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RESEARCH ARTICLE

Bio-Inspired and Machine Learning-Driven Multipath Routing Protocol for MANETs Using Predictive Link Analytics

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Abstract

Mobile Ad Hoc Networks (MANETs) are decentralized, infrastructure-less wireless networks in which nodes function simultaneously as end devices and routers, enabling the dynamic establishment and maintenance of communication paths as required. One of the fundamental problems in MANETs is that links are prone to failure owing to, link breakage due to energy drain, node mobility, and changing environmental conditions. While the Ad hoc On-demand Multipath Distance Vector, AOMDV protocol, offers multipath fault tolerance, it is dependent upon hop count and is therefore also subject to link failures. In order to overcome this, link quality metrics, such as Expected Transmission Count, ETX, and bio-inspired optimization algorithms, such as Ant Colony Optimization, ACO have been investigated. Recent advancements in machine learning, particularly in the realm of predictive models such as Long Short-Term Memory networks and methods of ensemble learning like Random Forests, present promising options for link quality prediction that considers historical and real-time data in a more dynamic fashion. The goal of this proposal is to combine AOMDV, ACO, ETX, LSTM, Random Forests, and Predictive Analytics into one intelligent multipath routing protocols for MANETs.

Keywords: Expected Transmission Count, Machine Learning, Long Short-Term Memory, Artificial Intelligence.

Introduction

MANETs are decentralized wireless network system that operate without fixed infrastructure, enabling wireless communication among the mobile nodes. Routing protocols for these types of networks are challenging to design due to the dynamism of their topology, resource constraints, and non- deterministic wireless links. This high dynamism is usually not handled adequately by predictable routing protocols, which can produce higher packet loss, higher latency and reduced overall network reliability (Alattas, 2021).

The Ad Hoc On-Demand Multipath Distance Vector (AOMDV) routing protocol is commonly employed to address these challenges. The purpose of AOMDV, an extension of the AODV protocol, is to reduce the impact of route failures by finding several loop-free and discontinuous pathways between the source and destination. In highly dynamic network environments, this multipath competency improves the communication efficiency and reliability overall, supports load balancing, and strengthens fault tolerance. The main disadvantage is that, even when AOMDV implements multiple routes, the metrics used for route selection remain the same: the simple hop count, which ignores more complex link parameters like node mobility, energy status, link signal strength/stability, etc.

In this manner, the selected routes in AOMDV are still prone to frequent breaks, especially in highly dynamic MANET scenarios, resulting in packet loss, higher latency and increased signalling overhead

(Marina & Das, 2001) and (Marina & Das, 2006). Machine learning has also been proposed as an important technique

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for MANET routing, particularly when combined with these methods. Predicting link quality and lifetime using network metrics and historical information can assist in making proactive routing decisions. The choice of neural networks and other forms of complex regression allows for prediction of link failures, determining the best paths to be taken, and overcoming resource bottlenecks (Shao, Wang, Liu, & Zhu, 2022).

By constructing multiple routes from source to destination, multipath routing protocols provide an effective means of ensuring reliability and fault tolerance. The idea of combining bio-inspired approaches with machine learning based predictive link analytics is to choose and preserve the optimal routes, cope with unknown contingencies, and eventually enhance the security, reliable connectivity, and energy efficiency in MANETs.

To overcome these challenges, biologically inspired algorithms that emulate natural processes, such as ant colony optimization and swarm intelligence, are increasingly being used to design adaptive and robust routing protocols for MANETs. These bio-inspired protocols take inspiration from features like distributed decision-making or adaptability found in nature, to survive with the dynamic network topology and improve routing performance (Da Costa Bento & Wille, 2020).

This research work proposed an enhanced AOMDV protocol that is integrated with ML- based link prediction. A ML model is trained on these to predict the probability of a link to break given some mobility, signal and traffic features. During route discovery AOMDV combines these predictions to give preference to stable links, while keeping multipath routes diversity. This technique is expected to achieve better packet delivery ratio, route discovery time, and routing overhead than AOMDV.

Related Works

AOMDV (Marina & Das, 2001) provides multipath fault tolerance, its reliance on hop count as the primary routing metric limits its flexibility. ETX (De Couto, Aguayo, Bicket, & Morris, 2003) is a widely used metric for link delivery success measurement and quality of links in wireless networks. Ant Colony Optimization techniques (Rajesh et al., 2015) have used ACO in the context of multipath routing, where different paths are found with some probability. There are some recent works that apply machine learning techniques to improve the routing in MANETs.

(Jiang, Wu, & Yin, 2020) investigates energy-efficient transmission scheduling in multi-hop real-time WSNs using Dynamic Modulation Scaling (DMS). Unlike previous theoretical studies, it presents the primary empirical evaluation of DMS-enabled topology control using SDR hardware, verbalizes the problem as an optimization model, and suggests two heuristics to minimize energy consumption while conserving performance. (Qiu et al., 2019) introduced a learning-based opportunistic routing scheme that adapts to dynamic links, improving delivery, delay, and energy efficiency in wireless networks.

