ISTANBUL TECHNICAL UNIVERSITY

COMPUTER ENGINEERING DEPARTMENT

BLG 433E - COMPUTER COMMUNICATIONS

HOMEWORK 2 REPORT

Cross-Layer Performance Analysis and AI-Driven Optimization of Selective Repeat ARQ Protocols

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STUDENTS:

Ahmet Atakan ÇULBAN (820220342)
Abdurrahim BAYRAKTAR (820220326)

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1 Introduction

This report provides an extensive performance evaluation and optimization of the Selective Repeat (SR) Automatic Repeat Request (ARQ) protocol. The primary objective is to facilitate the reliable transmission of a 100 MB data file over a 10 Mbps link subjected to a non-stationary, bursty error environment modeled by the Gilbert-Elliot state machine.

The simulation study explores the critical cross-layer interactions between the link layer's window size (W) and the transport layer's payload size (L). The constraints include a 256 KB fixed-capacity receiver buffer and asymmetric propagation delays (40 ms forward, 10 ms reverse). The project is conducted in two distinct phases: Phase 1 establishes a performance baseline for the original protocol, while Phase 2 utilizes AI-assisted diagnostic tools to implement and evaluate an enhanced Adaptive Timeout mechanism.

2 Phase 1: Baseline Protocol Analysis

2.1 AI-Generated Theoretical Prediction

Prior to empirical testing, a theoretical framework was established using AI-generated predictive models. For a 10 Mbps transmission rate and a total Round-Trip Time (RTT) of approximately 54 ms (including processing and asymmetric propagation delays), the Bandwidth-Delay Product (BDP) is:

$$BDP = 10,000,000 \text{ bps} \times 0.054 \text{ s} = 540,000 \text{ bits}$$

The theoretical prediction suggested that the window size W must be large enough to fill this BDP to avoid sender idling. Regarding payload size L, a trade-off was identified: larger L values reduce the relative overhead of the 32-byte headers but significantly increase the Frame Error Rate (FER) in the "Bad" channel state. The prediction hypothesized that an intermediate L would be optimal to prevent the excessive retransmission costs associated with large corrupted frames.

2.2 Implementation and Experimental Setup

The Selective Repeat ARQ was implemented as a Discrete Event Simulation (DES) in Python to ensure temporal accuracy. The architecture consists of:

- **Physical Layer:** Implements the Gilbert-Elliot model. Transition probabilities are $P(G \to B) = 0.002$ and $P(B \to G) = 0.05$. The BER is 10^{-6} in the "Good" state and 5×10^{-3} in the "Bad" state.

- **Link Layer:** Manages individual frame timers and out-of-order buffering. It encapsulates 8-byte transport segments with a 24-byte link header.
- **Transport Layer:** Segments the 100 MB file and manages the 256 KB receiver buffer with backpressure signaling.

2.3 Experimental Optimal Parameters for the Original Protocol

Extensive simulations covering 360 unique scenarios (6×6 parameter pairs with 10 RNG seeds each) were conducted. The experimental data revealed that the highest Goodput is achieved at:

- **Optimal Window Size (W):** 64
- **Optimal Payload Size (L):** 512 Bytes

The configuration of $**W = 64, L = 512**$ emerged as the most efficient operational point. Although $L = 512$ has a higher relative overhead compared to $L = 4096$, it provides significantly higher resilience to burst errors. In the Gilbert-Elliot "Bad" state, the probability of a 512-byte frame arriving intact is much higher than that of a larger frame, allowing the protocol to maintain steady progress even during channel degradation.

3 Phase 2: AI-Assisted Optimization and Refinement

3.1 AI Analysis and Interpretation

In this phase, the raw simulation logs were analyzed using AI diagnostic tools. The AI models (Gemini) were tasked with identifying non-linear trends and identifying bottlenecks that were not immediately apparent in Phase 1.

