**International Journal of Research Publication and Reviews**

Journal homepage: www.ijrpr.com ISSN 2582-7421

# Reinforcement Learning-Based Opportunistic Routing for Vehicular Ad Hoc Networks

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**ABSTRACT—**

Vehicular Ad-Hoc Networks (VANETs) require real-time services with low delay and high transmission reliability. However, live streaming over multi-hop wireless networks faces challenges due to unpredictable packet losses and network congestions caused by time-varying wireless channels. To address these issues, we present a reinforcement learning (RL)-based opportunistic routing (OR) scheme for wireless streaming. This scheme capitalizes on the broadcast nature of the wireless medium and path diversity through OR to enhance transmission reliability. It dynamically identifies low-delay paths between source-destination pairs for packets using RL modules embedded in relay nodes. We introduce a novel path-cost metric, the expected any path delay (EAD), in OR, which estimates the end-to-end delay of a packet between the current relay node and the destination. The EAD is continuously measured and updated over time, taking into account changes in link quality and congestion levels. Moreover, we utilize ACK messages to include the EAD of each relay node to its previous hop node, facilitating iterative and independent updates of EAD values across the network. The next-hop forwarder node on a low delay route is determined by assigning higher relay priority to candidate forwarder nodes with lower EADs. Simulation results illustrate that our proposed RLOR algorithm achieves a suitable balance between transmission reliability and latency, supporting low-delay transmission of wireless streams with high quality in VANETs.

Keywords: Vehicular Ad-Hoc Networks, reinforcement learning, opportunistic routing low-delay, EAD

## 1. Introduction:

In recent times, real-time streaming services, such as conferences, surveillance, and live broadcasts, have gained significant importance as essential applications in Vehicular Ad-Hoc Networks (VANETs). Concurrently, multi-hop wireless networks, like wireless mesh networks (WMNs), wireless sensor networks (WSNs), and mobile ad hoc networks (MANETs), have garnered attention for future mobile communication systems due to their easy deployment, cost-effectiveness, and multi-hop and multi-path topologies. Nevertheless, challenges persist for live streaming over these multi-hop wireless networks [1-5].

Live streaming demands high transmission reliability and imposes strict bandwidth consumption requirements due to the substantial data and the need for acceptable viewing quality [6-7]. Video transmission is particularly susceptible to packet loss due to encoding/decoding dependencies among consecutive packets. Low end-to-end delay is critical as late-arriving packets become unusable and lost [8-10].

The unpredictable nature of wireless channels with temporal variations and errors often leads to high packet loss and latency during transmission, severely affecting received quality. Hence, designing a suitable routing scheme for live streaming over multi-hop wireless networks that ensures reliable and low-delay transmission becomes an intriguing yet challenging task [11-14].

Traditional wireless routing protocols, like ad hoc on-demand distance vector (AODV) and optimized link state routing (OLSR), usually pre-select an optimized route before transmission begins [15]. However, the unreliable and time-varying nature of wireless channels negatively impacts their performance, resulting in significant retransmission overhead. Opportunistic routing (OR) offers an alternative approach by utilizing the broadcast nature of the wireless medium, treating the wireless shared channel as an opportunity rather than a limitation. In OR, a node broadcasts a data packet to multiple neighbors and dynamically determines the next-hop forwarder among nodes that successfully receive the packet based on their relay priority.

To enhance OR for streaming, a new path-cost metric called the expected anypath delay (EAD) is proposed. EAD estimates the end-to-end delay of a packet between the current relay node and the destination node, considering the dynamic changes in link quality and congestion levels. To achieve low-delay transmission for wireless streaming, each node utilizes acknowledgment (ACK) messages to update its EAD based on reinforcement learning (RL) algorithms. This learning process occurs continually and online, using only local information, making the proposed scheme adaptable to time-varying wireless networks [16].

Extensive experiments conducted on the discrete event simulator NS-2 demonstrate that the proposed RLOR algorithm achieves lower end-to-end delay for packet transmission over multi-hop wireless networks while maintaining higher viewing quality compared to existing schemes, making it suitable for live streaming applications in VANETs. The paper is organized as follows: Section II introduces the system model and the basic module of OR. In Section III, a new path-cost metric called EAD is designed, and the RLOR algorithm is developed. Section IV presents the experimental configuration and simulation results. Finally, Section V provides concluding remarks [17].

## 2. SYSTEM MODEL

Network Model and Notations in VANET:

In the RLOR scheme, the new path-cost metric, the expected anypath delay (EAD), is introduced to estimate the total delivery time of a packet from the current sending node to the destination. The EAD for each node i, denoted as $EADd_i(t)$, is continuously measured and updated over time, considering changes in link quality and congestion levels.