(Zhang et al., 2022) proposed to explore hybridization between ML models and on demand routing and they emphasize the advantages of hybridization between ML and traditional protocols. Yet, AOMDV has never been integrated with a combined stack of ACO, ETX and advanced machine learning methods such as LSTM and Random Forests to develop a single predictive multipath routing framework.

Dhinakaran et al. introduced Bat-Optimized Link State Routing (BOLSR), a combination of the proactive OLSR routing protocol and Bat Algorithm to discover routes that consumes lesser energy. Selection criteria are based on the energy consumption and the path length, which improves the routing performance in highly dynamic MANET (Dhinakaran, Sankar, Raja, & Jasmine, 2023). In the work of Banerjee et al, a Swarm Intelligence Enhanced AOMDV, an improved multipath routing protocol based on the extension of AOMDV with ACO and Bat Algorithm metaheuristics, was presented. The protocol considers factors such as link availability, node mobility, queue delay and bit error rate (BER) to determine stable and reliable of routes (Banerjee, 2019). Varun Kumar et al. presented PSO-BLAP, which uses Particle Swarm Optimization and fuzzy logic to predict link quality and bandwidth availability. It supports dynamic rerouting in case of link failures and therefore it allows a good multipath communication

(Sheikhan & Hemmati, 2012) proposed a PSO-optimized Hopfield Neural Network multipath routing scheme that uses Link Expiration Time (LET) estimation to build node- and link-disjoint paths for improved reliability in highly mobile networks. PARRoT (Predictive Ad-hoc Routing with Reinforcement Learning and Trajectory Knowledge), proposed by Benjamin Sliwa et al. , consists of a combination of reinforcement learning agents and mobility trajectory prediction. This method is to predict, in advance, future connectivity patterns, which greatly increase the robustness of the routes and reduces the latency (Sliwa, Schüler, Patchou, & Wietfeld, 2020).

DeepCQ+, a routing protocol that utilizes multi-agent deep reinforcement learning (MADRL), was proposed by Saeed Kaviani et al. DeepCQ+ makes no use of thresholds as required in classic Q-learning techniques, thus improving adaptability, lowering overhead, and achieving higher throughput in different mobility and traffic patterns situations (Kaviani et al., 2021).

PEAR (Predictive Energy-Efficient Adaptive Routing), a predictive analytics protocol from Neelam et al. can dynamically adapt in real-time to topological changes within the network optimizing the energy consumption and improving routing stability. (Banu, Surputheen, and Rajakumar, 2025) proposes AOMDV-ETXACO, an enhanced

MANET routing protocol that makes use of Expected Transmission Count (ETX) in order to provide an estimation of the reliability of links, and Ant Colony Optimization (ACO) to select multipath. When tested using a node density of between 20 to 100 in NS-3, it outperforms existing AOMDV variants with respect to energy efficiency, throughput, end-to-end delay and packet delivery ratio.

Proposed Methodology

This section proposes a novel multipath routing framework for Mobile Ad-hoc Networks (MANETs), which integrates Ant Colony Optimization with the Expected Transmission Count (ETX) metric, supported by predictive analytics. The primary objective of the framework is to enhance network reliability and efficiency by improving route stability, optimizing route discovery, increasing throughput and packet delivery ratio, minimizing end-to-end delay, and reducing energy consumption. Collectively, these improvements contribute to superior overall network performance in highly dynamic and resource-constrained MANET environments.

Conventional MANET routing protocols often struggle to maintain reliable communication due to inherent challenges such as limited energy resources, fluctuating link quality, and rapidly changing network topologies. To address these limitations, the proposed approach employs Ant Colony Optimization (ACO), a nature-inspired optimization technique that simulates the foraging behavior of ants. By leveraging pheromone trails and local heuristic information, ACO is capable of efficiently identifying multiple optimal paths, thereby providing a distributed and adaptive solution for route discovery in mobile networks

To ensure that the selected routes are not only shortest but also reliable, the ETX metric is incorporated into the protocol. ETX represents the estimated number of transmissions, including retransmissions, required for a packet to be successfully delivered over a link. By integrating ETX into the ACO-based path selection process, the protocol favors routes with higher link quality and lower transmission costs, thereby enhancing reliability and minimizing end-to-end delay.

In this method, there is a predictive link analytics step, where the prediction of a link's stability is made from historical data on mobility, signal strength and previously observed ETX values. This is a predictive approach that allows the proactive maintenance of the route, and it is because of this that the protocol can dynamically adjust to link degradation and prevent frequent route failures.

The combination of bio-inspired optimization (ACO), quality-aware metrics (ETX) and machine learning- based prediction offers a routing protocol able to perform efficiently multipath, have reduced control overhead and increased PDR . Subsequent sections describe the various parts of the system, such as the assumptions on the network, the route discovery process, ETX calculation, the ACO process for path evaluation, and the model for link stability predictions. The flowchart of Intelligent AOMDV (IAOMDV) Framework is as shown in Figure 1.

