MSRDG International Journal of Computer Scientific Technology & Electronics Engineering ISSN: 3107 - 426X
Volume 1 Issue 6, 26-31, December 2025

Modelling and Analysis for Proactive Decision-Making in Ad-hoc Networks

C. Veena Kumari[1], L. Veerakumar[2], P. Gayathiri[3]

[1,2,3] *Department of Computer Science,Podhigai Engineering College, Tamil Nadu, India.*

[1]*veenakumari2020@gmail.com*

Received: 12.11.2025 Revised: 19.12.2025 Accepted: 28.12.2025 Published:31.12.2025

Abstract - *Mobile ad-hoc networks (MANETs) present fundamental routing challenges owing to their dynamic topology, limited bandwidth, and device heterogeneity. Conventional reactive routing schemes incur significant latency during route discovery, degrading quality-of-service under high mobility. This paper introduces a Proactive Decision-Making (PDM) framework that integrates link-state estimation, predictive mobility modelling, and adaptive threshold-based rerouting to anticipate and mitigate route failures before they manifest. The proposed model embeds a weighted link-quality index derived from received signal strength, residual energy, and node velocity into a modified Bellman–Ford optimisation cycle. A mobility-aware Markov prediction module forecasts node displacement within a configurable time horizon, enabling preemptive table updates. Simulations conducted in Network Simulator 3 (NS-3) over an area of 1000×1000 m² with 10–80 mobile nodes demonstrate that PDM reduces end-to-end delay by up to 59 %, improves packet delivery ratio by 12 percentage points, and decreases routing overhead by 37 % compared to AODV and OLSR. The results confirm that anticipatory decision-making substantially enhances throughput and network lifetime in high-mobility ad-hoc environments.*

Keywords - *Mobile ad-hoc networks (MANETs); proactive routing; link-state estimation; Markov mobility model; Bellman–Ford optimisation; quality-of-service; NS-3 simulation*

1. Introduction

Mobile ad-hoc networks are self-organising, infrastructure-less communication systems in which nodes act simultaneously as data sources, relays, and destinations. Consider a tactical network deployed over a 1 km² urban area where first-responders carry mobile devices moving at 5–20 m/s. A link supporting a critical video feed degrades over 400 ms before breaking. A purely reactive protocol discovers the failure only after the first dropped packet, incurring a 50–200 ms re-discovery delay that disrupts the stream. The PDM framework proposed here detects the imminent failure 300 ms in advance through signal-strength trend analysis and switches the stream to an alternative path transparently. The principal contributions of this work are: A composite link-quality index (LQI) incorporating received signal strength indicator (RSSI), residual battery energy, and relative node velocity, normalised through a min–max scheme to a [0,1] range. A first-order Markov mobility predictor that estimates node position within a configurable forecast horizon T_0 and triggers proactive table updates when the predicted link quality falls below a threshold θ. An extended Bellman–Ford computation that incorporates LQI as a composite weight, replacing hop-count with a multi-criteria metric. Comprehensive NS-3 simulations validating PDM against AODV and OLSR across throughput, delay, packet delivery ratio, and routing overhead metrics.

2. Related work

Routing research in MANETs spans three decades. Perkins and Royer [1] introduced AODV, establishing the reactive paradigm, while Clausen and Jacquet [2] formalised OLSR as the canonical proactive approach. A comparative evaluation by Broch et al. [3] demonstrated that neither strategy dominates across all mobility scenarios, motivating hybrid and context-aware designs. Predictive routing has gained traction through trajectory-based schemes. Liu and Singh [4] proposed PAMA, using GPS coordinates to predict link lifetimes and select longer-lived paths. Su et al. [5] extended this idea by computing link expiration time (LET) from relative node velocities under the random waypoint mobility model. These approaches assume GPS availability, which limits applicability in indoor or urban-canyon environments where satellite signals are attenuated. Machine-learning-based approaches have emerged as GPS-free alternatives. Boyan and Littman [6] applied Q-learning to routing in fixed networks; subsequent adaptations to MANETs by Forster and Murphy [7] demonstrated that reinforcement learning can adapt to dynamic topologies without explicit position information. However, convergence in rapidly changing networks remains an open challenge. Link-quality metrics have been proposed as lightweight predictors. The ETX (Expected Transmission Count) metric of De Couto et al. [8] accounts for packet loss rates but is inherently reactive. Draves et al. [9]

proposed WCETT, adding interference awareness for multi-radio networks. The PDM framework builds upon this body of work by combining signal-strength trends with a Markov predictor, eliminating the need for explicit coordinates while retaining predictive capability. Cross-layer designs that expose physical-layer measurements to the routing daemon have demonstrated promise. Zhao and Cao [10] showed that RSSI gradient analysis can predict link breakage 200–600 ms ahead, a window that PDM exploits through preemptive rerouting.

