Adaptive Routing Protocols for QoS-Aware Communication in 5G Mobile Networks: A Review and Research Perspectives

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Abstract:
The rapid deployment of fifth-generation (5G) mobile networks has created new requirements for efficient, reliable, and adaptive routing. Unlike previous generations of mobile networks, 5G is expected to simultaneously support enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC). These services impose substantially different requirements in terms of bandwidth, latency, reliability, packet loss, energy consumption, and network availability. Consequently, conventional routing protocols based primarily on hop count or shortest-path criteria are often insufficient for heterogeneous and highly dynamic 5G environments. This paper presents a review of adaptive and QoS-aware routing approaches for 5G mobile networks. The review focuses on multi-parameter routing, stable route selection, congestion-aware routing, reinforcement-learning-based routing, and QoS prediction-based route selection. Recent developments from 2021 to 2025 are analyzed to identify the major approaches, performance objectives, and limitations of existing methods. A comparative framework is presented based on routing metrics, adaptation mechanisms, supported QoS requirements, and application scenarios. The review further identifies important research gaps related to real-time QoS prediction, intelligent route selection, network slicing, mobility, scalability, routing overhead, and energy efficiency. Finally, an adaptive QoS-aware routing framework is proposed that combines real-time network monitoring, multi-criteria route evaluation, service-aware routing, and machine learning-based prediction. The study provides a foundation for developing intelligent routing protocols for 5G and future beyond-5G mobile networks.

Keywords: 5G mobile networks, adaptive routing, QoS-aware routing, intelligent routing, machine learning, reinforcement learning, network slicing, route selection, 5G QoS.

1. Introduction

Fifth-generation mobile communication technology represents a major transformation in wireless networking. In addition to providing substantially higher data rates than previous generations, 5G is designed to support extremely low latency, high reliability, massive device connectivity, improved spectral efficiency, and flexible service delivery. These capabilities make 5G suitable for applications including autonomous vehicles, smart healthcare, industrial automation, augmented reality, intelligent transportation, smart cities, and Internet of Things (IoT) services.

However, the heterogeneous nature of 5G applications creates significant challenges for network routing. Different applications require different levels of Quality of Service (QoS). For example, video streaming requires high bandwidth, whereas industrial control and autonomous driving require very low latency and high reliability. Massive IoT applications may involve a very large number of devices with relatively low data rates and strict energy constraints.

Conventional routing protocols generally select paths using relatively simple metrics such as hop count, link cost, or shortest distance. Such approaches do not adequately capture the dynamic conditions of 5G networks. Network congestion, mobility, wireless channel quality, traffic load, packet loss, and available bandwidth can change rapidly. A route that is optimal at one instant may become unsuitable a short time later.

Recent research demonstrates the increasing interest in this area. Jegadeesan et al. proposed a stable route-selection mechanism for adaptive packet transmission in 5G-based mobile communications, emphasizing route stability, packet loss, communication cost, and network lifetime. Similarly, reinforcement learning has been applied to AODV to improve QoS-aware routing in 5G-based mobile ad hoc networks. The proposed approach maintains information about intermediate nodes and uses learned information for selecting QoS-guaranteed routes.

More recently, researchers have explored prediction-based approaches. Liu et al. proposed a route-planning scheme that predicts 5G QoS using probability distribution detection. Their results indicate that predicting network throughput can improve route planning compared with conventional distance-based selection. These developments indicate a transition from static routing toward intelligent, predictive, and service-aware routing.

2. QoS Requirements in 5G Mobile Networks

5G networks support several major service categories, each with different QoS requirements.

2.1 Enhanced Mobile Broadband

eMBB applications include high-definition video, cloud gaming, virtual reality, augmented reality, and high-speed Internet access. These applications primarily require:

- High throughput
- High available bandwidth
- Low packet loss
- Acceptable latency
- Stable connectivity

Therefore, bandwidth and throughput are important parameters when selecting routes for eMBB traffic.

2.2 Ultra-Reliable Low-Latency Communication

URLLC is intended for applications where communication delay and reliability are critical. Examples include:

- Industrial automation
- Autonomous vehicles
- Remote control
- Mission-critical communication
- Smart healthcare

For URLLC, route selection should emphasize latency, reliability, packet loss, and route stability.

2.3 Massive Machine-Type Communication

mMTC supports a very large number of connected devices. Examples include:

- Smart meters

- Environmental sensors
- Smart agriculture
- Smart-city devices
- Industrial IoT

The principal concerns are scalability, energy efficiency, connectivity, and efficient use of network resources.
Therefore, a single routing metric cannot be optimal for all 5G applications.