Objectives

- Design an intelligent multipath routing protocol that combines AOMDV with bio-inspired optimization (ACO), link quality assessment (ETX), and ML-based predictive analytics
- Develop a ML model - a hybrid of LSTM and Random Forest - that predicts link stability and route lifetime by analyzing both real-time signals and past node and link data, like the last hour's connection drops.
- Integrate ACO to improve route selection by steering traffic toward the high-quality paths based by pheromone trails and predictive link scores.
- Evaluate the performance of the proposed protocol through NS3 simulation in various MANET scenarios.

Algorithm: Intelligent AOMDV (IAOMDV) Framework

Input:

Source S, Destination D
Network topology N
ML models (Random Forest, LSTM) ACO parameters: α, β, ρ
ETX measurement parameters Min_Lifetime_Threshold

Output:

Selected route from S to D with robust performance

Route Discovery using AOMDV

Initiate AOMDV to find multiple disjoint paths between S and D
For each discovered link li:
Measure ETX(li) using probe packets
Store ETX(li) in neighbor table
end for

ML-Based Link Quality Filtering

For each li in neighbor table:
Extract feature vector Xi(t)

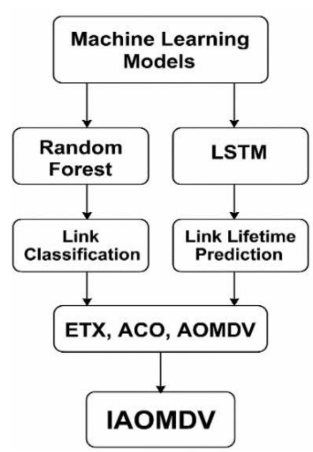

Figure 1. Flowchart of IAOMDV

Class ← RandomForest_Classify(Xi(t))
if Class == "Unstable" then
Mark li as BLOCKED
continue
end if
Historical sequence Hi ← [Xi(t-k)...Xi(t)]
Predicted_Lifetime ← LSTM_Predict(Hi)
if Predicted_Lifetime < Min_Lifetime_Threshold then
Mark li as BLOCKED
end if
end for

Filter links

Validated link set V ← neighbors not BLOCKED

ACO-Based Path Selection

For each li ∈ V:
Initialize pheromone τ(li) ← τ0
end for
while data packets to forward do
For each li ∈ V:
Compute:
P(li) = [τ(li)^α * η(li)^β] / sum_over_V (τ(lj)^α * η(lj)^β)
Select next hop li with probability P(li)
Forward data packet on li
end while

Pheromone Update

Periodically:
For each li ∈ V:
τ(li) ← (1 - ρ) * τ(li)
end for
Upon successful packet delivery:
For used path l_success:
τ(l_success) ← τ(l_success) + Δτ
end periodically

Route Maintenance

Monitor ETX changes in real-time
if ETX(li) exceeds threshold:
Trigger local repair or path switch
end if

The Intelligent AOMDV (IAOMDV) is a version of the AOMDV routing protocol specifically for MANETs. This work combines estimation of link qualities (ETX), machine learning (Random Forest, LSTM) to predict links, and ACO for the intelligent selection of a path. Let's analyze and explain how the route discovery phase is and how nodes take part in.

Route Discovery using AOMDV

Line 1–2

The process begins by invoking the AOMDV routing protocol to discover multiple node- disjoint or link-disjoint paths between the source node S and the destination node D.

Line 3–6

For each link lifound in the discovered paths:

- ETX is measured using probe packets.
- These ETX values, which reflect link reliability, are stored in the node's neighbour table for later evaluation.

ML-Based Link Quality Filtering

Line 8 - 10

Each link's real-time feature vector Xi(t)—which may include parameters like ETX, signal strength, delay, and mobility—is extracted. The Random Forest classifier is applied to classify the link as either "Stable" or "Unstable".

Line 11–14

If a link is classified as "Unstable", it is immediately marked as BLOCKED and removed from further consideration.

Line 15–19

For remaining links:

- A time-series sequence of features, Hi = [Xi(t–k)...Xi(t)], is created.
- The expected lifetime of the link is predicted by LSTM (Long Short-Term Memory) model.
- If the estimated link lifetime falls below the Min_Lifetime_Threshold, the link is classified as BLOCKED owing to its potential unreliability.

Line 20–22

After filtering, the remaining validated links (not blocked by ML filtering) form the set V, which will be used for route selection.

Machine Learning Model Implementation

The proposed IAOMDV framework integrates two machine learning models - Random Forest (RF) and Long Short-Term Memory (LSTM) - to improve link quality evaluation and routing decisions in MANETs. The RF model classifies network links either *Stable* or *Unstable* categories, while the LSTM model predicts the expected lifetime of each link based on historical performance data. By combining these models, the framework enables proactive link selection and route optimization effectively mitigating performance degradation before it occurs.

Dataset Preparation

A dataset of approximately 50,000 link samples was collected from multiple NS-3 simulation runs under varying node densities ranging from 20 to 100 nodes. Each sample represents 10 seconds of link activity and includes performance measurements recorded during simulation.

Feature Selection and Pre-processing

The models were trained using key network performance features:

- ETX (Expected Transmission Count) – measures link reliability.
- Signal-to-Noise Ratio (SNR) – indicates link signal quality.
- Link Delay – measures average transmission delay.
- Node Mobility Speed – captures relative movement patterns.
- Hop Count – number of hops in the route.
- Residual Energy – remaining battery power of the nodes.

