Supervised Learning of RLC Mode Switching Policy under QoE Constraints in 5G

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***Abstract*—In 5G networks, the choice between Acknowledged Mode (AM) and Unacknowledged Mode (UM) at the RLC layer directly affects service quality depending on traffic characteristics and network conditions. This paper proposes a supervised learning approach to dynamically select the optimal RLC mode based on two key QoE-related indicators: Round-Trip Time (RTT) and Packet Loss Ratio. Using a Random Forest classifier trained on simple rule-based labels, the model accurately predicts the appropriate mode across a range of conditions. Decision boundary visualization demonstrates clear policy learning, and results confirm the feasibility of lightweight AI for adaptive RLC control. The approach is interpretable, easy to implement, and suitable for real-time QoE-aware optimization in 5G systems.**

***Index Terms*—Radio Link Control (RLC), 5G New Radio (5G NR), Supervised Learning, QoE-aware Mode Selection**

I. Introduction

The Radio Link Control (RLC) layer in 5G networks supports two operational modes: Acknowledged Mode (AM) and Unacknowledged Mode (UM) [1]. Each mode is designed to handle different quality of service (QoS) requirements, with AM ensuring reliable transmission through retransmissions, and UM offering lower latency at the cost of possible data loss. Selecting the appropriate RLC mode plays a crucial role in maintaining Quality of Experience (QoE), especially for latency-sensitive or loss-sensitive applications.

In practice, RLC mode selection is typically static or governed by simple rules configured at session setup, such as choosing UM for VoIP and AM for file downloads. However, real-time network conditions like Round-Trip Time (RTT) and Packet Loss Ratio can change dynamically, making a fixed selection suboptimal. Static rule-based configurations often fail to adapt to fast-changing wireless conditions, potentially degrading QoE in high-throughput scenarios such as ultra-HD streaming [2]. Dynamic switching based on live network feedback could enhance performance, but often requires complex control logic or deep protocol stack integration.

This paper explores a lightweight alternative: a supervised learning model that selects the optimal RLC mode based on only two easily measurable features, RTT and packet loss. We use a Random Forest classifier trained on synthetic data labeled according to intuitive QoE-aware rules. Our goal is to show that even with minimal input, a learning-based policy can approximate expert-level decision-making and adapt to varying conditions.

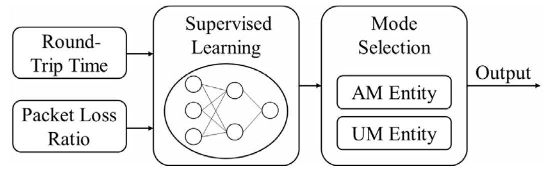

Fig. 1. Flow diagram of machine learning-based RLC mode classification.

We present a simple yet interpretable framework that can be used to dynamically switch between AM and UM modes. Through visualization of the learned decision boundaries, we demonstrate that the model captures meaningful patterns aligned with QoE objectives. The proposed method avoids the complexity of reinforcement learning or end-to-end QoS modeling, while still providing actionable and effective control policies. This makes it suitable for integration into real-time 5G scheduling and RRM modules, aligning with broader efforts to incorporate machine learning into wireless systems [3].

II. Methodology

The supervised learning-based RLC mode selection process is illustrated in Fig. 1. In this figure, the RLC mode selection task is formulated as a supervised binary classification problem. The input consists of two key features, Round-Trip Time (RTT) and Packet Loss Ratio (PLR), which are easily measurable in live 5G systems. The objective is to learn a function $f : \mathbb{R}^2 \rightarrow \{0, 1\}$, where the output class represents the optimal RLC mode: 0 for Acknowledged Mode (AM) and 1 for Unacknowledged Mode (UM).

