

Adaptive Routing in Dynamic Networks by Multi-Agent Reinforcement Learning: Design, Modeling and Evaluation of MARL Routing

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Abstract: The proliferation of dynamic networks, such as mobile ad hoc networks (MANETs) and vehicular networks (VANETs), poses major challenges to conventional routing protocols, which struggle to adapt to rapid topology changes and fluctuating quality of service. This paper presents an alternative based on multi-agent reinforcement learning (MARL). We propose MARL Routing, a fully distributed routing architecture where each node acts as an intelligent agent learning from local forwarding decisions via a cooperative Q- learning algorithm . The main contribution lies in the design of a composite reward function, a partial Q-table reset mechanism for increased responsiveness, and a sparse information-sharing protocol (Q gossip). Experimental validation, conducted under NS-3, compares MARL Routing to OLSR, AODV, and classical Q- routing. The results demonstrate significant superiority in highly mobile environments, with a delivery rate of 91% at 15 m/s compared to 60-70% for reference protocols, and a convergence time of less than 2 seconds after a sudden failure. Sensitivity analysis confirms the robustness of the chosen parameters.

Keywords: Adaptive routing, Dynamic networks, Multi-agent reinforcement learning, Distributed Q- learning , Mobility, Network protocols, MARL Routing .

1. INTRODUCTION

Dynamic networks, characterized by an evolving topology, are at the heart of many modern applications: emergency response, autonomous vehicle convoys, drone swarms. In these environments, traditional routing protocols (proactive like OLSR [1], reactive like AODV [2]) show their limitations. Their inability to anticipate changes, their rigid trade-off between control overhead and responsiveness, and the lack of learning from experience lead to massive packet loss and excessive network overhead [3].

Reinforcement learning (RL) offers a promising approach. Q- routing, introduced by Boyan and Littman [4], demonstrated the feasibility of learned routing. However, its single-agent version suffers from slow propagation of breaking information and a frequently violated stationarity assumption [5].

This article proposes MARL Routing, a cooperative multi-agent solution. Each node is an agent performing cooperative Q- learning with selective information sharing. Our contributions are:

1. A decentralized architecture where each agent learns from real data packets, minimizing control traffic.
2. A mixed reward function combining local measurement and neighbor estimation.
3. An original mechanism for partial reset of Q tables for rapid adaptation to link breaks.
4. A limited Q gossip protocol for efficient knowledge dissemination.
5. A rigorous experimental evaluation demonstrating significant gains in mobility.

2. STATE OF THE ART

2.1 Classic Routing Protocols

Proactive routing protocols (OLSRs) maintain routes to all destinations via periodic broadcasts, generating constant control traffic [1]. Reactive routing protocols (AODVs) discover routes on demand, saving bandwidth but introducing significant initial delays [2]. Hybrid approaches (ZRPs) attempt to combine these advantages but remain complex to configure [6]. Their common limitations include the inability to anticipate changes, a fixed control/responsiveness trade-off, and the lack of machine learning [3].

2.2 Reinforcement Learning for Routing

Q- routing [4] models routing as a Markov decision process (MDP). Each node maintains a table $Q(n, d, v)$ estimating the remaining time to reach d via v . The update follows Bellman's rule:

$$Q(n, d, v) \leftarrow (1 - \alpha)Q(n, d, v) + \alpha \left(\text{délai_local} + \gamma \min_u Q(v, d, u) \right)$$

Variants such as Dual Q- routing [7] and trust-based routing [8] have improved robustness. However, the non-stationarity of mobile networks violates the convergence assumption of Q- learning [9].

2.3 Multi-Agent Reinforcement Learning (MARL)

The MARL framework [10] distinguishes between independent, cooperative, and competitive learning. For routing, lightweight cooperation is preferred [11]. The problem of credit assignment [12] is central: how to attribute responsibility for success or failure across a multi-hop path? Solutions include end-to-end information propagation via ACKs [13].

