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Adaptive Broadcasting In Mobile Ad Hoc Networks Using Supervised Machine Learning-Based Node Reliability Prediction

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Abstract: Mobile Ad Hoc Networks (MANETs) facilitate infrastructure-less, multi-hop communication among mobile nodes, proving valuable for emergency response, disaster recovery, military operations, and temporary IoT deployments. However, broadcasting for route discovery and control messages often suffers from the broadcast storm problem in traditional flooding, causing redundancy, congestion, high energy consumption, and degraded performance. Optimized approaches like Fixed-Load Based Broadcasting (FLBB) mitigate some overhead through static rules but fail to adapt to node heterogeneity in residual energy, mobility, and link stability.

This paper proposes the Supervised Machine Learning-Based Reliability Routing Protocol (MLRP), employing lightweight logistic regression to predict node forwarding reliability. Nodes are evaluated using normalized features—residual energy, inverse mobility, and link stability—with an adaptive probability threshold selecting reliable forwarders only. A stochastic probabilistic network model enables scalable MATLAB simulation. Comparative evaluation against flooding and FLBB across 50–200 nodes shows MLRP achieves higher throughput and Packet Delivery Ratio (PDR), lower end-to-end delay and routing load, with classification accuracy improving from 84% to 91% in denser networks. MLRP offers a computationally efficient, intelligent broadcasting solution for dynamic MANETs.

Index Terms - Mobile Ad Hoc Networks, Broadcast Storm Problem, Supervised Machine Learning, Logistic Regression, Node Reliability Prediction, Adaptive Broadcasting, Packet Delivery Ratio, Routing Overhead

1. INTRODUCTION

Mobile Ad Hoc Networks (MANETs) are decentralized, self-configuring wireless systems where mobile nodes communicate directly via multi-hop paths without fixed infrastructure like base stations or centralized routers. Each node acts as both host and router, forwarding packets for others, enabling flexible deployment in scenarios such as disaster recovery, battlefield communications, remote monitoring, vehicular networks, and temporary IoT setups [10]- [2].

However, MANETs face inherent challenges: high node mobility causes frequent topology changes and link failures; limited bandwidth and shared wireless medium lead to congestion and collisions; energy constraints demand efficient protocols to extend network lifetime. Traditional routing often relies on simplistic metrics like hop count, inadequate for dynamic conditions, underscoring the need for intelligent, adaptive mechanisms [3]- [4].

Broadcasting is fundamental in MANETs for route discovery and control dissemination. Flooding—where every node rebroadcasts received packets—ensures high reachability but triggers the broadcast storm problem: exponential redundancy, excessive routing overhead, energy depletion, collisions, and reduced throughput in dense networks. Optimized techniques like Fixed-Load Based Broadcasting (FLBB) regulate forwarding via predefined load or probability thresholds, reducing some redundancy compared to pure flooding. Yet, FLBB remains static, ignoring node heterogeneity—nodes vary in residual energy (risking early failure), mobility speed (causing link breaks), and link stability (affecting delivery success). Unreliable nodes forwarding packets degrade performance through interruptions and losses [5]- [6].
Existing methods lack systematic, learning-based evaluation of node reliability before forwarding. This research addresses this gap by proposing a supervised machine learning framework—MLRP—that uses logistic regression to classify nodes probabilistically based on key features. By predicting reliability and selectively forwarding, MLRP minimizes redundancy while enhancing reliability, scalability, and efficiency. Simulations in a stochastic environment validate improvements over baselines in PDR, throughput, delay, and routing load across varying densities.
This work contributes a lightweight, decentralized intelligent broadcasting approach, bridging machine learning with practical MANET routing challenges.

