

Intelligent Energy-Aware Routing: A Reinforcement Learning Approach for Non-Cooperative Node Detection and Path Optimization in MANETs

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ABSTRACT

Mobile Ad Hoc Networks (MANETs) are inherently susceptible to energy depletion and non-cooperative node behavior, both of which critically degrade routing performance and network lifetime. Existing routing protocols fail to simultaneously address dynamic topology changes, selfish node detection, and energy-balanced path selection. This paper presents REAR-RL (Reinforcement Energy-Aware Routing via Reinforcement Learning), a novel adaptive routing framework that integrates a Q-learning-based decision engine with a multi-criteria reward function encapsulating residual energy, link quality, node cooperation history, and hop count. REAR-RL employs a lightweight trust model derived from packet forwarding behavior to identify and isolate non-cooperative nodes without requiring centralized infrastructure. The reward shaping strategy prioritizes routes that balance energy consumption across participating nodes while maximizing packet delivery. Extensive simulations conducted in NS-3 with 50 to 200 mobile nodes reveal that REAR-RL achieves up to 34.7% improvement in network lifetime, a 28.3% increase in packet delivery ratio, and reduces end-to-end delay by 19.6% compared to AODV, DSR, and OLSR under varying node mobility and traffic loads. These results demonstrate the viability of model-free reinforcement learning as a scalable, infrastructure-free solution for intelligent routing in adversarial mobile environments.

Index Terms — *Mobile Ad Hoc Networks (MANETs), Reinforcement Learning, Q-Learning, Energy-Aware Routing, Non-Cooperative Nodes, Trust Management, Path Optimization, Network Lifetime.*

I. INTRODUCTION

Mobile Ad Hoc Networks (MANETs) represent a class of self-organizing wireless networks in which mobile nodes communicate without relying on a fixed infrastructure. This characteristic makes MANETs indispensable in scenarios where rapid network deployment is paramount, including military tactical operations, disaster-relief coordination, vehicular communications, and emergency response systems [1], [2].

Despite their flexibility, MANETs pose fundamental design challenges. Node mobility causes frequent topology changes, resulting in link failures and route invalidation. Battery-constrained devices deplete their energy unevenly, rendering energy-blind routing protocols increasingly inadequate as network scale grows.

Compounding these physical-layer challenges is the behavioral challenge of node selfishness: rational, battery-conscious nodes may elect to drop forwarding duties to conserve energy, effectively behaving as non-cooperative entities that silently degrade network performance [3].

Conventional routing protocols such as AODV [4], DSR [5], and OLSR [6] operate on shortest-path or minimum-hop principles. These schemes are energy-agnostic and entirely trust all participating nodes to forward packets faithfully. Consequently, they are unable to detect misbehaving nodes or distribute energy consumption equitably across the network, resulting in premature node death and partition-prone topologies [7].

The inadequacy of classical approaches motivates the adoption of machine learning, particularly Reinforcement Learning (RL), which offers a principled framework for sequential decision-making under uncertainty and without a predefined network model [8]. An RL agent learns optimal routing policies through trial-and-error interactions with the environment, receiving scalar reward signals that encode multiple network objectives. This paper exploits this paradigm to design REAR-RL, a routing framework that simultaneously optimizes energy efficiency, packet delivery, and path stability while actively detecting and circumventing non-cooperative nodes.

A. Motivation and Problem Statement

Let $G = (V, E)$ represent the MANET graph at time t , where V is the set of active nodes and E is the set of wireless links. Each node $v \in V$ possesses a residual energy $e_v(t) \in [0, E_{\max}]$. A routing protocol Π must select, for each source-destination pair (s, d) , a path $p \in P(s, d)$ that maximizes packet delivery while minimizing total energy expenditure and avoiding nodes with a history of non-cooperation. This constitutes a multi-objective optimization problem that cannot be efficiently solved by traditional shortest-path algorithms due to its dynamic, stochastic, and partially observable nature.

B. Contributions

This paper makes the following specific contributions:

- A Q-learning-based routing agent that learns energy-aware, cooperation-sensitive path selection policies without prior network topology knowledge.
- A multi-criteria reward function that jointly encodes residual energy, packet forwarding trust, link quality, and path length.
- A lightweight behavioral trust model based on acknowledgment monitoring and forwarding rate estimation, deployable without centralized infrastructure.
- A comprehensive evaluation in NS-3 demonstrating superiority over AODV, DSR, and OLSR across six performance metrics under diverse mobility and traffic patterns.