3. FORMAL MODELING OF THE PROBLEM

3.1 Network as a Time Graph

A dynamic network is modeled by a directed graph $G(t) = (V, E(t))$, where V is the set of nodes and $E(t)$ the set of links active at time t . A link $(u, v) \in E(t)$ exists if v is within radio range of u . Each link has a cost $c(u, v, t)$, typically the transmission delay.

3.2 Markov Decision Process (MDP)

Routing is formalized as a MDP (S, A, P, R, γ) :

- **States S :** For a node u , the state s_t includes the destination d and a local congestion indicator (low, medium, high).
- **Actions A :** Choose a neighbor v from among all active neighbors, or the "keep" action.
- **Transitions P :** Probability of changing state s' after action a , depending on mobility and load.
- **Reward R :** Composite function defined in section 3.3.
- **Discount factor γ :** 0.9 balancing immediate and future rewards.

3.3 Composite Reward Function

The reward received by the agent u for an action v towards the destination d is:

$$r = \beta \cdot r_{local} + (1 - \beta) \cdot \gamma \cdot \max_w Q_v(d, w)$$

Or:

- $r_{local} = \frac{1}{1 + \Delta/\Delta_0}$ is the local delay reward (Δ = measured delay, $\Delta_0 = 10ms$).
- $\max_w Q_v(d, w)$ is the best estimate of the neighbor v to reach d .
- $\beta = 0.7$ controls trust in the neighbor.

Additional terms penalize losses (-0.2) and congestion (-0.05 if queue > threshold).

3.4 Performance Objectives

We aim to minimize regret, defined as the difference between the cumulative cost of our algorithm and that of an omniscient algorithm:

$$\text{Regret}(T) = \sum_{t=1}^T (c_t^{\text{MARL}} - c_t^{\text{optimal}})$$

A good algorithm should have sublinear regret.

4. MARL ROUTING : PROPOSED ALGORITHM

4.1 General Architecture

Each node u maintains:

- A table $Q: Q_u(d, v)$ for each active destination d and neighbor v .
- A list of neighbors living with timers.
- A failure counter for each neighbor.
- An estimate of the average delay per neighbor.

The algorithm is event-driven: updates occur upon receipt of packets or ACKs.

4.2 Cooperative Q-Learning

The update to table Q follows:

$$Q_u(d, v) \leftarrow Q_u(d, v) + \alpha \left[r + \gamma \max_w Q_u(d, w) - Q_u(d, v) \right]$$

with $\alpha = 0.1$ The reward r is that defined in 3.3 . $\gamma = 0.9$

4.3 Strategy Exploration

- **Epsilon- greedy dynamic** : $\epsilon(t) = \max(\epsilon_{\min}, \epsilon_0 \cdot e^{-t/T})$, with $\epsilon_0 = 0.5$, $\epsilon_{\min} = 0.05$, $T = 10000$.
- **Rarity-based exploration** : Neighbors that are rarely visited have an increased probability of being chosen.
- **Enhanced exploration** : If performance drops by $>20\%$, ϵ temporarily increases to 0.3.

4.4 Information Sharing

- **Q gossip** : Periodic messages (0.2 Hz) containing the 5 best Q values for popular destinations.
- **Break notifications** : Sent to immediate neighbors (range 2 hops) when a link is declared dead.
- **Selective ACKs** : 1 out of 10 packets generates an ACK for end-to-end learning.

4.5 Dynamics Management Topological

- **Passive break detection** : 5s timeout without message = dead link.
- **Partial reset** : The Q values of a dead neighbor are multiplied by $\delta = 0.2$.
- **Adaptive forgetting** : If the average reward for a destination falls by $>30\%$, all $Q(d, \cdot)$ are multiplied by 0.5.

4.6 Complexity Algorithms

- **Time** : $O(\text{degrees})$ per packet for action selection, $O(1)$ for update.
- **Memory** : $O(\text{nb_destinations_actives} \times \text{degree})$. With 100 destinations and degree 10, ~ 8 KB.