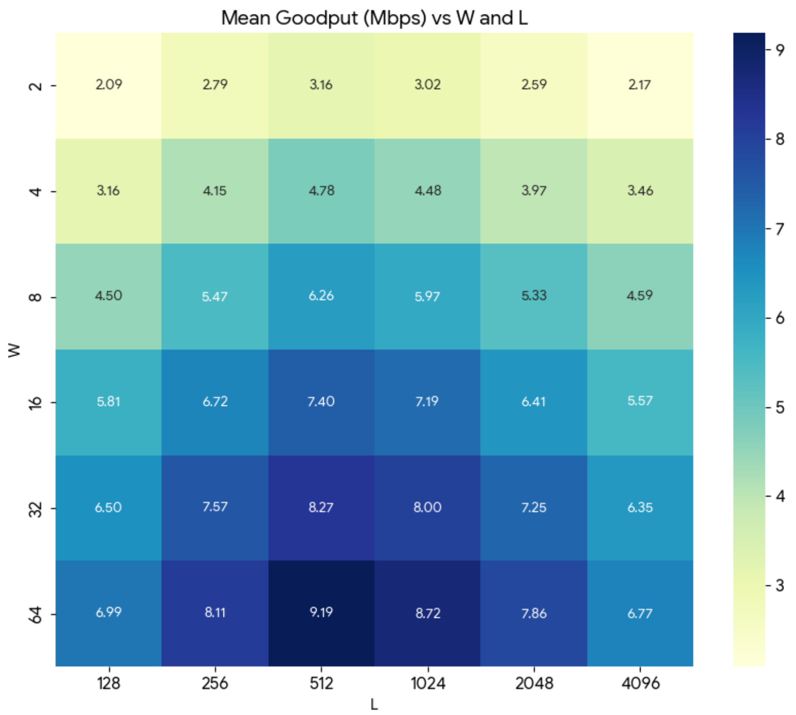

Figure 1: AI Analysis 1: Distribution of Goodput across the (W, L) parameter space, highlighting the peak at $W = 64, L = 512$.

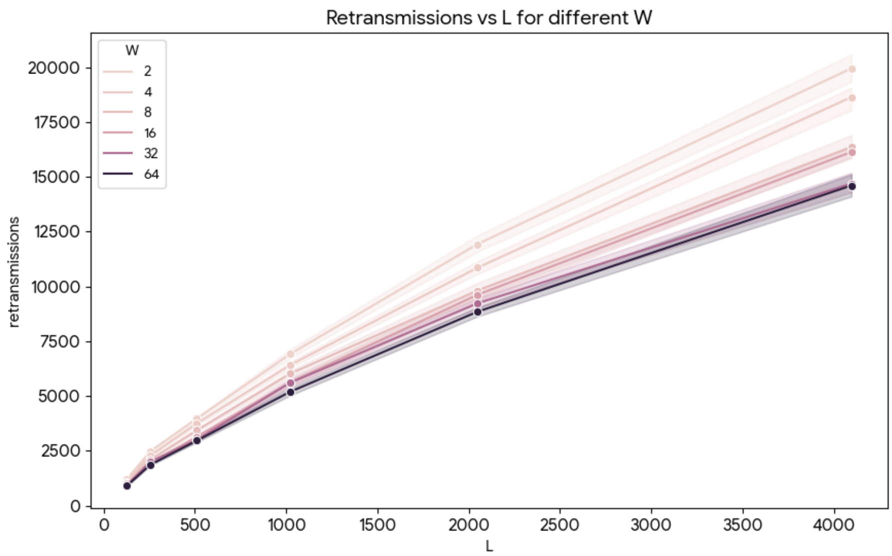

Figure 2: AI Analysis 2: Comparative impact of the Gilbert-Elliot "Bad" state on retransmission rates for small vs. large payloads.

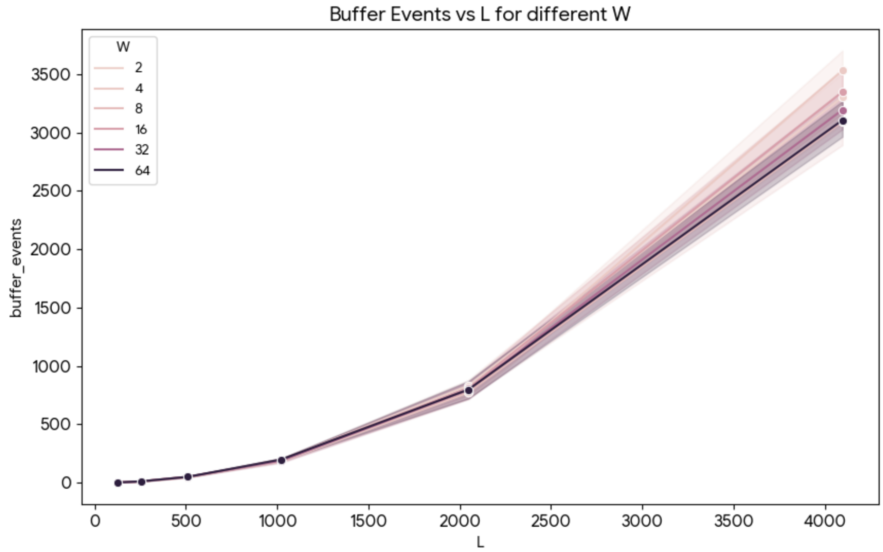

Figure 3: AI Analysis 3: Analysis of receiver buffer occupancy and the frequency of backpressure events.