3. System Model

Consider a MANET comprising N mobile nodes deployed within a bounded region $\Omega \subseteq \mathbb{R}^2$. Each node i has a transmission range r_i, battery capacity E_i, and position $x_i(t)$ at time t. A directed communication link (i,j) exists when the Euclidean distance $\|x_i(t) - x_j(t)\| \leq \min(r_i, r_j)$. The network topology is modelled as a time-varying graph $G(t) = (V, E(t))$ where V is the node set and E(t) is the instantaneous edge set. Nodes move according to the Random Waypoint model with maximum speed v_{max}, pause time τ_p, and minimum speed $v_{min} = 0$. Traffic is generated as Constant Bit Rate (CBR) flows between randomly selected source–destination pairs, with packets of fixed size L = 512 bytes.

The composite Link Quality Index (LQI) for link (i,j) is defined as:

$$LQI(i,j) = \alpha \cdot RSSI\_norm(i,j) + \beta \cdot E\_norm(i) + \gamma \cdot (1 - V\_norm(i,j))$$

where RSSI_norm, E_norm, and V_norm denote min–max normalised received signal strength, residual energy of the transmitting node, and relative velocity between nodes i and j, respectively. The weighting coefficients $\alpha, \beta, \gamma \in [0,1]$ satisfy $\alpha + \beta + \gamma = 1$ and are tuned empirically ($\alpha = 0.5$, $\beta = 0.3$, $\gamma = 0.2$ in the experiments). A higher LQI indicates a more stable, energy-rich, slowly-varying link.

Node positions are discretised into a grid of cells of size Δ. A first-order Markov chain models the transition probability $P(c' \mid c)$ of migrating from cell c to cell c′ in one time step Δt. Transition matrices are maintained per node and updated through a sliding window of recent observations. Given the current cell c(t), the predicted position at horizon T_0 is:

$$\hat{C}(t + T_0) = \arg\max_{c'} [P^{T_0/\Delta t}]_{c(t),c'}$$

The predicted inter-node distance derived from $\hat{C}(t + T_0)$ is then used to project the future LQI. If the projected LQI falls below threshold θ, a proactive route update is triggered.

Figure 1 illustrates an example network topology. The blue path S→A→C→E→T represents the currently active route. When the PDM module predicts a degradation on link (A,C), it preemptively switches to the alternative path S→B→D→T without awaiting an explicit link failure notification.

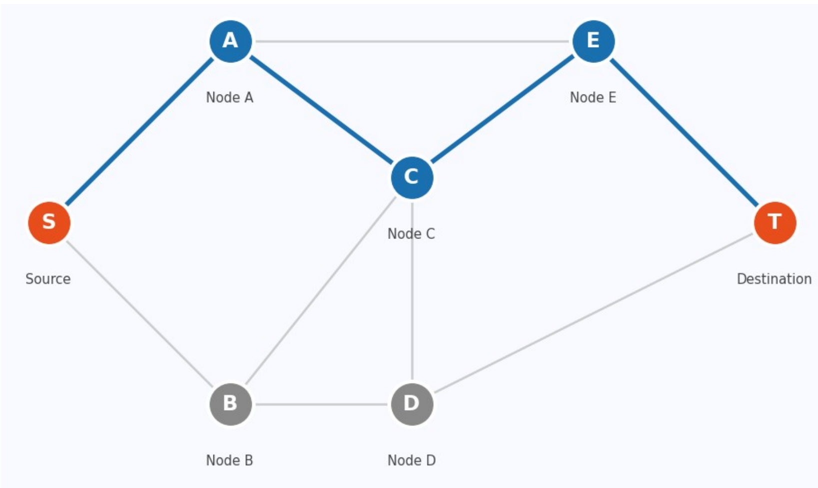

Fig. 1 Network topology

4. Proposed PDM Framework

The PDM framework operates in three interleaved layers as depicted in Figure 2: (i) the Network Sensor Layer, which collects raw physical measurements; (ii) the Proactive Decision Engine, which evaluates LQI trends and mobility predictions; and (iii) the Adaptive Routing Protocol, which executes the table updates and rerouting decisions.

