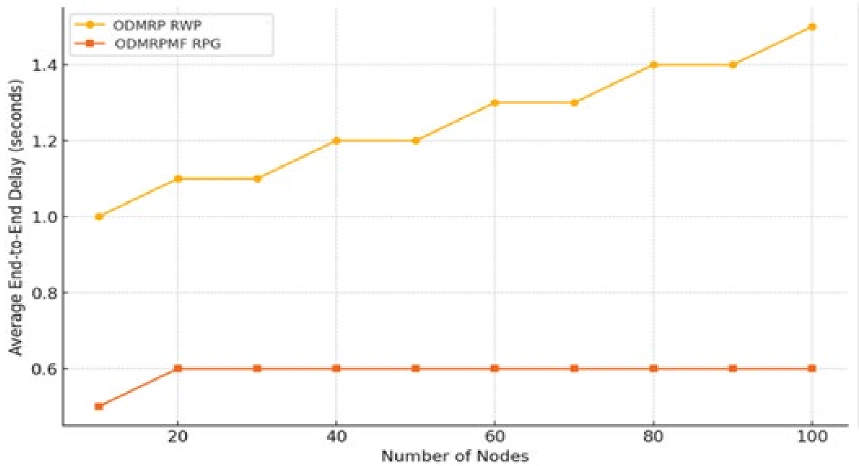

Figure 1: Comparison of Average End-to-End Delay Between ODMRP RWP and ODMRPMF RPGM Across Varying Node Counts

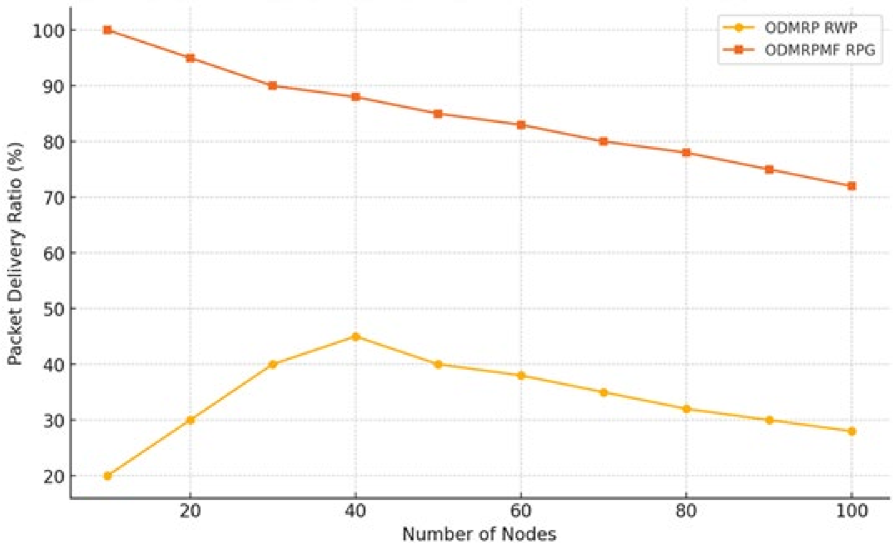

Figure 2: comparison of packet delivery ratio between ODMRP RWP and ODMRPMF RPGM across varying node counts

Figure 3 compares the throughput of ODMRP RWP and ODMRPMF RPGM as node numbers increase. Both models show improved throughput with higher node densities, stabilizing at saturation points. However, ODMRPMF RPGM consistently outperforms ODMRP RWP, due to its group-based mobility, which enhances connection stability and data transmission efficiency. ODMRP RWP lags due to frequent link breakages caused by unpredictable node movements. At lower node counts, ODMRPMF RPGM achieves a sharper rise in throughput, proving more reliable in sparse networks. At higher node counts, it effectively handles traffic and reduces collisions, maintaining its advantage. ODMRPMF RPGM is ideal for dynamic applications like IoT-enabled livestock monitoring, while ODMRP RWP struggles in highly mobile environments.

From Figure 4, it can be observed that ODMRP RWP consumes consistently high energy due to frequent route maintenance from random node mobility, making it inefficient for resource-constrained environments. In contrast, ODMRPMF RPGM shows a scalable, linear energy increase aligned with network activity, optimizing resource utilization.