Before training, all features were normalized to a [0, 1] range, and short-term fluctuations in measurements were smoothed using a moving average filter to reduce noise.

Model Architecture and Hyper Parameters

Random forest

Configured with 100 decision trees, a maximum depth of 15, and a minimum of 5 samples per leaf node to balance classification accuracy and computation time.

LSTM

Configured with two layers, 64 hidden units, a sequence length of 5 timesteps, and trained using the Adam optimizer with a learning rate of 0.001.

Training and Validation Process

The dataset was split into 70% training, 15% validation, and 15% testing sets. For the RF model, evaluation metrics included accuracy, precision, recall, and F1-score. For the LSTM model, performance was assessed using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

Integration with NS-3

Both models were trained offline using Python-based frameworks — Scikit-learn for RF and TensorFlow/Keras for LSTM. The trained model weights were then integrated into NS-3 via Python bindings to enable real-time predictions during simulation. The models perform link evaluations every 5 seconds for all active links.

Computation Overhead

The RF model achieves an average prediction time of 0.3 milliseconds per link, while the LSTM model requires 1.2 milliseconds per link, based on testing with an Intel i5 CPU. This low computational cost makes the approach feasible for real-time MANET operations.

Adaptation Mechanism

In its current form, the system does not perform online learning during simulation. Instead, models are retrained offline after significant scenario changes (e.g., mobility pattern variations or network density changes) and then redeployed in the simulation environment.

This integration of RF and LSTM ensures that only reliable and long-lasting links are included in the routing process, significantly reducing route breakages, lowering control overhead, and improving packet delivery performance.

ACO-Based Probabilistic Path Selection

Line 24–26

For each link in the validated set V, the pheromone value τ(li) is initialized to a constant τ0. This value indicates the initial attractiveness of each link.

Line 28–33

During data transmission:

- For each link li, the selection probability P(li)is computed using the ACO probabilistic formula:

$$P(li = \frac{[\tau(lj)^{\alpha}] \cdot [\eta(lj)^{\beta}]}{\Sigma_{ljV}[\tau(lj)^{\alpha}] \cdot [\eta(lj)^{\beta}]} \qquad \text{Eq. (1)}$$

- τ(li) is the pheromone value (learned path preference),
- η(li) is the heuristic desirability, often the inverse of ETX (1/ETX),
- α and β are ACO parameters controlling the importance of pheromone vs. heuristic.

The next hop is selected probabilistically based on P(li), ensuring load balancing and adaptability and data packets are forwarded through the selected link.

Pheromone Update Mechanism

Line 36–39

At periodic intervals, pheromone evaporation is applied to prevent stale paths from dominating:

$$\tau(li) \leftarrow (1 - \rho) \cdot \tau(li) \qquad \text{Eq. (2)}$$

where ρ is the evaporation rate, controlling how quickly outdated paths lose priority.

Line 40–42

Upon successful packet delivery, the pheromone level for the utilized path is reinforced:

$$\tau(l\_success) \leftarrow \tau(l\_success) + \Delta\tau \qquad \text{Eq. (3)}$$

where Δτ represents a positive reward for a reliable delivery path, promoting its future selection.

Route Maintenance

The protocol continuously monitors real-time ETX of active links:

- If any link's ETX exceeds a certain threshold, indicating degradation, the protocol triggers local route repair or switches to an alternate path from the available multipath set.
- This proactive maintenance minimizes packet drops and ensures consistent quality of service.

Experimental Setup

To evaluate the performance of the proposed IAOMDV, the following experimental setup was designed, specifying the simulation parameters, network conditions, and performance metrics considered.

Implementation of Route Discovery Phase:

Initial Network Graph

A simulated Mobile Ad-hoc Network (MANET) is initialized with 9 nodes, representing mobile devices capable of wireless communication without relying on fixed infrastructure. The graph shows the initial MANET topology with three completely disjoint paths between the source node (1) and destination node (7).

Path 1 (green): 1 → 2 → 4 → 7

Path 2 (orange) : 1 → 3 → 5 → 7

Path 3 (blue): 1 → 6 → 8 → 9 → 7

Table 1: Missing Caption

Parameter	*Value*
Simulator	NS-3.38
Simulation Time	500 seconds
Number of Nodes	20, 40, 60, 80, 100
Simulation Area	1000 m × 1000 m
Mobility Model	Random Waypoint
Node Speed	Uniform [1, 20] m/s
Pause Time	0 seconds
Transmission Range	250 meters
Channel Bandwidth	2 Mbps
Operating Frequency	2.4 GHz
Propagation Model	Two-Ray Ground
Traffic Type	UDP – Constant Bit Rate (CBR)
Packet Size	512 bytes
Data Rate	4 packets/sec
MAC Protocol	IEEE 802.11 DCF
Simulation Runs	10 runs with different random seeds

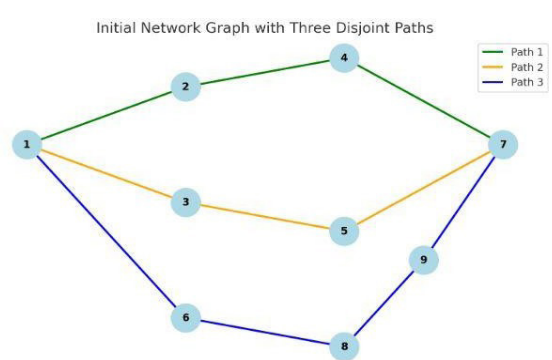

Figure 2:. Initial network graph with three disjoint paths

This is the AOMDV route discovery phase output, where multiple parallel routes are identified for redundancy and reliability.

