

Supplementary Materials for AraLive

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1 OVERVIEW OF THE SUPPLEMENTARY MATERIALS

In the main text, we compare various methods in the live video streaming scenario and show that AraLive can enhance the performance of RL-based BCAs effectively. In the supplementary materials, we discuss how AraLive improves RL-based Bitrate Control Algorithms (BCAs) for Video on Demand (VoD) scenarios, which are not presented in the main text due to space limitations. Through experiments, we observe that AraLive can also boost the QoE performance of RL-based BCAs across diverse VoD sessions.

2 EXPERIMENT EVALUATION IN VOD SCENARIOS

Baselines and experimental methodologies: (i) Pensieve [2], a BCA optimization scheme through a reinforcement learning algorithm named A3C [3]. It optimizes QoE by analyzing past network state changes to assess the most suitable bitrate for the next video chunk. In particular, we substitute Pensieve’s formula-based reward function as AraLive and renamed it to *Pensieve-AraLive*. (ii) Fugu [4], which employs general neural networks to predict future video download times based on historical data. The VoD system is implemented based on the Dash framework [1]. We conducted more than 80 sessions, each lasting over 10 minutes, culminating in a total of over 14 hours of VoD streaming. Moreover, our analysis mainly centered on 3 application layer metrics, *i.e.*, *video bitrate*, *rebuffering time*, and *streaming smoothness*.

Overall comparisons. Figure 1 provides a summary of performance metrics for the evaluated BCAs across all VoD sessions. Notably, *Pensieve-AraLive* achieves the highest video bitrate, marking an improvement of 5.2% to 7.4% over Fugu and Pensieve, respectively. It also significantly reduces rebuffering times by 57.6% and 69.8%, and enhances streaming smoothness with reductions of 40.2% and 45.5% against Fugu and Pensieve, respectively. Moreover, the data shows that while Pensieve initially underperforms compared to Fugu, AraLive help Pensieve dramatically improve its performance. This enhancement effectively minimizes rebuffering time and maintains a high bitrate, leading to a superior overall performance.

Newtork breakdown. We further divide those VoD sessions into two categories based on throughput: robust networks with throughput higher than the average of all sessions (taking a fraction of 35%), and weak networks with throughput lower than the average of all sessions (taking a fraction of 65%). Figure 2 illustrates the performance of different methods under two distinct network conditions. In weak network sessions, *Pensieve-AraLive* not only enhances the video bitrate but also reduces rebuffering time. For instance, compared to Pensieve and Fugu, the video bitrate of *Pensieve-AraLive* has increased by 6.1% and 3.1%, respectively, while the rebuffering time has decreased by 60.1% and 51.4%. In robust network sessions, although Pensieve performs less effectively than Fugu, *Pensieve-AraLive* stands out by increasing the bitrate by 8.3% and decreasing rebuffering by 29.9% compared to

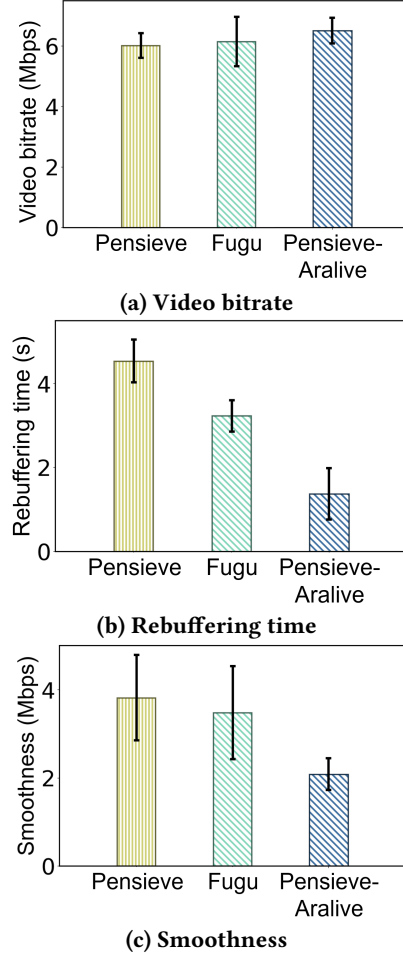


Figure 1: Overall comparisons on VoD scenarios.

Fugu, due to its advantages in automatic reward adaptation. These improvements demonstrate that AraLive significantly enhances the performance of RL-based BCAs under both weak and robust network conditions.

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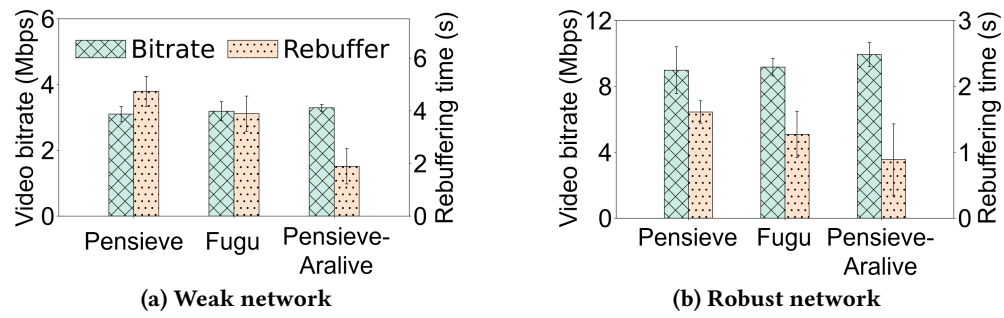


Figure 2: Performance comparisons of different methods in two network conditions.