2. LITERATURE REVIEW
MANET routing and broadcasting have been extensively studied due to dynamic topology and resource constraints. Early works classified protocols as proactive (e.g., OLSR, DSDV), reactive (e.g., AODV, DSR), or hybrid, focusing on metrics like hop count but struggling with mobility-induced overhead.
The broadcast storm problem, identified by Tseng et al. (2002), highlighted redundancy, contention, and collision in flooding. Probabilistic schemes (Ni et al., 2002) rebroadcast with fixed probability $P < 1$ to reduce duplicates, while counter-based, distance-based, and location-based approaches further mitigate storms. Optimized methods like FLBB regulate forwarding by load, but remain static and ignore node-specific attributes [7]- [8].
Recent advances integrate machine learning for adaptive routing. Chen et al. (2017, 2020) applied ML for energy-efficient and congestion-aware protocols. Rahman et al. (2021) used deep learning for mobility prediction in reliable routing. Trust models (Wang et al., 2014) employed logit regression for service-oriented MANETs. Reliability-focused studies (Singh et al., 2021) estimated node reliability via features like energy and link quality. Sivapriya et al. (2024) proposed QoS-aware ML routing.
While deep/reinforcement learning shows promise (Kaviani et al., 2021; Alanazi et al., 2025), computational overhead limits resource-constrained nodes. Lightweight supervised models like logistic regression offer balance, predicting reliability from normalized features without excessive complexity. This review identifies the gap in adaptive, probabilistic node selection for broadcasting, addressed by the proposed MLRP framework [9]- [10].

3. MATERIALS AND METHODS
The proposed methodology employs a stochastic probabilistic network model for scalable simulation, avoiding $O(N^2)$ geometric computations. The network comprises N mobile nodes (N = 50, 100, 150, 200), each with features [11]- [12]:
residual energy $E_i \in [0, E_{max}]$, mobility speed $S_i \in [0, S_{max}]$, link reliability $L_i \in [0,1]$.
Connectivity is modeled probabilistically: link existence probability p = 1 - P_loss, transforming the network into a random graph. Packet transmission succeeds with probability $1 - P_{loss}$ (Bernoulli). Energy depletes linearly per forwarding:
$E_i(t+1) = E_i(t) - \alpha$
Forward_i. Mobility is abstracted stochastically, with link duration inversely proportional to speed:
$L_i \approx R / (S_i + \varepsilon)$.
Node reliability score:
$R_i = \alpha (E_i / E_{max}) + \beta (1 - S_i / S_{max}) + \gamma L_i$,
where $\alpha + \beta + \gamma = 1$ (weights emphasize energy, stability, link quality).
MLRP uses supervised logistic regression for binary classification
(reliable/unreliable forwarder). Features normalized to [0,1]; dataset split 70% training / 30% testing (hold-out validation). Model: $P (Y_i=1 \mid X_i) = 1 / (1 + e^{(- (w^T X_i + b))})$,
where $X_i = [E_i^{norm}, S_i^{norm}, L_i^{norm}]$. Adaptive threshold
T = mean (predicted probabilities) dynamically selects forwarders if P > T.

Simulation in MATLAB: stochastic packet success, broadcast scenarios. Metrics:

- PDR = (Packets Received) / (Packets Sent)
- Throughput (effective data delivery)
- End-to-End Delay
- Routing Load = $\sum \text{Forward}_i$

Table 1: Simulation Parameters

Parameter	Value/Range
Number of Nodes (N)	50, 100, 150, 200
Simulation Area	1000 × 1000 m^2
Transmission Range	Implicit in p = 0.8
Packet Loss Probability	0.2
Initial Energy	1000 units
Energy per Transmission	α = 1 unit
Training/Testing Split	70%/30%