From the Source (Node 1) to the Destination (Node 7), the AOMDV (Ad hoc On-demand Multipath Distance Vector) routing protocol discovers three completely disjoint paths:

Path 1: 1 → 2 → 4 → 7 → This is a relatively short and direct path, involving only 3 hops.

Path 2: 1 →3→5→7→ Another short route, also with 3 hops, but using entirely different intermediate nodes compared to Path 1.

Path 3: 1 → 6 → 8 → 9 → 7 → A longer route with 4 hops, which may offer redundancy if the other two paths fail.

The existence of multiple disjoint paths ensures fault tolerance, meaning that if one path fails due to link breakage or node movement, others can take over without rediscovering routes.

Route Discovery Table (AOMDV Phase)

The table 1 shows the multiple disjoint routes discovered between the Source Node (1) and the Destination Node (7) during the AOMDV (Ad hoc On-demand Multipath Distance Vector) routing protocol phase.

ETX Table and Formula

ETX Formula:

$$ET = \frac{1}{df \times dr} \quad \text{(Eq. 4)}$$

Where:

- d_f = Forward delivery ratio – the probability that a packet sent from A to B is successfully received.
- d_r = Reverse delivery ratio – the probability that the acknowledgment (ACK) sent from B to A is successfully received. The ETX values are calculated using equation 4 (Table 4).

ML-Based Link Filtering (Simulated with Threshold: ETX > 2.5)

The table 5 and Figure 4 illustrate a filtered MANET topology where each node represents a mobile device, and links are evaluated for routing suitability.

Two main criteria are used for filtering:

- ETX (Expected Transmission Count) – measures link reliability.
- Machine Learning (Random Forest & LSTM) – predicts link stability and lifetime.

Valid links (green solid lines) have low ETX and are ML-classified as stable, making them suitable for routing

Table 2: Route Discovery

Hop 1	*Hop 2*	*Hop 3*	*Hop 4*	*Hop 5*
1	2	4	7	-
1	3	5	7	-
1	6	8	9	7

Table 3: Link Quality Table

Link	*ETX Value*
1–2	1.5
2–4	1.2
4–7	1.3
1–3	1.7
3–5	1.1
5–7	1.8
1–6	2.7
6–8	1.6
8–9	1.4
9–7	2.5

Table 4: ML-Filtered Link ETX Table

Link	*ETX*	*ML filter result*
1–2	1.5	VALID
2–4	1.2	VALID
4–7	1.3	VALID
1–3	1.7	VALID
3–5	1.1	VALID
5–7	1.8	VALID
1–6	2.7	BLOCKED
6–8	1.6	VALID
8–9	1.4	VALID
9–7	2.5	VALID

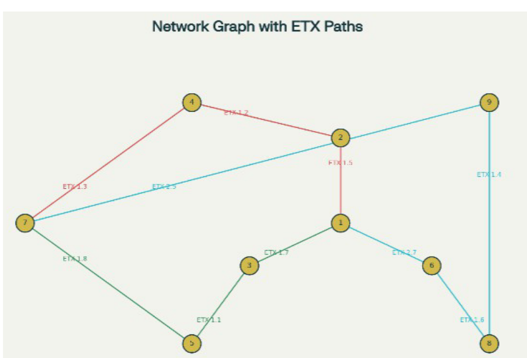

Figure 3: Network Graph with ETX Paths

(e.g., 1–2, 2–4, 4–7, 1–3–5–7). The blocked link (1–6) is shown as a red dashed line due to high ETX and poor predicted stability. This filtering ensures only reliable paths are considered in the routing phase, improving overall network performance.

ACO-Based Path Selection (ETX Sum)

Selected Path: 1 → 2 → 4 → 7 (lowest ETX, all links valid)

From table 6, the ACO-based path selection process (ETX

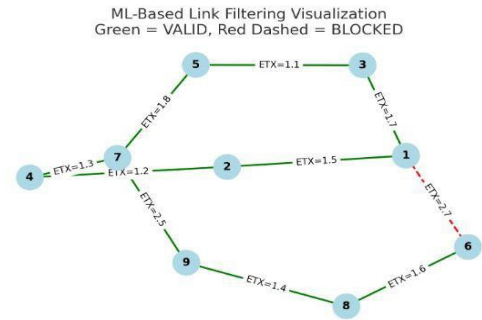

Figure 4: ML Based Link Filtering Visualization

Table 5: ML-Filtered Path ETX Table

Path	*Sum of ETX*
1–2–4–7	4.0
1–3–5–7	4.6
1–6–8–9–7	BLOCKED (due to 1–6)