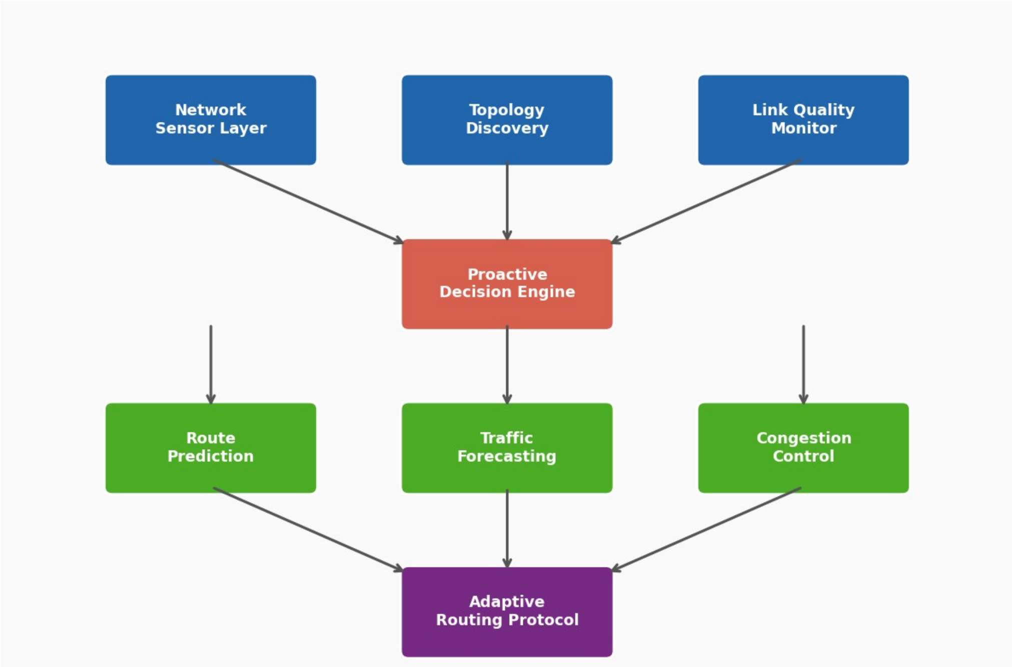

Fig. 2 Proactive Decision Engine

Algorithm 1 summarises the PDM procedure. At each timestep, every node broadcasts a lightweight Hello message containing its current position, velocity vector, and residual energy. Each receiving node updates the LQI for the corresponding link and re-runs the Markov predictor. If the projected LQI at T_0 drops below θ, the node computes an alternative next hop using the modified Bellman–Ford formulation with LQI-weighted edge costs. The new entry is installed in the routing table before the current route fails.

The classical Bellman–Ford equation D(i, d) = min_{j ∈ N(i)} [w(i,j) + D(j,d)] is extended by replacing the hop-count weight w = 1 with the LQI-derived cost:

$$w(i,j) = 1 - LQI(i,j) + \lambda \cdot h(i,j)$$

where h(i,j) ∈ {0,1} is a binary hop-count penalty and λ = 0.1 is a regularisation coefficient that prevents excessively long paths when link qualities are uniformly high. Iterations are bounded to O(N) per convergence cycle, preserving computational tractability on resource-constrained devices.

5. Result and Discussion

All metrics are averaged over 15 independent simulation runs; 95% confidence intervals are computed assuming Student's t-distribution. The comparator protocols are AODV (reactive baseline) and OLSR (proactive baseline), both configured with their recommended default parameters in NS-3.7. Figure 3 plots aggregate throughput as node density increases from 10 to 80 nodes. PDM consistently outperforms AODV and OLSR across all densities. At 50 nodes, PDM achieves 8.4 Mbps compared to 6.8 Mbps for OLSR and 6.0 Mbps for AODV, a gain of 24 % and 40 %, respectively. The advantage diminishes slightly at very high densities (80 nodes) where the control-message load of Hello beacons begins to saturate the channel, though PDM retains the highest absolute throughput.