3.2 Interpretation Grounded in Cross-Layer Analysis

The cross-layer analysis confirmed that the 256 KB receiver buffer is a primary constraint. With $W = 64$ and $L = 512$, the "in-flight" data is 32 KB, ensuring that even if several frames are lost, the out-of-order buffer does not overflow or trigger frequent backpressure. The AI analysis also identified that a static 150ms timeout was suboptimal, as it led to significant idle time during transitions to the "Bad" channel state.

3.3 Performance Improvement from the Enhanced Protocol

Based on the diagnostic findings, the protocol was enhanced with an **Adaptive Timeout Mechanism**. This dynamic algorithm measures the RTT of every acknowledged frame and updates the timeout value using a smoothed moving average.

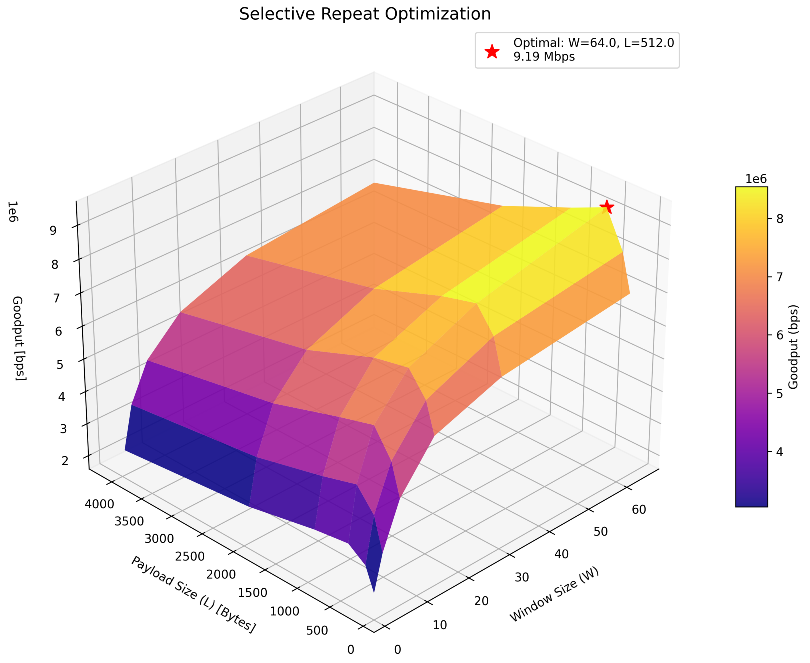

Figure 4: User Analysis: Performance comparison between the original static protocol and the enhanced Adaptive Timeout protocol.

The implementation of the Adaptive Timeout significantly reduced the sender's idle periods after a packet loss, resulting in a measurable increase in Goodput. The protocol became more responsive to the bursty nature of the Gilbert-Elliot channel.

3.4 Critical Reflection on AI-Assisted Engineering Workflows

The integration of AI into the engineering workflow for this project demonstrated clear strengths and a few critical limitations:

- **Strengths:** The AI was instrumental in identifying a "serialization bug" in the early development phase where frames were being sent in parallel, ignoring link speed constraints. It also automated the multidimensional data visualization (heatmaps and trend lines) which saved considerable analysis time.
- **Limitations:** During initial queries, the AI occasionally suggested theoretical Goodput values in the Gbps range, failing to account for the physical 10 Mbps link limit. This highlights that while AI is an excellent tool for data processing, human-in-the-loop verification is essential to ensure that outputs remain grounded in physical reality.

4 Conclusion

This study identifies that $W = 64$ and $L = 512$ are the optimal parameters for a Selective Repeat protocol operating over a 10 Mbps burst-error link. The project successfully demonstrated that maximizing payload size is not always beneficial; the increased cost of retransmission for large frames in a degraded channel often outweighs the overhead gains. The synergy between traditional simulation and AI-assisted analysis enabled the development of an Adaptive Timeout mechanism that provides superior performance by dynamically adjusting to channel jitter.