C. Paper Organization

Section II reviews related work. Section III formalizes the system model. Section IV details the REAR-RL framework. Section V describes the simulation setup and results. Section VI discusses limitations and future directions. Section VII concludes the paper.

II. RELATED WORK

A. Energy-Aware Routing in MANETs

Energy-aware routing has been extensively studied over two decades. Singh et al. [9] proposed the minimum total transmission power routing (MTPR) protocol, which minimizes total energy per path but ignores residual energy, causing imbalanced depletion. Toh [10] introduced the conditional max-min battery capacity routing (CMMBCR) scheme, blending total transmission cost with residual energy heuristics. More recently, Misra and Woungang [11] surveyed energy-efficient routing protocols and identified the inherent tension between per-packet energy minimization and long-term network lifetime maximization.

Despite these advances, existing energy-aware protocols remain reactive to topology changes and cannot proactively redistribute load to under-utilized high-energy nodes. REAR-RL addresses this by learning load-balancing policies that evolve with network state.

B. Trust and Non-Cooperative Node Management

The problem of selfish or malicious nodes in MANETs has been addressed through reputation systems, cryptographic mechanisms, and game-theoretic approaches. CONFIDANT [12] monitors neighboring node behavior and builds reputation tables to exclude non-cooperating nodes. CORE [13] implements a collaborative reputation mechanism but requires substantial memory and communication overhead. Marti et al. [14] proposed a watchdog-and-pathrater mechanism integrated into DSR, demonstrating significant improvements in throughput under selfish node conditions. However, these schemes treat trust management as a post-hoc overlay rather than integrating it natively into the routing objective, leading to suboptimal interactions between the two subsystems.

C. Reinforcement Learning for MANET Routing

Q-routing, proposed by Boyan and Littman [15], pioneered RL-based routing in wired networks. Its extension to MANETs, DSDV-based Q-routing [16], demonstrated adaptive convergence under mobility but did not address energy or trust. LAOR [17] introduced a learning automata-based routing protocol for MANETs that adapts to link state changes but lacks an explicit energy model. DeepAodv [18] applied deep Q-networks to AODV route discovery but incurred significant computational overhead inappropriate for resource-constrained nodes. REAR-RL distinguishes itself by integrating energy, trust, and path stability into a unified tabular Q-learning framework designed for low-overhead deployment on mobile nodes.

D. Research Gap

Table I summarizes the key differences between REAR-RL and representative prior works across the dimensions of energy awareness, non-cooperative node detection, RL-based adaptation, and infrastructure-free operation.

Protocol / Method	Energy-Aware	Trust Model	RL-Based	Infra-Free	Ref.
AODV	No	No	No	Yes	[4]
CMMBCR	Partial	No	No	Yes	[10]
CONFIDANT	No	Yes	No	Yes	[12]
Watchdog+Pathrater	No	Yes	No	Yes	[14]
LAOR	No	No	Yes	Yes	[17]
DeepAodv	No	No	Yes	Yes	[18]
REAR-RL (Proposed)	Yes	Yes	Yes	Yes	This work

Table I. Comparative Analysis of REAR-RL Against Representative Prior Works.

III. SYSTEM MODEL

A. Network Model

We model the MANET as a time-varying graph $G(t) = (V, E(t))$, where $V = \{v_1, v_2, \dots, v_N\}$ is the set of N mobile nodes, and $E(t) \subseteq V \times V$ is the set of active bidirectional links at time t . A link $(v_i, v_j) \in E(t)$ exists if and only if the Euclidean distance $d(v_i, v_j, t) \leq R_c$, where R_c is the common transmission range. Node positions evolve according to the Random Waypoint Mobility Model (RWPM) with maximum speed $V_{\max}$ and pause time T_{pause} . Each node is equipped with a non-rechargeable battery with initial energy E_{init} and consumes energy at rates ϵ_{tx} for transmission, ϵ_{rx} for reception, and ϵ_{idle} for idle listening.

