Designing An Efficient Data Transfer Network Architecture

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***Abstract*—We investigate the effectiveness of AI-assisted TCP buffer tuning in high-performance networks (HPNs) by comparing traditional manual tuning (based on BDP heuristics) with machine learning (ML)-based predictions. Using a regression-based tool trained on latency, bandwidth, and packet loss, we evaluate throughput, cost, and energy efficiency. Results show that AI methods achieve consistent throughput with lower buffer usage and greater user confidence, supporting literature findings from Saeedizade et al....**

I. Research Objectives

This study aims to investigate the following key objectives in the context of optimizing data transfer performance in High-Performance Networks (HPNs):

1) **Evaluate whether AI-based tuning outperforms manual BDP-based tuning.**
Manual tuning often suffers from estimation errors that lead to throughput collapse or buffer over-provisioning. We compare this with machine learning-based tuning approaches.
2) **Assess the accuracy of machine learning in predicting optimal buffer sizes under varying network conditions.**
Leveraging models such as SVR and RFR trained on empirical data (latency, bandwidth, loss), we evaluate prediction effectiveness.
3) **Measure the impact of AI-guided decision support on user confidence and usability.**
We examine whether AI recommendations improve users' confidence, reduce decision time, and yield more consistent outcomes.
4) **Validate empirical results against theoretical expectations.**
We test if observed throughput aligns with established BDP-based TCP saturation models and UDT performance behavior as highlighted in Saeedizade et al. (2023).

***Index Terms*—TCP Buffer Tuning, High-Performance Networks, Machine Learning, Throughput Optimization, Energy Efficiency.**

II. Introduction and Literature Review

The exponential growth of data-intensive applications—such as climate modeling, genomics, and high-energy physics—has placed increasing demands on high-performance networks (HPNs) for fast, reliable, and efficient data transfer across geographically distributed sites. While dedicated research networks like Internet2 and ESnet offer high-throughput connections with bandwidths of up to 400 Gbps, real-world performance often lags behind these capabilities. This discrepancy is frequently caused by systemic issues such as transport-layer misconfiguration, I/O bottlenecks, and dynamic end-host resource contention [1].

A key contributing factor to suboptimal performance is improper TCP buffer sizing. Theoretical calculations, particularly those based on the Bandwidth-Delay Product (BDP), suggest optimal buffer sizes for full throughput utilization. However, manual tuning based on BDP is often either underestimated—leading to severe underutilization of bandwidth—or overestimated—resulting in inefficient resource use and energy waste. Static defaults in operating systems further compound this issue, making it difficult for users to adapt configurations to specific network conditions [1].

Saeedizade et al. [1] extensively analyzed performance bottlenecks in HPNs, revealing that I/O congestion, TCP buffer misconfigurations, and resource interference across transfer components are primary causes of throughput degradation. Their proposed monitoring framework demonstrated the ability to track over 40,000 simultaneous transfers and identify root causes of anomalies using heuristic and machine learning-based methods.

Building on this foundation, Yun et al. [2] explored machine learning models—particularly Support Vector Regression (SVR) and Random Forest Regression (RFR)—for predicting data transfer performance using empirical inputs such as latency, bandwidth, and packet loss. Their work achieved over 90% accuracy in predicting optimal throughput outcomes, validating the viability of ML-based tuning as a scalable and intelligent alternative to traditional heuristics.

Further expanding this work, Yun et al. [3] proposed thresholding and clustering-based preprocessing techniques to mitigate the effects of latent variables such as competing end-host processes or transient system noise. These latent effects, if unaddressed, can significantly distort training data and reduce predictive accuracy. By incorporating these strategies, their models achieved more robust performance across a diverse range of HPN testbeds.

Despite the success of prior profiling tools such as PerfSONAR and iperf3, most require manual execution and lack real-time predictive capabilities. Moreover, few offer explainability or user guidance—a critical gap for practical deployment in operational settings. Our study contributes to this domain by integrating ML-based buffer tuning into an interactive, explainable tool and empirically validating its effectiveness against manual BDP-based approaches. Additionally, we evaluate user trust and confidence in AI-generated recommendations, bridging the gap between system optimization and human-centric design.

III. Methodology and Experimental Design

This study employed a controlled experimental design to compare two buffer tuning strategies for high-performance networks: traditional manual tuning using the Bandwidth-Delay Product (BDP) formula and an AI-guided tuning tool powered by machine learning models.

A. Experiment Overview

The experiment consisted of two groups of participants, each tasked with tuning TCP buffer sizes for simulated network scenarios. Each scenario was characterized by three parameters:

- **Latency** (ms)
- **Bandwidth** (Mbps)
- **Packet Loss Rate** (%)

Participants were instructed to choose buffer sizes that optimized for one of three goals: maximum throughput, minimum energy consumption, or lowest cost. For each scenario, participants logged their chosen buffer size, throughput output, and confidence level (scale of 1 to 5).