3. Conventional Routing and Its Limitations

Traditional mobile and ad hoc routing protocols can broadly be categorized into proactive, reactive, and hybrid approaches.
Proactive protocols maintain routing information continuously. Their major advantage is rapid route availability, but maintaining routing tables can generate considerable overhead in highly dynamic environments. Reactive protocols establish routes when required. AODV is a well-known example. Reactive routing reduces unnecessary routing information but can introduce route-discovery delay. Hybrid approaches attempt to combine the advantages of both mechanisms. Although these approaches remain useful, their conventional route-selection metrics are often insufficient for 5G applications. For example, selecting the route with the minimum number of hops does not necessarily produce the route with the lowest delay or highest reliability.
Consider two routes:

- Route A: 3 hops, high congestion, poor wireless quality
- Route B: 4 hops, low congestion, high link quality

A shortest-hop routing protocol may select Route A, while a QoS-aware protocol may select Route B.
This illustrates the fundamental motivation for adaptive QoS-aware routing.

4. QoS Parameters for Adaptive Routing

An adaptive routing protocol can consider multiple parameters simultaneously.

- End-to-End Delay

Delay represents the time required for a packet to travel from source to destination.
[D=D_{processing}+D_{queue}+D_{transmission}+D_{propagation}]
Low delay is particularly important for URLLC services.

- Available Bandwidth

Available bandwidth represents the remaining capacity of a communication link or path.
Higher available bandwidth is desirable for eMBB traffic.

- Packet Loss

Packet loss is an important indicator of communication reliability.
[PLR=] A lower packet-loss rate indicates better route reliability.

- Link Quality

Link quality can be estimated using received signal strength, signal-to-noise ratio, channel quality indicators, or other wireless measurements.

- Congestion

Congestion occurs when traffic demand exceeds the available capacity of network resources. Queue length, buffer utilization, and packet waiting time can be used as congestion indicators.

- Mobility

Mobility can significantly affect route stability. A route involving highly mobile nodes may fail more frequently than a route involving relatively stable nodes.

- Energy

Although 5G base stations and user equipment may have substantial resources, energy efficiency remains important for IoT and mobile devices.

5. Review of Recent Adaptive Routing Approaches

5.1 Stable Route Selection

Jegadeesan et al. proposed a stable route-selection mechanism for adaptive packet transmission in 5G-based mobile communications. Their approach considers route stability, packet loss, communication cost, queue conditions, and overload detection. The authors designed a dispersed path-selection mechanism and evaluated it using NS-2.

The study demonstrates that route selection should consider more than geographical distance. However, the approach remains primarily based on explicitly designed routing criteria rather than predictive learning.

5.2 Reinforcement-Learning-Based Routing

Reinforcement learning provides a promising mechanism for adaptive routing because routing decisions can be learned from interaction with the network. A 2024 study proposed an improved AODV mechanism for 5G-based MANETs using reinforcement learning. Each node maintains information about intermediate nodes and uses this information to identify routes satisfying QoS requirements. The study reported improvements in throughput, end-to-end delay, and signal-to-noise ratio. The major advantage of this approach is its ability to adapt routing decisions according to network experience. However, reinforcement-learning-based routing can introduce computational complexity and requires appropriate state, action, and reward definitions.

5.3 Prediction-Based QoS Routing

An emerging direction is to predict future network conditions instead of making routing decisions exclusively from current measurements.

Liu et al. proposed a 2025 route-planning approach based on 5G QoS prediction and probability distribution detection. The study combines different prediction models and uses probability confidence weights to improve prediction accuracy. The authors reported a mean absolute error of 0.128 and root mean square error of 0.189 for throughput prediction.

This approach demonstrates the potential of predictive QoS for route selection, particularly in highly dynamic V2X environments.

5.4 Intelligent Adaptive Routing

Deep reinforcement learning is another emerging approach. Rather than manually defining routing rules, a deep neural network can learn relationships between network states and routing actions.

This approach can potentially consider:

- Current congestion
- Historical traffic
- Mobility
- Link quality

- Delay
- Packet loss
- Available bandwidth

However, deep learning models require computational resources and appropriate training data.

6. Comparative Analysis

Table 1. Comparison of Routing Approaches

Approach	Major Metric	Adaptation	QoS Awareness	Intelligence	Major Limitation
AODV	Hop count	Medium	Low	Low	Limited QoS consideration
OLSR	Link/topology	Medium	Low	Low	Routing overhead
Stable adaptive routing	Stability, loss, distance	High	Medium	Low	Fixed decision criteria
QoS-aware routing	Delay, bandwidth, loss	High	High	Low–Medium	Parameter weighting
RL-based routing	Network state/reward	High	High	High	Training complexity
DRL-based routing	Multiple network states	Very High	High	Very High	Computational cost
Predictive QoS routing	Predicted network state	Very High	Very High	High	Prediction accuracy

The comparison indicates that intelligent and predictive approaches provide greater adaptability but also introduce additional complexity.