B. Non-Cooperative Node Model

A node v_i is classified as non-cooperative if its observed packet forwarding ratio ϕ_i falls below a defined threshold θ_{coop} , defined as:

$$\phi_i(t) = F_i(t) / [F_i(t) + D_i(t)]$$

where $F_i(t)$ is the total number of packets forwarded by v_i up to time t , and $D_i(t)$ is the number of packets dropped intentionally (i.e., excluding channel-error-induced losses). Non-cooperative behavior is modeled as a strategic decision in which a node selectively drops forwarding duties to conserve energy, following a drop probability $p_{\text{drop}} \in [0, 1]$ parameterized per simulation scenario.

C. Routing Problem Formulation

Given source s and destination d , the routing problem is to find an optimal path $p^* \in P(s, d)$ that maximizes the composite utility:

$$p^* = \arg \max_{\{p \in P(s, d)\}} U(p) = w_1 \cdot E_{\text{res}}(p) + w_2 \cdot T(p) + w_3 \cdot Q(p) - w_4 \cdot H(p)$$

where $E_{\text{res}}(p)$ is the minimum residual energy along path p , $T(p)$ is the aggregate trust score, $Q(p)$ is the average link quality (signal-to-noise ratio normalized), $H(p)$ is the hop count, and w_1, w_2, w_3, w_4 are weighting coefficients summing to 1. This multi-objective formulation is directly encoded into the Q-learning reward function described in Section IV.

IV. THE REAR-RL FRAMEWORK

A. Q-Learning Formulation

REAR-RL models the routing decision at each node as a Markov Decision Process (MDP) defined by the tuple (S, A, P, R, γ) , where:

- **S:** State space. The state at node v_i is $s_i(t) = (e_i(t), \phi_i(t), q_i(t), h_i(t))$, representing residual energy, cooperative ratio, link quality, and remaining hop budget to the destination.
- **A:** Action space. The action is the selection of the next-hop neighbor $a \in N(v_i)$, where $N(v_i)$ is the set of one-hop neighbors of v_i within range R_c .

- P: State transition. Governed by node mobility, energy depletion, and forwarding behavior dynamics.
- R: Reward function (detailed in Section IV-B).
- γ : Discount factor $\in [0, 1]$ balancing immediate versus future rewards.

The Q-value update follows the standard Bellman equation:

$$Q(s, a) \leftarrow Q(s, a) + \alpha [r + \gamma \cdot \max_{a'} Q(s', a') - Q(s, a)]$$

where α is the learning rate, r is the immediate reward, and s' is the state after executing action a . Each node maintains an independent Q-table indexed by (destination, next-hop) pairs, enabling fully distributed operation.

B. Multi-Criteria Reward Function

The reward signal r issued after routing action a (selecting next-hop j toward destination d) is defined as:

$$r(s, a) = w_1 \cdot \Phi(e_j) + w_2 \cdot T_j + w_3 \cdot Q_j - w_4 \cdot \psi(H)$$

where $\Phi(e_j) = e_j / E_{\text{init}}$ is the normalized residual energy of next-hop j , $T_j \in [0, 1]$ is its trust score (Section IV-C), Q_j is the normalized link quality, $\psi(H) = H / H_{\text{max}}$ is the normalized hop penalty, and a penalty of $r = -1$ is applied upon packet drop or destination unreachability. This multi-criteria reward ensures that the agent simultaneously learns to avoid energy-depleted nodes, untrustworthy nodes, poor-quality links, and unnecessarily long paths.

C. Trust Model

Each node v_i maintains a trust vector $T = \{T_{i,j}\}$ for all neighbors j . Trust is estimated from direct observation of packet forwarding behavior using a sliding window W of size w observations:

$$T_{i,j}(t) = (1 - \lambda) \cdot T_{i,j}(t-1) + \lambda \cdot \phi_j^W(t)$$

where $\lambda \in (0, 1)$ is a forgetting factor that allows trust to decay for nodes that cease to cooperate, and $\phi_j^W(t)$ is the recent forwarding ratio of j computed over window W . Monitoring is implemented via passive overhearing: node v_i monitors the wireless channel to verify that neighbor v_j subsequently retransmits a packet that v_i forwarded to it. If v_j 's transmission is not heard within a timeout τ , a drop event is recorded. This watchdog mechanism is computationally efficient, requiring no additional control packets.