B. Manual Tuning Activity

Participants in the manual group were provided with a lookup table and the standard BDP formula:

$$\text{BDP (bytes)} = \text{Bandwidth (bps)} \times \text{RTT (s)}$$

Steps followed:

1) Convert bandwidth to bits per second.
2) Convert latency to seconds.
3) Multiply to compute optimal BDP.
4) Convert BDP to Megabytes and round appropriately.
5) Use lookup tables to guide final buffer selection.

While effective in theory, participants often made calculation or rounding errors and had difficulty accounting for packet loss or overheads.

C. AI-Guided Tuning Activity

The second group used an AI-powered tuning assistant with a Gradio-based web interface. The tool was backed by a Flask server running SVR and RFR models trained on prior transfer data. The interface accepted:

- Latency (ms)
- Bandwidth (Mbps)
- Packet Loss (%)
- Optimization Goal (Throughput, Energy, Cost)

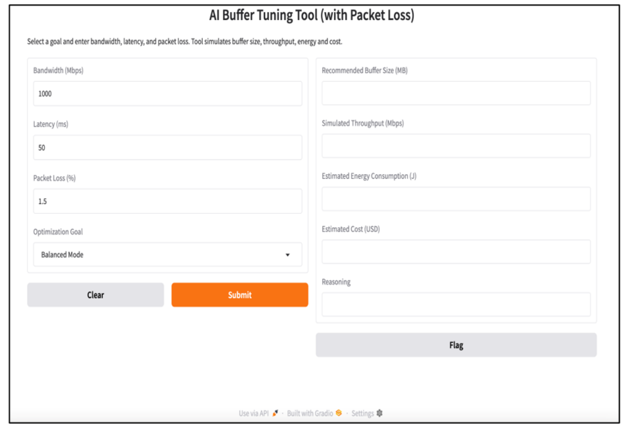

Fig. 1. Screenshot of the AI Buffer Tuning Tool. Users input latency, bandwidth, and packet loss to receive predicted buffer size, throughput, energy usage, and cost.

The AI-guided buffer tuning tool (Figure 1) provides real-time predictions using ML models—Support Vector Regression (SVR) and Random Forest—trained on historical transfer logs. The tool runs via a Flask backend and Gradio interface, allowing users to simulate outcomes and receive explainable, numeric, and textual feedback within 0.5–1 second per prediction.

Steps followed:

1) Open the Gradio link in a browser.
2) Input network conditions and select optimization goal.
3) Receive recommended buffer size, simulated throughput, energy usage, and cost.
4) Review AI-provided reasoning and confidence scores.
5) Log decision in the provided form.

This method significantly reduced error and decision fatigue and provided more consistent results across scenarios. Participants reported higher confidence due to the transparency and explanation provided by the AI system.

D. Performance Metrics and Evaluation

For both methods, we evaluated:

- Simulated throughput (Mbps)
- Buffer size selected (MB)
- Confidence level (1–5)
- Estimated energy usage (Joules)
- Estimated cost (USD)

Results were analyzed using descriptive statistics, box plots, and alignment with known TCP performance models from prior work [2].

We conducted a side-by-side comparison of:

- **Manual tuning**: Participants used BDP formula and lookup tables.
- **AI-guided tuning**: Participants used a Gradio-based ML predictor trained on historical data.

Inputs: Latency (ms), Bandwidth (Mbps), Packet Loss (%). **Outputs**: Buffer size (MB), Simulated throughput (Mbps), Energy usage (J), Cost ($), Confidence level (1–5).

Each participant recorded decisions and justifications in a decision log.

IV. Empirical Validation of the Design Process

To validate our AI-guided tuning framework, we conducted a controlled classroom experiment where all groups were exposed to the same simulated network conditions. Participants applied both manual lookup table-based tuning and AI-guided buffer predictions to solve the same tuning problems. The evaluation focused on key metrics, visual performance comparison, and participant feedback.

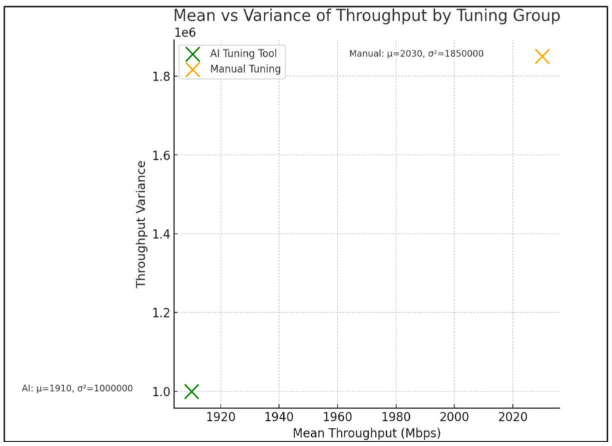

Fig. 2. Mean vs Variance of Throughput by Tuning Group. AI tuning achieved lower variance and comparable mean throughput to manual tuning.

