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FJSO-Based Optimized Multipath Routing in Mobile Ad-Hoc Networks

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Abstract

Mobile Ad Hoc Networks (MANETs) are characterized by dynamic topologies and decentralized architecture, posing significant challenges for stable and energy-efficient routing. This paper presents a Fractional Jellyfish Search Optimization (FJSO)–based routing framework that efficiently balances exploration and exploitation during route discovery. The FJSO algorithm introduces fractional-order adaptively, enhancing convergence and robustness against link failures. The proposed method optimizes multipath routing by adaptively learning the best communication paths based on energy, mobility, and stability metrics. Simulation results demonstrate that the FJSO-based routing approach outperforms existing protocols in terms of path maintenance efficiency, energy consumption, network lifetime, packet delivery ratio (PDR), and throughput, confirming its suitability for large-scale and highly dynamic MANET environments.

Introduction

A Mobile Ad Hoc Network (MANET) is a self-configuring, infrastructure-less wireless network composed of mobile devices, known as nodes, which communicate with one another without relying on any fixed infrastructure such as routers or access points [1].

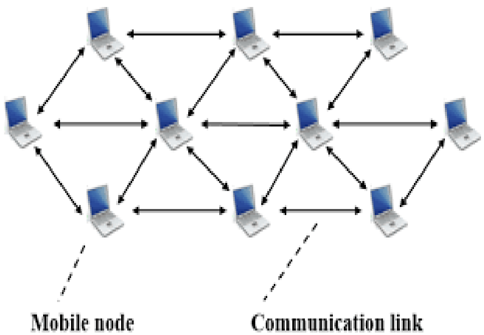

Figure 1: The general MANETs architecture

Each node in a MANET functions as both a host and a router, forwarding data packets to other nodes using multi-hop communication when they are not within direct transmission range as shown in Figure 1. The network is characterized by a dynamic topology due to node mobility, limited energy resources, and decentralized control, requiring adaptive and energy-efficient routing mechanisms [2]. MANETs are widely used in various applications such as military communication, disaster recovery, vehicular networks, emergency services, and IoT environments where rapid, temporary, and flexible network deployment is essential [3].

Mobile Ad Hoc Networks (MANETs) consist of self-configuring mobile nodes that communicate wirelessly without fixed infrastructure. Their decentralized nature and frequent topology changes make route stability and energy efficiency major design challenges. Traditional routing schemes such as AODV and DSR degrade in performance under high mobility due to frequent route breakages and retransmissions [4].

Recent research has introduced metaheuristic optimization algorithms—such as Particle Swarm Optimization (PSO), Genetic Algorithm

(GA), and Jellyfish Search Optimization (JSO)—to improve route discovery and maintenance in MANETs [5]. However, the classical JSO algorithm struggles to maintain an effective balance between exploration (searching new routes) and exploitation (refining discovered paths), often resulting in suboptimal convergence [6].
To overcome this limitation, this study introduces the Fractional Jellyfish Search Optimization (FJSO) algorithm for multipath routing in MANETs. By incorporating fractional-order dynamics, FJSO improves the memory effect and convergence rate of JSO, ensuring optimal route discovery, energy-efficient communication, and enhanced packet delivery performance [7].

Related Work

Swarm intelligence algorithms such as Ant Colony Optimization (ACO) and Firefly Optimization have been widely explored for route optimization in MANETs [8]. These methods rely on cooperative agent behavior but often incur significant computational and control overhead. Machine learning-based approaches, such as Graph Neural Networks (GNNs) and Reinforcement Learning (RL), have also shown promise for topology prediction and adaptive routing but require large training datasets and high computational power [9].
The Jellyfish Search Optimization (JSO) algorithm, inspired by the swarm foraging behavior of jellyfish in ocean currents, efficiently balances local and global search capabilities [10]. Nevertheless, in highly dynamic MANET environments, JSO's fixed exploration–exploitation balance results in unstable convergence and higher route recovery times. Fractional-order modeling extends standard JSO by incorporating a *memory factor* that allows partial retention of previous states, enabling more adaptive decision-making [11]. The FJSO model proposed in this research uses fractional calculus to dynamically adjust search intensity, ensuring stable and energy-aware routing.
The Jellyfish Search Optimization (JSO) algorithm is a nature-inspired metaheuristic that models jellyfish foraging and drift behaviors to alternate between global exploration and local exploitation; it has been validated on a variety of continuous optimization tasks and shown good global search capability compared with classic swarm methods [12]. Building on this baseline, researchers have proposed several modifications and hybrids to improve convergence speed, robustness and diversity maintenance—common goals when adapting JSO to dynamic problems such as routing [13].
A prominent direction of enhancement is the introduction of fractional-order dynamics into JSO. Fractional-order variants (commonly referred to as FJSO or fractional-order JSO hybrids) embed memory effects via fractional derivatives which effectively allow the optimizer to retain and weigh historical state information; this mechanism has been shown to improve convergence stability and to better balance exploration and exploitation in no stationary environments [14]. Experimental studies in control tuning and general optimization report that fractional-order modifications reduce premature convergence and improve solution quality across benchmark functions [15].
Several recent works have adapted JSO/FJSO ideas specifically for network-level problems. Variants of jellyfish-based optimizers have been used for multipath selection, energy-aware routing and resource allocation in wireless networks; these studies typically exploit JSO's population dynamics to explore multiple candidate paths while using local exploitation steps to refine route choices for energy or delay objectives [16]. For example, improved JSO variants have been proposed for multipath routing and energy efficiency in MANET/WSN contexts, demonstrating gains in lifetime and packet delivery in simulation studies [17].
Beyond routing, fractional and hybrid jellyfish optimizers have also been employed in allied networking tasks such as anomaly/attack detection and parameter tuning for controllers in cyber-physical systems [18]. Recent applications combine fractional-JSO with deep models or quantum neural networks for traffic classification and intrusion detection, indicating the method's flexibility for feature-rich, time-varying network problems where retaining temporal context (a benefit of fractional dynamics) helps performance [19].
Gaps and opportunities. Although the literature demonstrates that (1) JSO provides a useful exploration/exploitation template and (2) fractionalization enhances memory and convergence, most existing studies either target static benchmark problems or apply JSO variants in ad-hoc ways to specific sub problems (PID tuning, anomaly detection, or WSN clustering) [20]. Few works provide a systematic analysis of how fractional parameters (fractional order q, scaling α explicitly control the exploration–exploitation tradeoff in the context of highly dynamic MANET routing, including quantitative impacts on route recovery time, multipath diversity, and energy balancing under mobility. This gap