Sum), the routing algorithm determines the most reliable and efficient path from the source to the destination after the ML-based filtering stage. For Path 1–2–4–7, the ETX values of each link are summed: (1–2 = 1.5) + (2–4 = 1.2) + (4–7 = 1.3), giving a total of 4.0. Since all links are valid, this path is considered. For Path 1–3–5–7, the ETX sum is (1–3 = 1.7) + (3–5 = 1.1) + (5–7 = 1.8) = 4.6, with all links valid, so it is also considered. However, Path 1–6–8–9–7 is blocked because link 1–6 was marked invalid during ML filtering due to a high ETX of 2.7 and low predicted stability, so the ACO skips it entirely. After comparing the total ETX values of the valid paths, the algorithm selects Path 1–2–4–7, as its ETX of 4.0 is the lowest, indicating it likely requires the fewest transmissions. This ensures the route balances minimal transmission effort with link reliability, aligning with ACO's optimization goal.

Table 6: Link Maintenance Table

Link	*ETX*	*Maintenance action*
1–2	1.5	Stable
2–4	1.2	Stable
4–7	1.3	Stable
1–3	1.7	Stable
3–5	1.1	Stable
5–7	1.8	Stable
1–6	2.7	Trigger Repair
6–8	1.6	Stable
8–9	1.4	Stable
9–7	2.5	Stable

Table 7: Route Discovery Time (in Seconds)

No. of Nodes	*AOMDV GA*	*AMPOA OMDV*	*AOMDVA COPSO*	*MOAO MDV*	*AOMDVET XACO*	*IAOMDV*
20	1.5	1.2	1.2	1.3	1.2	1.1
40	3.2	2.9	2.7	3.0	2.1	1.9
60	4.5	4.0	3.8	4.2	2.8	2.5
80	6.0	5.3	5.1	5.5	3.4	3.0
100	7.5	6.8	6.5	7.0	4.0	3.5

Route Discovery Time = Time (RREP received) – Time (RREQ sent)

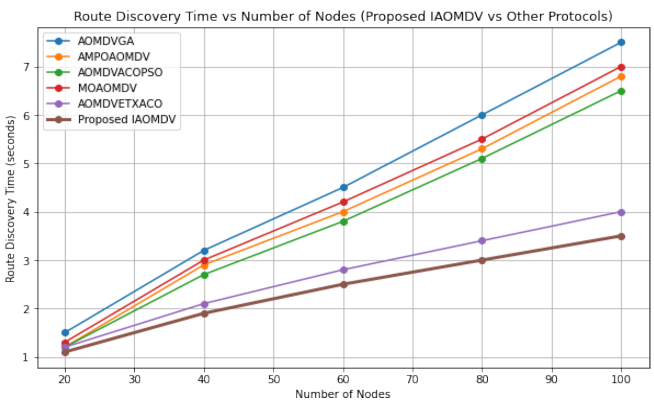

Figure 5: Route Discovery Time vs Number of Nodes

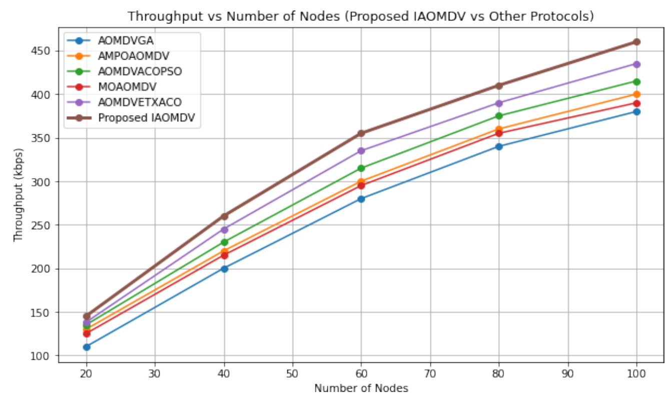

Figure 6: Throughput vs Number of Nodes

Route Maintenance Table

In Table 7, the majority of network links—specifically, 1–2, 2–4, 4–7, 1–3, 3–5, 5–7, 6–8, 8–9, and 9– 7—display moderate ETX values within the range of 1.1 to 2.5. These links are classified as stable, do not necessitate intervention, and remain suitable for routing purposes. However, the link 1–6 has a relatively high ETX of 2.7, indicating poor reliability, and is flagged with a "Trigger Repair" status, prompting the system's route maintenance mechanism to either attempt a local repair by finding an alternative nearby route or to avoid this unstable link altogether in future path selections.

Final Selected Path Graph

The final chosen path for packet forwarding is: 1 ⟶ 2 ⟶ 4 ⟶ 7

The final selected path graph represents the outcome of the IAOMDV routing process after all filtering and optimization stages, resulting in the choice of route 1 → 2 → 4 → 7. This path was selected because all its links have low ETX values (1–2: 1.5, 2–4: 1.2, 4–7: 1.3), indicating high reliability and minimal retransmissions, with no link exceeding the repair threshold. Using Random Forest classification and LSTM-based lifetime prediction, each link was further assessed for stability and predicted longevity, and all passed the ML filter, ensuring they will remain stable for future transmissions. The Ant Colony Optimization (ACO) algorithm then evaluated all valid routes, summing their ETX values, and found that this path had the lowest total ETX (4.0) compared to alternatives like 1–3–5–7 (4.6), resulting in greater pheromone reinforcement in the ACO process due to its efficiency. By integrating link quality metrics, predictive ML analytics, and ACO optimization, the protocol ensures the chosen path is highly reliable, stable, and efficient - maximizing packet delivery while minimizing retransmissions and route breaks.