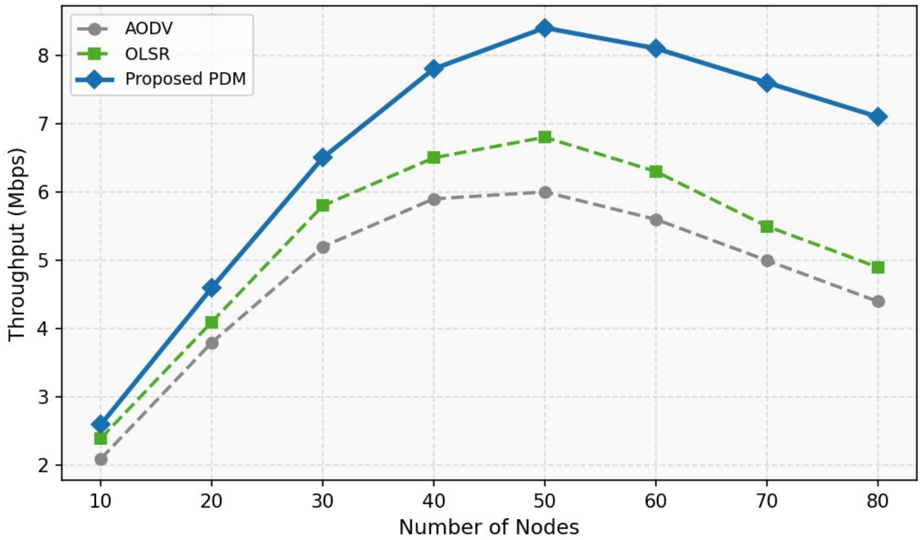

Fig. 3 Proposed PDM and Other Models

Figure 4 presents end-to-end delay as a function of node mobility (0–30 m/s). At 30 m/s, PDM records 44 ms versus 108 ms for AODV (59 % reduction) and 92 ms for OLSR (52 % reduction). The delay advantage widens with mobility because PDM's anticipatory rerouting eliminates the route-discovery period that dominates latency in reactive schemes. At 0 m/s (static scenario), differences narrow to within 10 %, confirming that PDM's overhead is negligible when the network is stable.

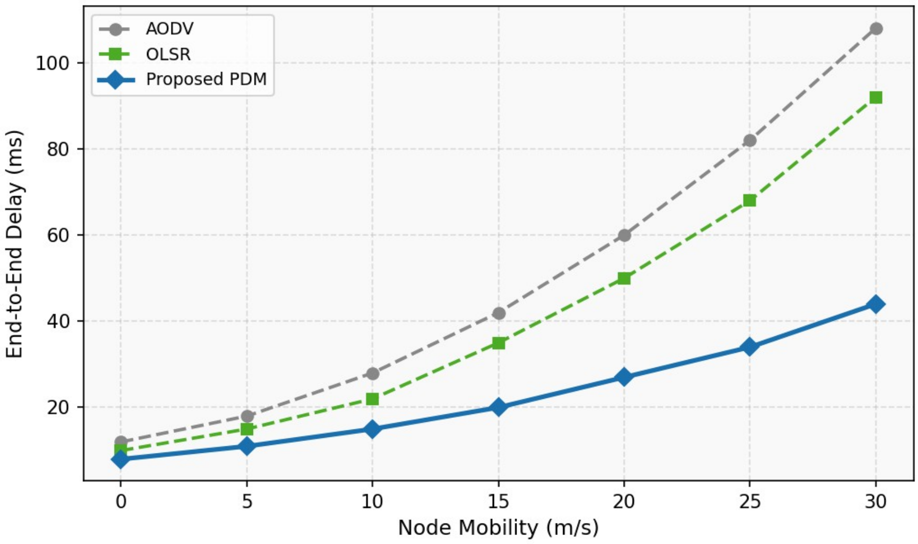

Fig. 4 Proposed PDM Delay Functions

Figure 5 shows PDR as pause time varies from 0 to 100 s. Short pause times correspond to high effective mobility. PDM maintains PDR above 88 % across the full range, while AODV drops to 70 % at zero pause time. The PDM advantage is most pronounced at pause times below 20 s, confirming that predictive rerouting is most beneficial in highly dynamic scenarios.