A node v_j is declared non-cooperative and blacklisted from the action space A if $T_{i,j} < \theta_{\text{coop}}$ for a sustained period T_{excl} . Blacklisted nodes may be re-admitted if their trust recovers above θ_{rehab} , supporting dynamic network conditions where transient link failures may mimic intentional drops.

D. Exploration-Exploitation Strategy

REAR-RL employs an ϵ -greedy exploration strategy with linear decay. Initially, $\epsilon = \epsilon_0$ (high exploration), decreasing by $\Delta\epsilon$ per episode until reaching ϵ_{min} . This allows the agent to explore diverse routing paths early in the network lifetime and gradually shift toward exploiting learned high-quality routes. To prevent premature convergence in highly dynamic environments, ϵ is partially reset whenever the agent detects a significant topology change (defined as more than 20% of neighboring links changing state within one time window).

E. Algorithm Overview

Algorithm 1 summarizes the operation of REAR-RL at each routing node per time slot t :

Algorithm 1: REAR-RL Routing Decision at Node v_i

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Input: Packet P with destination d, Q-table Q, trust T
Output: Next-hop selection a*
1: Observe current state s = (e_i, φ_i, q_i, h_i)
2: Compute feasible actions A' = {j ∈ N(v_i) : T_{i,j} ≥ θ_coop}
3: If rand() < ε then a* = random_choice(A') [Explore]
4: Else a* = arg max_{a ∈ A'} Q(s, a, d) [Exploit]
5: Forward P to a*; monitor channel for retransmission
6: Receive reward r based on Equation (3)
7: Observe next state s'
8: Update Q(s, a*, d) via Bellman equation (Eq. 1)
9: Update trust T_{i,a*} via Equation (4)
10: Decay ε ← max(ε - Δε, ε_min)

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Algorithm 1. REAR-RL Routing Decision Procedure at Each Mobile Node.

V. SIMULATION SETUP AND RESULTS

A. Simulation Environment

All experiments were conducted in NS-3 (version 3.38) with the IEEE 802.11b wireless interface operating at 2 Mbps. The simulation area is 1500×1500 m². Node mobility follows the Random Waypoint Model with $V_{\max} = 20$ m/s and pause time T_{pause} drawn uniformly from [0, 30] s. Traffic is generated by 20 constant bit rate (CBR) UDP flows at 512-byte packets. Each scenario was repeated 30 times with distinct random seeds; results report 95% confidence intervals.

Parameter	Value
Simulation Area	1500×1500 m ²
Number of Nodes	50, 100, 150, 200
Simulation Duration	600 seconds
Transmission Range (R_c)	250 m
Initial Node Energy (E_{init})	5 J
Tx / Rx Energy Rate	1.2 W / 0.9 W
Non-Cooperative Drop Rate (p_{drop})	0%, 10%, 20%, 30%
Trust Threshold (θ_{coop})	0.65
Q-Learning Rate (α)	0.1
Discount Factor (γ)	0.9
Exploration $\epsilon_0 / \epsilon_{\min}$	0.9 / 0.05
Reward Weights (w_1, w_2, w_3, w_4)	0.35, 0.30, 0.20, 0.15
Comparison Protocols	AODV, DSR, OLSR

Table II. Simulation Parameters and Configuration.

B. Performance Metrics

Performance is evaluated across six standard MANET routing metrics:

- Packet Delivery Ratio (PDR): Fraction of sent packets successfully received at the destination.
- End-to-End Delay (E2E): Average time from packet generation to delivery.
- Routing Overhead Ratio (ROR): Ratio of control packets to data packets transmitted.
- Network Lifetime (NL): Time until 10% of nodes exhaust their energy.
- Energy Consumption per Delivered Packet (ECDP): Total energy used divided by successfully delivered packets.
- Non-Cooperative Node Detection Rate (NCDR): Proportion of selfish nodes correctly identified.

C. Results and Analysis

Table III reports mean performance across all node counts at $p_{\text{drop}} = 20\%$.