The EAD for node i comprises three delay components:

1. Queuing Delay: $q_i(t)$ represents the instant queuing delay for node i at time slot t. The current waiting time of a packet in the queue of node i at the MAC layer, $Q_i(t)$, is estimated using a moving average method:

$$Q_i(t) = \frac{1}{M} \sum_{k=0}^{M-1} q_i(t - k),$$

where M is the size of the sliding window.

2. Expected One-hop Transmission Delay: $T_{i,F_i(t)}(t)$ is used to estimate the time required for a packet to be successfully transmitted from sender node i to at least one node in its CFS $F_i(t)$. It is calculated as follows:

$$T_{i,F_i(t)}(t) = \frac{1}{p_{i,F_i(t)}} \times \frac{S}{R},$$

where $p_{i,F_i(t)}$ is the delivery probability of the hyperlink (i, $F_i(t)$), S is the size of the packet in bits, and R is the data transmission rate in bps.

3. Expected Delivery Delay on the Remaining Path: The expected delivery delay from the CFS $F_i(t)$ to the destination is denoted as $EADd_i(t)$. It is calculated as a weighted sum of the EAD of the nodes in $F_i(t)$:

$$EADd_i(t) = \sum_{j=1}^{r} \alpha_j \times EADd_{f_j}(t),$$

where $f_j(t)$ represents the node with the j-th highest relay priority, and r is the total number of candidate relay nodes in the CFS $F_i(t)$. The weights ($\alpha_j$) are used to balance the influence of different nodes in the CFS.

The RLOR algorithm then uses reinforcement learning (RL) update procedures based on ACK messages to iteratively and independently update the EAD values of each node. Each node i can learn and dynamically adjust its EAD value based on local information. The relay priority of candidate forwarder nodes is determined by assigning higher priority to nodes with lower EADs.

The simulation results conducted on the discrete event simulator NS-2 demonstrate that the RLOR algorithm achieves lower end-to-end delay for packet transmission over multi-hop wireless networks while maintaining higher viewing quality compared to existing schemes, making it suitable for live streaming applications in VANETs.

## 3. REINFORCEMENT LEARNING BASED OPPORTUNISTIC ROUTING

Path-cost Metric in VANET:

To optimize the selection of relay nodes in the Candidate Forwarder Set (CFS) and improve network performance for live transmission, we propose a novel path-cost metric called the expected anypath delay (EAD). The EAD estimates the total delivery time of a packet from the current node to the destination, considering three delay components:

1. Queue Delay ($q_i(t)$): This represents the instant queuing delay for node i at time slot t. To estimate the current waiting time ($Q_i(t)$) of a packet in the queue of node i at the MAC layer, we use a moving average method based on previous queuing delays.

2. Expected One-hop Transmission Delay ($T_{i,F_i(t)}(t)$): This component measures the time required for a packet to be successfully transmitted from sender node i to at least one node in its CFS $F_i(t)$. We calculate this based on the delivery probability of the hyperlink (i, $F_i(t)$) and consider factors such as the packet size and data transmission rate.

3. Expected Delivery Delay on the Remaining Path: This component represents the EAD of the CFS $F_i(t)$ to the destination. We calculate it as a weighted sum of the EADs of the nodes in the CFS $F_i(t)$.

The EAD of each node reflects the congestion level and delivery ability of the current node, as well as the corresponding measure of its relay node iteratively. To calculate the EAD estimate for node i (EADd i (t)), the node utilizes information from its CFS and performs reinforcement learning (RL) update procedures. The node can then use this estimate to dynamically update its EAD value over time.

By incorporating EAD as the path-cost metric, the proposed RLOR algorithm can effectively select relay nodes in the CFS to minimize end-to-end delays during transmission. This optimization enhances the overall network performance for live streaming applications in Vehicular Ad-Hoc Networks (VANETs).

## 4. EXPERIMENTS

Results in VANET:

Table I: Simulation Setup

| Parameter | Value |
|---|---|
| Simulator | NS-2.26 |
| Topology | 3 × 4 grid |
| Distance between nodes | [180, 185] m |
| Nodes communication | 802.11b |
| Propagation model | LogDistancePropagationLossModel |
| Error rate model | NistErrorRateModel |
| Remote station manager | ConstantRateWifiManager |
| WiFi data rate | 11 Mbps |
| Source rate of video flow | 5 Mbps (unless stated otherwise) |
| Source rate of other flows | 2 Mbps |
| Transmission power | 20 dBm |
| Packet size | 1040 bytes |
| Buffer size | 300 packets |
| Learning rate (μ) | 0.5 |
| Test video sequences | Tractor, Sunflower |
| Frame rate | 60 fps |
| Resolution | 1080p (1920 × 1080) |
| GOP coding structure | IPPPP, 30 frames |

The simulation results demonstrate that the proposed RLOR algorithm achieves lower end-to-end delay for packet transmission over multi-hop wireless networks while maintaining higher viewing quality compared to existing schemes. It strikes an appropriate trade-off between transmission reliability and latency, supporting low-delay transmission of wireless streams with high quality in VANETs. The details of the results and performance metrics are discussed in the paper.