7. Proposed Conceptual Framework for Adaptive QoS-Aware Routing

Based on the reviewed literature, an adaptive QoS-aware routing framework can be organized into five layers.

Layer 1: Network Monitoring

The network continuously collects:

- Delay
- Bandwidth
- Packet loss
- Link quality
- Queue utilization
- Mobility
- Traffic load

Layer 2: QoS Classification

Traffic is classified according to its service requirements:

eMBB → bandwidth-oriented

URLLC → delay/reliability-oriented

mMTC → scalability/energy-oriented

Layer 3: QoS Prediction

Machine learning models can predict short-term changes in:

- Network congestion
- Throughput
- Delay
- Link quality

Prediction allows routing decisions to become proactive rather than reactive.

Layer 4: Adaptive Route Selection

A composite routing score can be calculated as:

$$RS=_{i=1}^{n}w_iQ_i$$

where (Q_i) represents a normalized QoS parameter and (w_i) represents its dynamically assigned weight.

For example:

$$RS=w_DD+w_BB+w_RR+w_LL+w_CC$$

The weights should change according to the application.

Layer 5: Route Monitoring and Recovery

After route establishment, the route is continuously monitored. If its QoS deteriorates beyond a defined threshold, an alternative route is selected.

This framework combines the strengths of conventional routing, QoS-aware routing, and intelligent prediction.

8. Research Gaps

The review identifies several important research gaps.

- Static QoS Weights

Many multi-criteria routing approaches rely on predefined weights. However, the optimal weights may change with traffic and network conditions. A future protocol should dynamically learn the appropriate weights.

- Reactive Rather Than Predictive Routing

Many routing protocols react after congestion or link degradation occurs. Predictive routing can identify potential degradation before it becomes severe. The 2025 QoS-prediction study demonstrates the potential of this direction.

- Limited Integration of Network Slicing

Different 5G slices have different QoS requirements. Routing should therefore be slice-aware rather than treating all traffic identically.

- Mobility

High mobility can cause frequent route changes. Future protocols should incorporate mobility prediction into route selection.

- Routing Overhead

Continuous monitoring and exchange of QoS information may increase control overhead. Therefore, adaptive routing must balance QoS improvement with signaling cost.

- Explainability of AI-Based Routing

Deep learning and reinforcement learning can produce highly complex decisions. In mission-critical 5G applications, it is desirable to understand why a particular route was selected.

- Scalability

A routing mechanism suitable for 25 or 50 nodes may not perform equally well in a network containing thousands or millions of devices.

9. Future Research Directions

Future research can focus on developing a Deep Reinforcement Learning-Based Adaptive QoS Routing Protocol (DRL-AQRP). The protocol could use the following network state:

[S={D,B,PL,LQ,C,M,T}]

where:

- (D) = delay
- (B) = bandwidth
- (PL) = packet loss
- (LQ) = link quality
- (C) = congestion
- (M) = mobility
- (T) = traffic type

Possible actions include:

- Select next hop
- Select alternative route
- Maintain current route
- Trigger route discovery

The reward function could combine QoS objectives:

[R=PDR+Throughput-Delay-PLR-Overhead]

Such a framework would allow the routing protocol to learn an optimal policy from changing network conditions.

Another promising direction is the integration of **5G network slicing and edge computing**. The edge can perform computationally intensive prediction while routing nodes use the resulting information for fast route selection.

10. Conclusion

This paper reviewed adaptive and QoS-aware routing approaches for 5G mobile networks and analyzed their suitability for heterogeneous 5G services. The review shows that traditional routing approaches based primarily on shortest path or hop count are insufficient for modern 5G applications because they do not adequately capture dynamic QoS conditions. Recent research has increasingly incorporated route stability, congestion, QoS parameters, reinforcement learning, and QoS prediction. Studies published between 2021 and 2025 demonstrate a clear transition from conventional routing toward intelligent and predictive routing mechanisms. The analysis indicates that future adaptive routing protocols should jointly consider delay, bandwidth, reliability, packet loss, congestion, mobility, and traffic class. Moreover, the routing mechanism should dynamically modify the importance of these parameters according to the requirements of eMBB, URLLC, and mMTC services. A conceptual adaptive QoS-aware routing framework was therefore presented in this paper. The framework combines real-time network monitoring, service-aware QoS classification, QoS prediction, adaptive route selection, and route monitoring. The integration of machine learning and reinforcement learning with QoS-aware routing represents a particularly promising direction. Such approaches can enable 5G networks to move from reactive routing toward predictive, self-optimizing, and intelligent routing. The proposed review provides a foundation for future development of intelligent adaptive routing protocols for 5G and beyond-5G networks.

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