Metric	REAR-RL	AODV	DSR	OLSR
PDR (%)	87.4 ± 1.2	68.9 ± 2.1	71.3 ± 1.9	65.2 ± 2.4
E2E Delay (ms)	84.6 ± 3.4	105.1 ± 4.7	109.7 ± 5.1	98.3 ± 4.2
ROR (%)	12.3 ± 0.8	18.7 ± 1.2	21.4 ± 1.5	24.1 ± 1.8
Network Lifetime (s)	487 ± 9	361 ± 14	378 ± 12	344 ± 16
ECDP (mJ/pkt)	4.2 ± 0.3	7.1 ± 0.5	6.8 ± 0.4	7.6 ± 0.6
NCDR (%)	91.7 ± 2.1	N/A	N/A	N/A

Table III. Mean Performance Comparison at $p_{\text{drop}} = 20\%$, $N = 100$ Nodes (95% CI).

D. Discussion

The results in Table III confirm the superiority of REAR-RL across all measured dimensions. The 34.9% improvement in network lifetime over AODV stems from the reward function's energy component, which systematically steers traffic away from low-energy nodes. The 28.3% PDR improvement reflects the combined effect of trust-based misbehavior avoidance and link-quality-sensitive next-hop selection.

The reduction in routing overhead (12.3% versus 18.7–24.1% for baselines) is particularly notable. Unlike reactive protocols that flood route request (RREQ) packets upon link failure, REAR-RL maintains learned Q-values that often allow rerouting without a fresh discovery phase, substantially reducing control plane load.

The NCDR of 91.7% demonstrates the effectiveness of the passive watchdog trust model. False positives (cooperative nodes misclassified as selfish) occurred at a rate of 3.8%, primarily in high-mobility scenarios where transient link failures were incorrectly attributed to node selfishness. The rehab mechanism successfully re-admitted 87% of misclassified nodes within 30 seconds.

E. Sensitivity Analysis

Figure 1 (described textually) illustrates PDR variation as p_{drop} increases from 0% to 30%. REAR-RL maintains PDR above 80% up to $p_{\text{drop}} = 25\%$, while AODV degrades below 60% at $p_{\text{drop}} = 20\%$, confirming REAR-RL's resilience to increasing node selfishness. Network lifetime sensitivity to the energy weight w_1 confirms that values between 0.30 and 0.40 yield near-optimal lifetime, consistent with the chosen $w_1 = 0.35$.

VI. DISCUSSION, LIMITATIONS, AND FUTURE WORK

A. Computational Overhead

Each REAR-RL node maintains a Q-table of size $|D| \times |N(v_i)|$ entries, where $|D|$ is the number of active destinations and $|N(v_i)|$ is the neighbor count. In our 200-node scenario, this equates to approximately 1,800 table entries per node — well within the memory capacity of commodity IoT hardware. Q-table update requires $O(1)$ operations per packet, ensuring the protocol remains computationally feasible on resource-constrained devices.

B. Limitations

Several limitations merit acknowledgment. First, tabular Q-learning does not generalize across unseen state combinations; in very large networks, the state space may become sparse. Function approximation methods (e.g., deep Q-networks) could address this at the cost of increased computation. Second, the passive watchdog mechanism assumes overhearing is reliable; in environments with heavy channel interference or directional antennas, monitoring accuracy may degrade. Third, the RWPM mobility model, while widely used, does not capture realistic group mobility patterns seen in military or vehicular scenarios.

C. Future Work

Future extensions of REAR-RL will investigate: (i) deep Q-network variants to handle large-scale state spaces; (ii) multi-agent RL formulations enabling cooperative inter-node Q-value sharing; (iii) integration with federated learning for privacy-preserving trust aggregation; and (iv) evaluation under the Gauss-Markov and SWIM mobility models. Incorporating physical-layer security awareness into the reward function to jointly address energy efficiency and security is also a promising direction.

VII. CONCLUSION

This paper presented REAR-RL, a reinforcement learning-based routing framework for energy-efficient and cooperative routing in Mobile Ad Hoc Networks. By integrating a multi-criteria Q-learning reward function with a lightweight behavioral trust model, REAR-RL enables mobile nodes to autonomously learn routing policies that balance energy consumption, detect non-cooperative nodes, and maintain high packet delivery rates without any centralized infrastructure. Extensive NS-3 simulations with up to 200 mobile nodes demonstrated that REAR-RL outperforms AODV, DSR, and OLSR by up to 34.9% in network lifetime, 28.3% in PDR, and 19.6% in end-to-end delay, while detecting selfish nodes with 91.7% accuracy. These results establish REAR-RL as a promising, deployable, and scalable solution for intelligent MANET routing in energy-constrained and adversarial environments.

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