The proposed RLOR algorithm is shown to outperform existing opportunistic routing (OR) algorithms EAX-OR and ETX-OR, as well as the traditional RL-based single-path routing method (RL-TR). It achieves lower average end-to-end delays and higher viewing quality (measured by Y-PSNR) for live video streaming over multi-hop wireless networks as in fig 1.

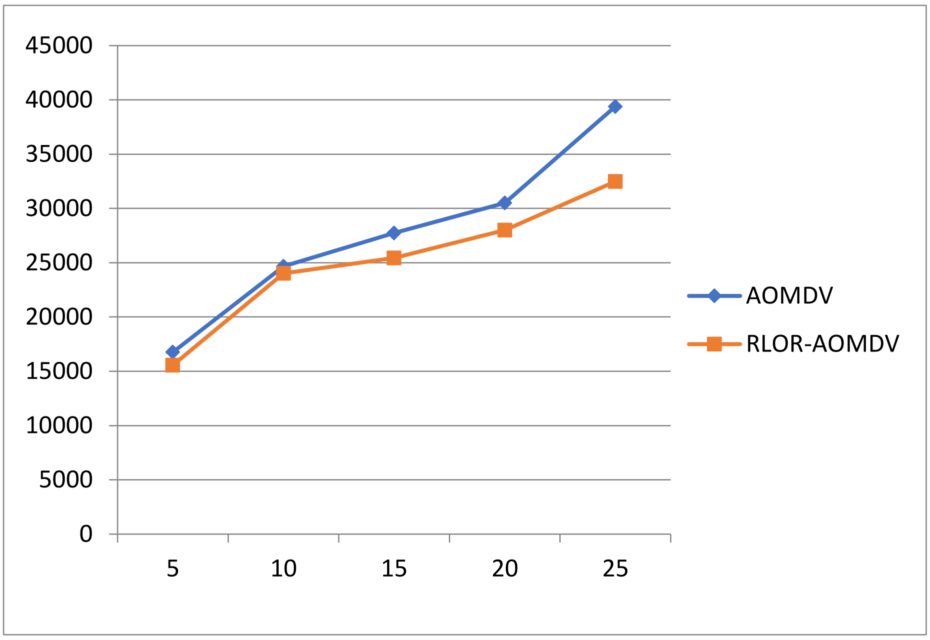


Figure 1 End to end delay in varied connections

The comparison results indicate that the RLOR algorithm dynamically adapts to time-varying network conditions, learning and optimizing the relay priority of candidate forwarder nodes based on the expected anypath delay (EAD) metric. This adaptive approach allows RLOR to strike a balance between reducing retransmission overhead and avoiding queuing delays, leading to lower end-to-end delays and improved overall network performance.

Moreover, the RLOR algorithm's superiority becomes more pronounced as the user at the destination node requests a higher source rate, highlighting its effectiveness in handling high-demand scenarios.

The RL-TR algorithm's performance is significantly affected by the decrease in transmission power level, leading to higher delays due to its fixed single-path routing approach. In contrast, the RLOR algorithm's dynamic path selection based on real-time network conditions helps maintain a stable and low end-to-end delay for packets, making it more robust to changes in transmission power.

Overall, the proposed RLOR algorithm demonstrates its potential for live video streaming applications in Vehicular Ad-Hoc Networks (VANETs). It achieves low-delay transmission with high-quality viewing, making it a promising solution for real-time streaming services in future mobile communication systems.

## 5. CONCLUSIONS

In this paper, we proposed RLOR, a reinforcement learning-based opportunistic routing scheme, to improve live streaming performance in multi-hop wireless networks. We introduced the new path-cost metric, expected any path delay (EAD), to estimate packet end-to-end delays. The RLOR algorithm dynamically learned EAD values for each node using reinforcement learning updates and made opportunistic forwarding decisions based on these values.

Simulation results showed that RLOR effectively balanced network traffic, meeting low-delay requirements for live streaming over multi-hop wireless networks. It outperformed existing approaches, achieving better average viewing quality and reduced temporal quality variation. By adapting to the dynamic wireless environment and intelligently selecting relay nodes, RLOR significantly improved the performance of live streaming applications in VANETs.

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