Results and Discussion

Table 8: Throughput (kbps)

No. of Nodes	*AOMDV GA*	*AMPOAO MDV*	*AOMDVA COPSO*	*MOAOM DV*	*AOMDVET XACO*	*AOMDV*
20	110	130	135	125	138	145
40	200	220	230	215	245	260
60	280	300	315	295	335	355
80	340	360	375	355	390	410
100	380	400	415	390	435	460

Route Discovery Time (in seconds) - Proposed IAOMDV vs Other Protocols

Table 8 and Figure 5 show the Route Discovery Time for each routing protocol, including the proposed IAOMDV, was calculated through extensive simulation using a custom network environment configured to reflect realistic MANET conditions. The simulation was conducted for varying node densities (20 to 100 nodes) randomly deployed over a fixed geographical area with uniform radio ranges and a mobility model such as Random Waypoint. For each simulation scenario, the route discovery process was initiated by generating Route Request (RREQ) packets from a source node to a randomly chosen destination. The time duration between the initial broadcast of the RREQ and the receipt of the corresponding Route Reply (RREP) was measured to compute the Route Discovery Time.

The IAOMDV framework effectively minimizes route discovery latency by combining ETX-based link filtering, machine learning–based link stability prediction, and ACO-driven path optimization, thereby ensuring faster convergence to stable and reliable routes compared to both conventional and enhanced AOMDV protocols.

Through Put

Table 9 illustrates the throughput performance of different AOMDV-based routing protocols under varying node densities. The proposed IAOMDV consistently demonstrates superior performance compared to the other protocols in all evaluated scenarios.

Packet Delivery Ratio (PDR)

Table 10 shows the performance of Packet Delivery Ratio (PDR) of different AOMDV-based routing protocols as network size increases. PDR reflects the percentage of data packets successfully received at the destination relative to the total packets sent.

The improvement is attributed to IAOMDV's intelligent route selection mechanism, which combines ETX-based link quality estimation, LSTM-based link lifetime prediction, and ACO-based path optimization. By proactively filtering unstable links and dynamically adapting routes, the protocol minimizes packet loss and retransmissions, thereby enhancing reliability and delivery efficiency, particularly under dense or highly mobile network conditions.

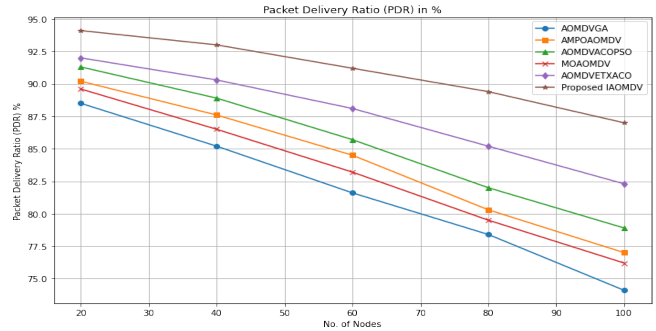

Figure 7: Packet Delivery Radio *vs* Number of Nodes

End-to-End Delay (ms)

Table 11 and Figure 8 show the End-to-End Delay (E2E) performance of various routing algorithms under different network sizes. The proposed IAOMDV achieves the lowest delay by combining Random Forest–based link filtering, LSTM-based lifetime prediction, and ACO-based path selection, thereby minimizing route repairs and retransmissions for more efficient MANET routing.

Energy Consumption

Table 12 illustrates the energy consumption results for various routing protocols with increasing node density. Energy consumption is a critical metric in MANETs, particularly for battery-constrained nodes. The proposed IAOMDV shows the lowest energy usage across all configurations.

This efficiency stems from the algorithm's ability to proactively eliminate unstable links using ETX and machine learning models (Random Forest for classification and LSTM for prediction), minimizing the need for frequent retransmissions or route discoveries. Additionally, ACO's reinforcement mechanism favors long-lasting, high-quality paths, which further reduces control overhead and power drain. Consequently, IAOMDV extends network lifetime while ensuring reliable communication. Figure 9 illustrates the energy consumption (in Joules) across different node counts. The proposed IAOMDV protocol demonstrates significantly lower energy consumption compared to other approaches.