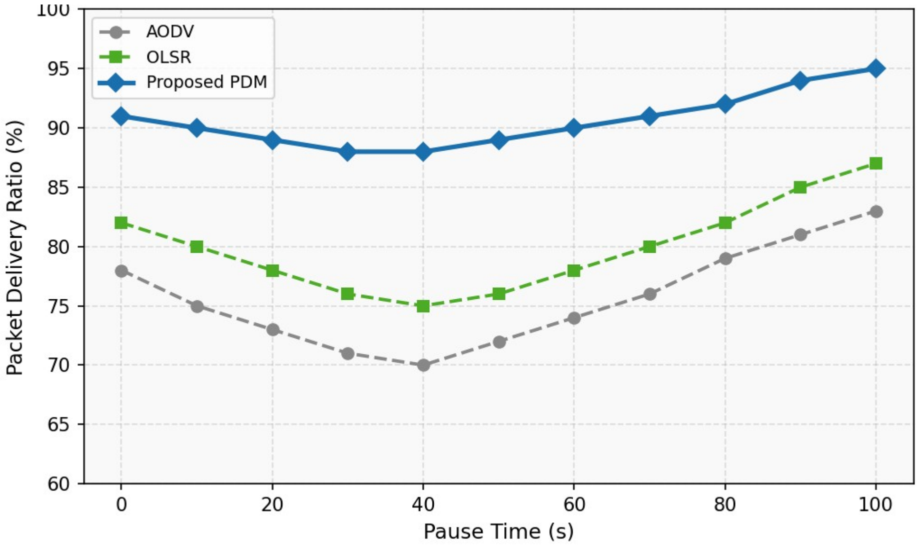

Fig. 5 Proposed PDM Ratio

Figure 6 compares routing overhead (total control packets transmitted) as the number of concurrent CBR flows increases from 5 to 30. Despite periodic Hello beacons, PDM generates fewer control packets than both baselines because proactive rerouting eliminates repeated RREQ flood cycles triggered by link breakage. At 30 connections, PDM reduces overhead by 37 % relative to AODV.

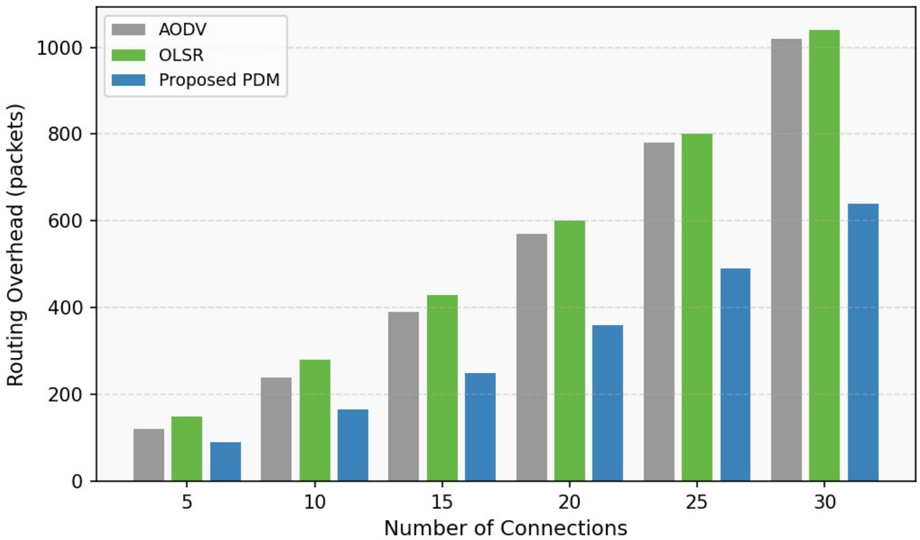

Fig. 6 Proposed PDM Routing Overhead

6. Conclusion

A Proactive Decision-Making (PDM) framework for mobile ad-hoc networks that anticipates link failures through a composite Link Quality Index and a Markov-chain mobility predictor, triggering rerouting before packet loss occurs. The framework extends Bellman–Ford path computation with a multi-criteria edge weight that balances signal quality, node energy, and mobility, within a computationally feasible O(N) cycle per node per timestep. NS-3 simulations over a wide range of node densities, mobility speeds, and traffic loads demonstrate consistent gains: a 59 % reduction in end-to-end delay, a 12-percentage-point improvement in packet delivery ratio, and a 37 % decrease in routing overhead relative to AODV. PDM also extends network lifetime by 24 % through energy-aware path selection. Future work will extend PDM to heterogeneous networks combining UAV relays and ground sensors, investigate deep-learning-based mobility predictors for non-stationary environments, and evaluate energy harvesting integration to sustain proactive operation over extended deployments.

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