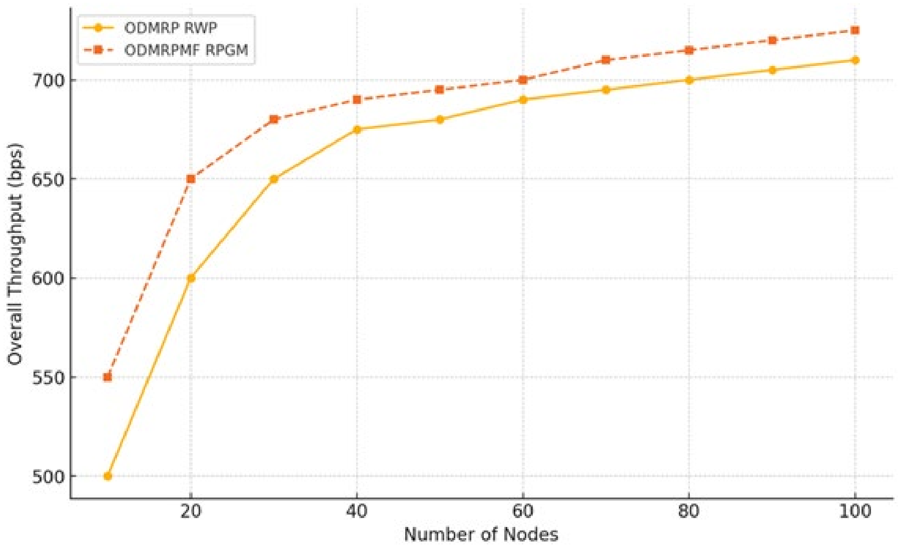

Figure 3: Comparison of overall throughput between ODMRP RWP and ODMRPMF RPGM across varying node counts

This makes ODMRPMF RPGM more energy-efficient, especially in small to medium-sized networks, and ideal for dynamic applications like IoT-enabled livestock monitoring, while ODMRP RWP is less suitable for such scenarios.

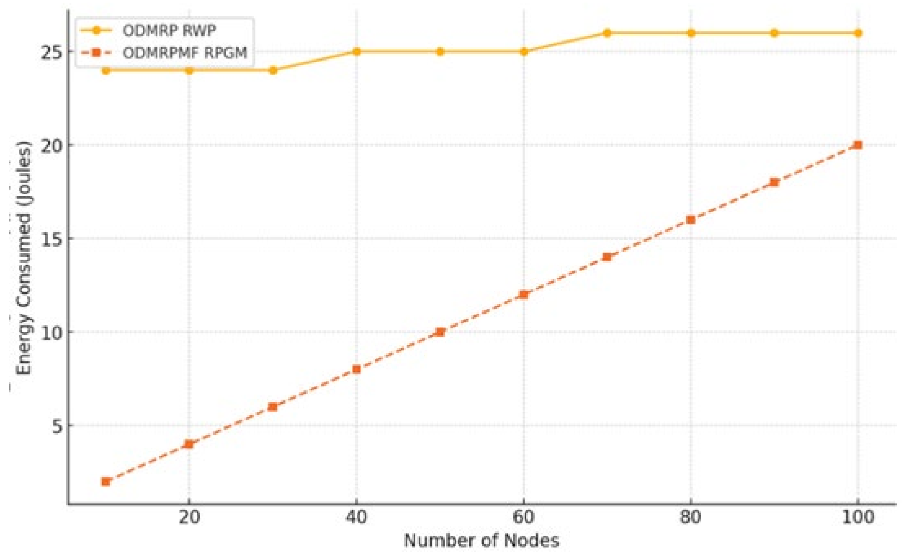

Figure 4: Comparison of energy consumption between ODMRP RWP and ODMRPMF RPGM across varying node counts

4.0 Conclusion

This study explores the integration of the On-Demand Multicast Routing Protocol (ODMRP) with the Mayfly Optimization Algorithm (MOA) and the Reference Point Group Mobility (RPGM) model to improve real-time livestock monitoring in IoT-enabled networks. By leveraging the group-based mobility structure of RPGM and the optimization capabilities of MOA, the proposed framework enhances routing efficiency, energy consumption, and network scalability compared to traditional random mobility models. The results demonstrate that the enhanced ODMRPMF RPGM outperforms ODMRP RWP in terms of throughput and energy efficiency, making it particularly suitable for dynamic and resource-constrained environments like cattle migration tracking.

5.0 Future Work

Future research could focus on integrating machine learning techniques to further optimize routing decisions and adapt dynamically to complex mobility patterns. Additionally, hybrid approaches that combine MOA with other evolutionary algorithms or edge computing technologies could also be explored.

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