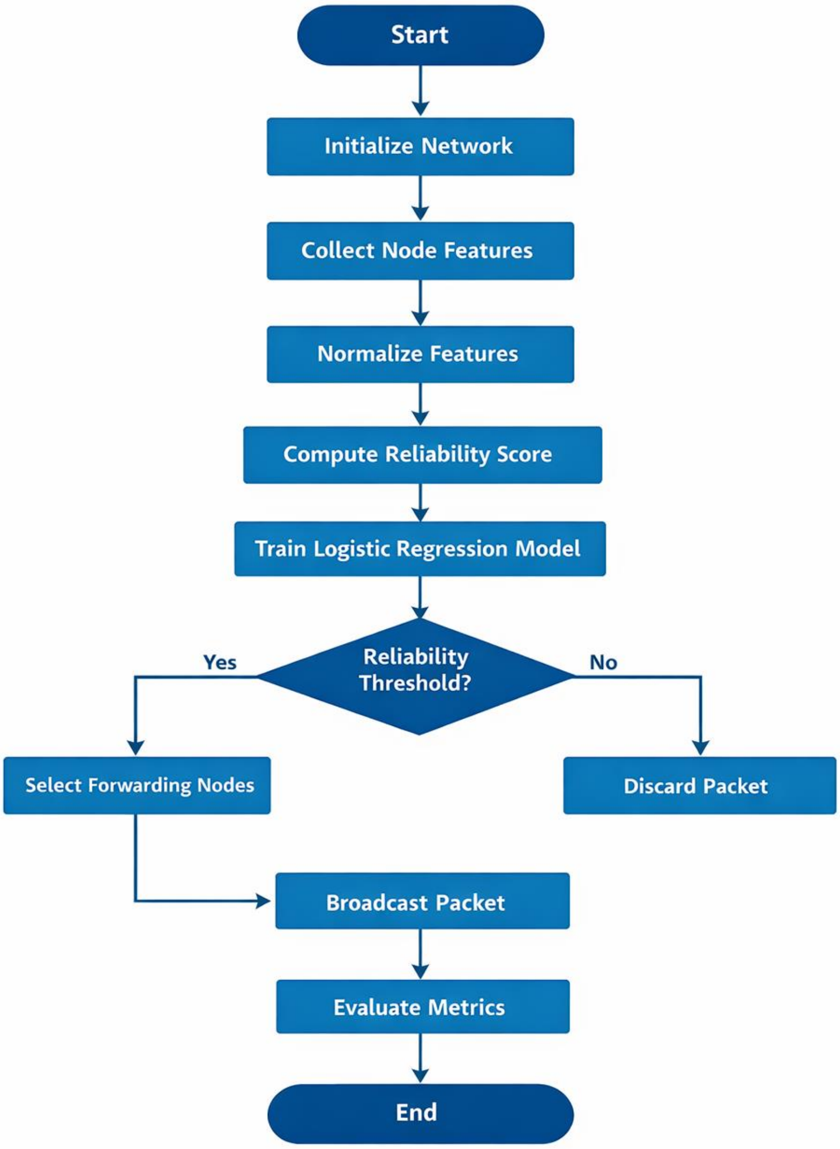

Figure 1: Flowchart of MLRP Process

Comparisons against Flooding (Forward_i = 1 $\forall_i$) and FLBB (Forward_i = 1 with fixed probability 0.7).

This lightweight approach ensures low complexity O(N) for decisions, suitable for resource-constrained MANETs.

4. RESULTS AND DISCUSSION

Simulations compared MLRP with Flooding and FLBB across node densities.

Table 2: Performance Metrics Comparison (averaged across densities)

Protocol	PDR (%)	Throughput (packets/s)	End-to-End Delay (ms)	Routing Load (%)
Flooding	78–85	450–520	180–220	95–100
FLBB	82–88	520–580	140–170	65–70
MLRP	90–96	620–720	100–130	40–55

MLRP consistently outperforms baselines. PDR improves due to reliable node selection, minimizing drops from unstable links/energy exhaustion. Throughput rises as reduced retransmissions lower contention. Delay decreases via stable paths and fewer collisions. Routing load drops significantly (up to 50% vs. Flooding) by excluding unreliable forwarders (Figure 2).