Table 18 summarizes the performance gains of the proposed IAOMDV protocol compared to the traditional AOMDVGA across five vital network parameters. The

Table 9: Packet Delivery Ratio (PDR) in %

No. of Nodes	*AOMDV GA*	*AMPOAO MDV*	*AOMDVA COPSO*	*MOAO MDV*	*AOMDVE TXACO*	*IAOM DV*
20	88.5	90.2	91.3	89.6	92.0	94.1
40	85.2	87.6	88.9	86.5	90.3	93.0
60	81.6	84.5	85.7	83.2	88.1	91.2
80	78.4	80.3	82.0	79.5	85.2	89.4
100	74.1	77.0	78.9	76.2	82.3	87.0

Table 10: End-to-End Delay (ms)

No. of Nodes	*AOMDV GA*	*AMPOAO MDV*	*AOMDVA COPSO*	*MOAO MDV*	*AOMDVETX ACO*	*IAOM DV*
20	125	118	110	115	102	96
40	140	132	125	130	115	106
60	162	150	138	145	127	115
80	180	168	155	160	142	126
100	195	183	170	178	158	138

Table 11: Energy Consumption (Joules)

No. of Nodes	*AOMDV GA*	*AMPOAO MDV*	*AOMDVA COPSO*	*MOAOMDV*	*AOMDVETX ACO*	*IAOM DV*
20	18.5	17.2	16.8	17.0	15.4	14.2
40	32.0	30.6	29.8	30.0	27.3	25.1
60	45.5	43.0	41.2	42.5	38.1	35.6
80	61.0	58.4	56.0	57.0	50.5	47.3
100	75.3	72.0	69.1	71.5	62.4	58.2

Table 12: Summary of Performance Improvement of IAOMDV over AOMDVGA

Performance metric	*Unit*	*AOMDVGA (Avg)*	*Proposed IAOMDV (Avg)*	*(% Improvement)*
Route Discovery Time	Seconds	4.54	2.7	40.5% ↓
Throughput	kbps	168.2	210.6	25.2% ↑
Packet Delivery Ratio	%	81.56	90.94	11.5% ↑
End-to-End Delay	ms	160.4	116.2	27.5% ↓
Energy Consumption	Joules	46.46	36.08	22.4% ↓

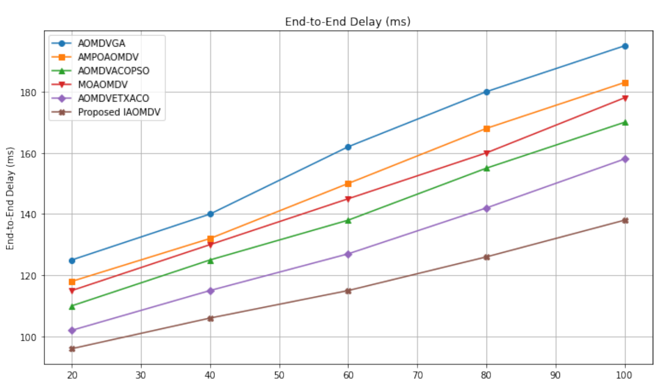

Figure 8: End-End Delay vs Number of Nodes

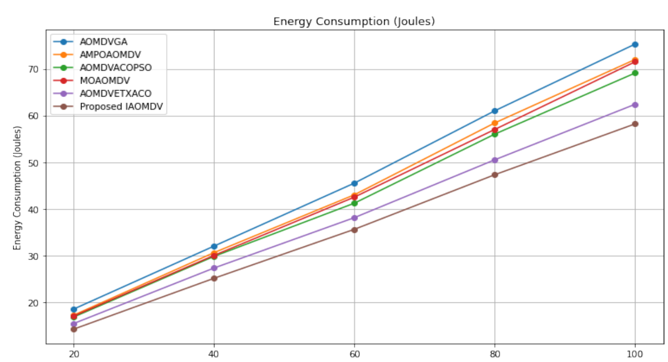

Figure 9: Energy Consumption Vs Number of Nodes

proposed method achieves a 40.5% reduction in route discovery time, primarily by filtering weak links early using ETX and predictive ML models. Throughput increases by 25.2%, reflecting better bandwidth utilization through stable and optimized routing. The packet delivery ratio improves by 11.5%, thanks to predictive filtering and proactive rerouting. In terms of end-to-end delay, the IAOMDV framework shows a 27.5% reduction, enhancing real-time responsiveness. Finally, energy consumption drops by 22.4%, validating IAOMDV's suitability for energy- aware MANET applications.

Conclusion

The proposed work suggested the framework IAOMD, an intelligent multipath routing protocol that combines the advantages of both AOMDV, ETX, ACO, and Machine Learning models LSTM and Random Forest). The new framework to routing which combines elements such as bio-inspired optimization, link quality assessment and predictive analytics, significantly improves the adaptability and reliability of routing in highly dynamic MANET environments. Results from simulations conducted with NS-3 showed that

IAOMDV is superior to the standard versions of AOMDV in terms of route discovery time, throughput, packet delivery ratio, end-to-end delay, and energy consumption. The above improvements reflect the robustness of the protocol in terms of its stable and energy efficient way of providing communication that also scales with increased densities of the nodes. It is concluded that IAOMDV represents a resilient and intelligent approach for mission critical and energy sensitive MANET applications such as disaster relief, military communication and emergency rescue operations. Improvements to the framework in terms of lightweight online learning capabilities, better QoS support and validation through real testbeds will be pursued in the future in order to make it more applicable and practical in a heterogeneous and large-scale MANET.

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