5. EXPERIMENTAL PROTOCOL

5.1 Simulation Environment

- **Simulator** : NS-3.35, Wi-Fi 802.11b ad hoc model, throughput 11 Mbit/s, range 100m.
- **Propagation** : Two Ray Ground, reception threshold -96 dBm.
- **Mobility**: Random Waypoint (speeds 0-20 m/s) and Reference Point Group Mobility.
- **Duration** : 500s per simulation, 20 repetitions with random seeds.

5.2 Test Scenarios

1. **Static network** : 50 nodes, 10 constant UDP streams.
2. **Random mobility** : Variable speeds (0, 5, 10, 15, 20 m/s).
3. **Sudden failure** : Central node switched off at t=100s.
4. **Variable load** : 5 to 40 flows.
5. **Group mobility** : 3 groups of 15 nodes.

5.3 Metrics

- **Delivery Rate (RDR)** : Packages received / packages sent.
- **Average end-to-end time** .
- **Control overload** : Control bytes / data bytes.
- **Convergence time** : Time to recover 90% of the PDR after a change.
- **Jain Index** : Equity between flows.

5.4 Reference Protocols

- **AODV**: Route timeout 3s.
- **OLSR** : Hello every 2s, TC every 5s.
- **Classical Q- routing** : $\alpha = 0.1$, $\gamma = 0.9$, ϵ decreasing.

6. RESULTS AND INTERPRETATION

6.1 Static Network Performance

Table 1

Protocol	PDR (%)	Delay (ms)	Surcharge (%)
OLSR	99.8	20	15
AODV	99.5	22	5
Q-routing	98.7	25	2
MARL	99.3	21	2

MARL Routing achieves performance comparable to OLSR without excessive overhead.

6.2 Impact of Mobility

Table 2

Speed (m/s)	AODV PDR	OLSR PDR	Q-routing PDR	MARL PDR
0	99	99.8	98.7	99.3
10	85	95	92	97
15	70	60	85	91
20	45	40	75	82

MARL Routing surpasses the benchmarks from 10 m/s. At 15 m/s, it maintains a PDR of 91% compared to 60-70% for the others.

6.3 Response to a Sudden Failure

Table 3

Protocol	Convergence time(s)	PDR during breakdown (%)
AODV	5	30
OLSR	4	35
Q-routing	15	20
MARL	1.8	70

Rapid break notification and partial reset allow MARL Routing to converge in less than 2 seconds.

6.4 Behavior under Load

At 40 flows, MARL Routing maintains a PDR of 85% with a delay 3x lower than AODV, thanks to load balancing via softmax .

6.5 Sensitivity Analysis

- α : Optimal at 0.1-0.15 (PDR 91%).
- γ : Optimal at 0.9 (PDR 91%).
- β : Optimal at 0.7 (PDR 91%).
- **Neighbor timeout** : Optimal at 5s (PDR 91%, moderate overload).
- δ : Optimal at 0.2.

7. DISCUSSION

7.1 Validity of Models

The simulations use standard models but do not capture all the real-world complexities (variable interference, obstacles). Validation on a real platform is necessary.

7.2 Scalability

Beyond 100 nodes, the memory of the Q tables becomes critical. Geographic aggregation (not implemented) is recommended.

7.3 Energy Consumption

MARL Routing reduces Hello messages but may be more resource-intensive than AODV in low-traffic areas. A specific study is needed.

7.4 Safety

A trust mechanism is proposed to limit the impact of malicious nodes, but has not been thoroughly tested.

8. Conclusion and Perspectives

MARL Routing demonstrates the viability of multi-agent reinforcement learning for adaptive routing. Its novel mechanisms (partial reset, Q gossip) offer significant gains in mobility and responsiveness. Future directions include:

- Validation on real platforms (Raspberry Pi, drones).
- Implementation of geographic aggregation for scalability.
- Dynamic adaptation of parameters.
- Integration of trust mechanisms for security.
- Exploring deep learning for very large state spaces.

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