motivates using FJSO together with topology-aware fitness definitions (energy, link stability, hop count) and co-training or hybrid learning components (e.g., GNN-based link predictors) to obtain robust, low-overhead multipath routing—exactly the direction your FJSO-EFIGNN approach pursues [21].

Proposed Methodology

The FJSO-based routing model enhances multipath route discovery and maintenance by introducing adaptive fractional-order dynamics [22, 23, 24]. During route discovery, the algorithm simultaneously explores multiple candidate paths and exploits the most stable and energy-efficient routes [25].

The position update rule in FJSO is expressed as:

$$x(t+1) = x(t) + \propto * D^{q}\left(f(x_{best})\right) - f(x(t)) \quad (01)$$

Where:

- DqD is the fractional derivative of order q ($0 < q \leq 1$),
- α is a scaling coefficient controlling exploration and exploitation,
- f(x) represents the fitness of a node based on residual energy, link stability, and hop count, and
- xbest denotes the globally optimal route.

The fitness function (F) is defined as:

$$f = w_1 * \frac{1}{Eavg} + W_2 * \frac{1}{Hc} + W_3 * L_s \quad (02)$$

Where Eavg is average energy consumption, Hc is hop count, and LS is link stability. This design minimizes energy use and delay while maximizing reliability and throughput.

Experimental Setup

The simulation of the proposed FJSO-based MANET routing protocol was implemented using Python 3.10 on a system equipped with an Intel Core i7 processor (2.50 GHz), 16 GB RAM, and Windows 10 OS. The simulated network consisted of 500 mobile nodes randomly deployed over a 1000 m × 100 m area. Each node communicated using a TCP bidirectional connection, and the simulation ran for 120 seconds.

The model was evaluated against existing protocols — MPRP-HM-MANET, ELB-AMNC-MANET, and DSRP-DRL-MANET — using performance metrics such as:

- Path Maintenance Efficiency (PME)
- Energy Consumption (EC)
- Network Lifetime (NL)
- End-to-End Delay (EED)
- Throughput
- Packet Delivery Ratio (PDR)
- Routing Overhead Ratio (ROR)

Results And Discussion

Experimental results confirm the superior performance of the proposed FJSO-EFIGNN-MANET protocol compared with existing methods. The integration of fractional-order dynamics enabled more stable route selection and reduced control packet overhead.

Quantitatively, the proposed method achieved:

- 20.34%, 18.64%, and 28.51% higher network lifetime,
- 22.45%, 18.44%, and 19.49% lower energy consumption, and
- 16.28%, 30.78%, and 25.29% higher throughput

  when compared to MPRP-HM-MANET, ELB-AMNC-MANET, and DSRP-DRL-MANET, respectively.

The results indicate that FJSO successfully balances exploration and exploitation phases, ensuring stable data transmission with reduced packet loss. Additionally, the algorithm's adaptive control over fractional parameters improves link stability, reduces route recovery time, and maintains high packet delivery ratios under varying node mobility conditions.

The efficiency gain observed in FJSO is primarily due to:

1. Fractional-order adaptive control, allowing nodes to retain partial memory of prior network states.
2. Energy-based fitness optimization, selecting routes with minimal energy variance.
3. Dynamic exploration–exploitation switching, maintaining balance between discovering new routes and reinforcing reliable ones.

Conclusion And Future Work

This research proposed a Fractional Jellyfish Search Optimization (FJSO)–based routing model for MANETs that efficiently balances exploration and exploitation during route discovery. The algorithm's adaptive fractional-order behavior enhances convergence, energy utilization, and path stability. Simulation results verified that the proposed model significantly improves performance across all major MANET routing metrics compared to state-of-the-art methods.

Future work will focus on integrating security-aware mechanisms, such as encryption and key exchange protocols, to improve routing security in adversarial environments. Additional extensions will explore reinforcement learning-based parameter tuning and QoS-aware routing for heterogeneous MANET applications.

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