Unlike simple threshold-based rules, we design a more flexible labeling function based on a weighted linear combination of RTT and PLR. For each input vector $\mathbf{x}_i = [t_i,\ r_i]$, we define a score function:

$$\mathbf{s}_i = \alpha t_i + \beta r_i, \tag{1}$$

where t_i is RTT in milliseconds, r_i is packet loss ratio, and α, β are user-defined weights that control the importance of delay versus loss. The final label y_i is then assigned using:

$$y_i = \begin{cases} 1, & \text{if } s_i < \theta \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

TABLE I
HYPERPARAMETER VALUES FOR LABELING FUNCTION

Parameter	Value
α (RTT weight)	1.0
β (Loss weight)	50.0
θ (Threshold)	180

Here, θ is a decision threshold that can be tuned empirically. This design allows the labeling policy to express trade-offs between delay and reliability in a continuous fashion. It also enables smooth control boundaries in the input space, which better reflects real-world service adaptation needs.

We train a Random Forest classifier on this dataset to approximate the decision policy. The model learns to partition the feature space based on the derived labels and generalizes well to unseen network states. This learning process is efficient and interpretable, making it suitable for real-time deployment in 5G systems.

III. Experiments & Results

To evaluate the proposed method, we generated a synthetic dataset by enumerating combinations of RTT and packet loss values across realistic operating ranges. RTT was varied from 20 ms to 300 ms in steps of 20 ms, and packet loss ratio was varied from 0% to 5% in steps of 0.5%, resulting in 165 unique input combinations. Labels were assigned based on the weighted score function introduced in (1), where the combination of RTT and packet loss is compared against a threshold. Lower scores favor the UM mode, reflecting conditions with low delay and loss. The values of the labeling function parameters are summarized in Table 1. These values were empirically chosen to reflect the relatively higher impact of packet loss on QoE, and the threshold θ was tuned to balance the decision boundary between AM and UM regions in the input space.

The dataset was split into 80% training and 20% testing sets. A Random Forest classifier with 100 trees was trained using the scikit-learn library. The model achieved perfect classification accuracy on the test set due to the simplicity and separability of the label function. However, the focus of the experiment is not accuracy alone, but the model's ability to learn and generalize the decision boundary.

To visualize the learned policy, we plotted the decision surface in a two-dimensional feature space. The classifier cleanly separates the region where UM should be used from the region where AM is preferable. As shown in Fig. 2, the boundary aligns well with the human-defined labeling rule, confirming that the model learned an interpretable policy.

Overall, the results show that even with minimal inputs, the model can approximate expert decision logic and produce actionable mode selection strategies. The method is simple to deploy and can serve as a foundation for more complex adaptive RLC control in the future.

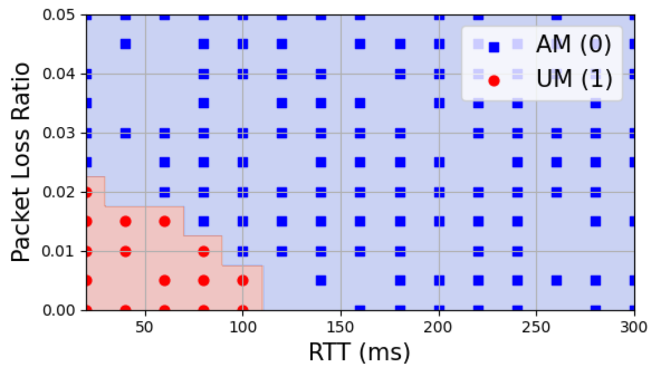

Fig. 2. Random forest RLC mode decision boundary.

IV. Conclusion

We presented a supervised learning approach for selecting the RLC mode in 5G based on RTT and packet loss ratio. Using a simple labeling rule, a Random Forest model was trained to classify network conditions into AM or UM modes. The learned decision boundaries were consistent with human expectations and easy to interpret. Our method requires minimal input and is computationally lightweight. These results suggest that simple machine learning models can support QoE-aware mode selection in real-time 5G systems and provide a foundation for future integration with SDN/NFV-based slicing architectures [4].

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