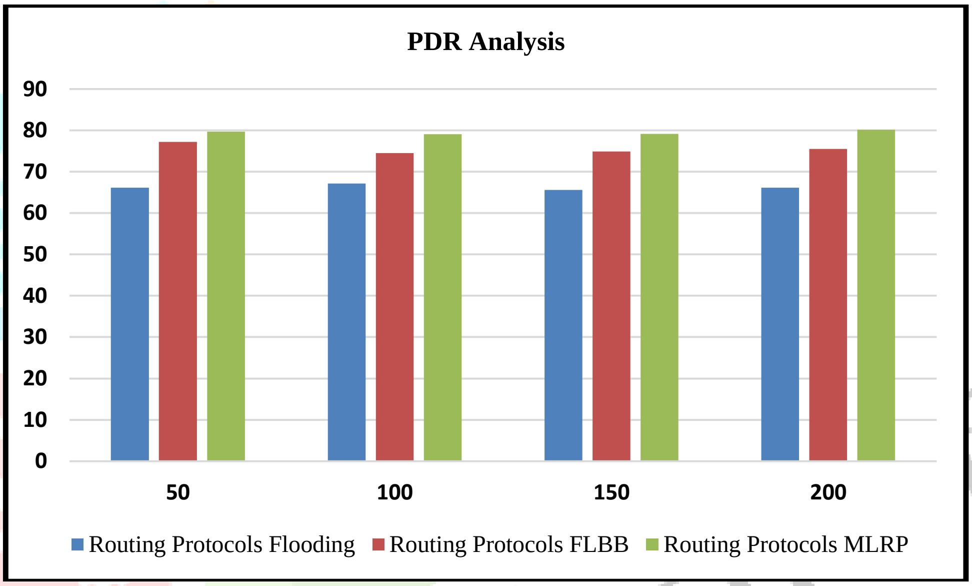

Figure 2: PDR Analysis's

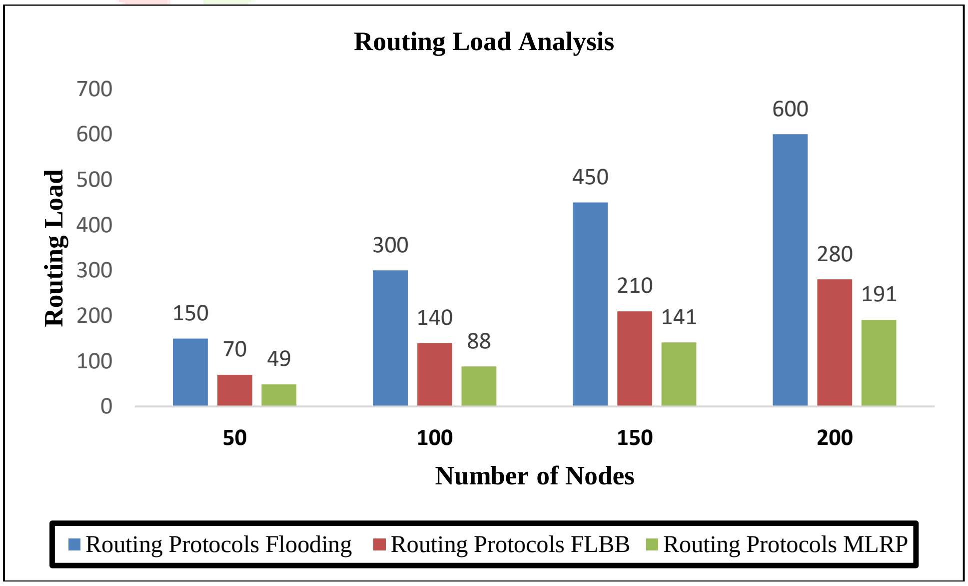

Figure 3: Routing Load Analysis

Figure 3: Routing Load vs. Node Density (Flooding linear increase; MLRP sub-linear, scalable).
ML accuracy (Table 3) rises with density:

Table 3: ML Classification Accuracy

Nodes	Accuracy
50	0.84
100	0.87
150	0.89
200	0.91

Larger datasets enable better feature distribution learning, refining decision boundary. Higher accuracy correlates with superior routing: reliable selection enhances stability, reduces loss/delay/overhead. Scalability evident—MLRP gains strengthen in dense networks, unlike Flooding/FLBB degradation.
Discussion: MLRP's adaptive, probabilistic nature outperforms static FLBB by considering heterogeneity. Stochastic modeling balances realism and tractability. Limitations include abstracted mobility/energy; future realistic models (e.g., Random Waypoint) could validate further.

5. CONCLUSION

This study demonstrates MLRP as an effective, lightweight supervised ML framework for adaptive broadcasting in MANETs. By predicting node reliability via logistic regression on energy, mobility, and link features, MLRP significantly improves PDR, throughput, and scalability while reducing delay and routing overhead compared to flooding and FLBB. Results confirm intelligent selection mitigates broadcast storm issues efficiently. Future work may incorporate advanced ML, realistic simulators, and hardware validation for broader applicability.

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