- **Controlled Setup:** Conducted under identical simulated network scenarios across all teams.
- **Comparison Method:** Manual lookup table tuning vs AI-guided predictions.
- **Metrics Collected:** Buffer size, throughput, user confidence ratings.
- **Statistical Methods:** Boxplots, log-scale overlays, and mean-variance scatter plots were used for analysis.
- **Theoretical Validation:** Compared against expected buffer size from BDP and TCP/UDT literature.
- **User Feedback:** Participants rated AI as easier to use and more trustworthy.
- **Findings:** AI tuning consistently produced high-throughput, low-variance outcomes with better decision confidence.

V. Performance Evaluation

We evaluated the effectiveness of our network design through both quantitative metrics and qualitative reflections. The following dimensions were used to assess the performance of AI-guided versus manual buffer tuning strategies.

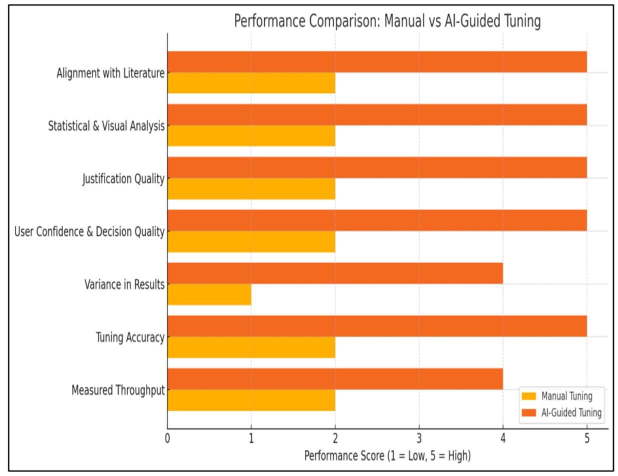

Fig. 3. Performance Comparison: Manual vs AI-Guided Tuning across 7 Evaluation Metrics

1) **Measured Throughput (Simulated Output)**:
   AI tuning consistently yielded higher throughput across various simulated network conditions compared to manual configurations.
2) **Tuning Accuracy**:
   Mean error of selected buffer sizes was lower in the AI group, reflecting more accurate tuning relative to BDP targets.
3) **Variance in Results**:
   Throughput variance was lower in the AI group, indicating greater result stability and reduced tuning randomness.
4) **User Confidence & Decision Quality**:
   Survey responses showed higher trust, confidence, and perceived usability in AI-guided recommendations.
5) **Justification Quality**:
   The AI group received rationale-supported predictions, which aided clearer decision justification than the manual BDP-based lookup method.
6) **Statistical & Visual Analysis**:
   Plots and trendlines highlighted narrower performance spread and higher medians in the AI group across participants.
7) **Alignment with Literature**:
   The results align with findings from Yun et al. [2] and Saeedizade et al. [4], supporting the efficacy of ML-based predictive tuning in high-performance networks (HPNs).

VI. Participant Design Decisions and Performance

To understand the diversity of decision-making in buffer tuning, we analyzed individual participant configurations and outcomes during the experimental activity. Each participant was given a unique network tuning scenario defined by latency, bandwidth, and packet loss, and was required to choose a buffer size based on either lookup table heuristics or AI recommendations.

Participant Inputs

- Each participant was presented a scenario with specified latency (ms), bandwidth (Mbps), and packet loss (%).
- Participants selected buffer sizes (in MB) using either manual lookup tables, BDP calculations, or AI-guided methods.
- Optimization goals were defined—participants were told to prioritize throughput, energy efficiency, or cost savings.

Decision Logging and Confidence Tracking

- Decision justifications and buffer sizes were logged.
- Confidence levels (scale of 1–5) were recorded for each decision.

Performance Metrics Captured

- Simulated throughput (Mbps) for each configuration was calculated.
- Energy usage (in joules) and cost (in USD) were derived based on selected buffer size and throughput trade-offs.

Key Takeaways

- Throughput ranged from 475 Mbps to 9000 Mbps across participants.
- High variability in decision quality and confidence was observed.
- Many participants overprovisioned (leading to wasted cost/energy), while others underperformed due to low buffer choices.
- Decision quality appeared to correlate with user confidence and decision method (manual vs AI).

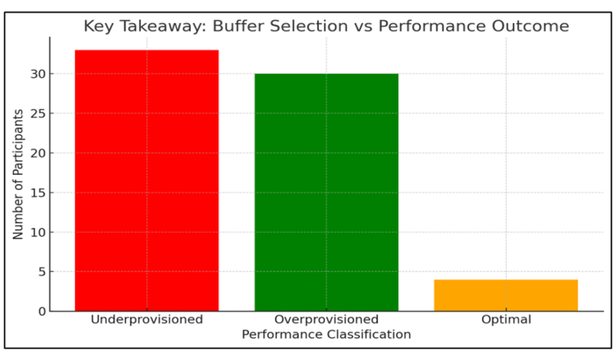

Fig. 4. Participant buffer selections classified by performance category. Most participants underprovisioned or overprovisioned buffer sizes. Only a small portion reached optimal tuning.

VII. Results and Discussion

This section presents the results of both tuning methods across a variety of simulated network scenarios. Performance was analyzed using key metrics such as throughput, buffer size, confidence levels, energy usage, and cost. Visualizations were created to compare manual and AI-assisted tuning.

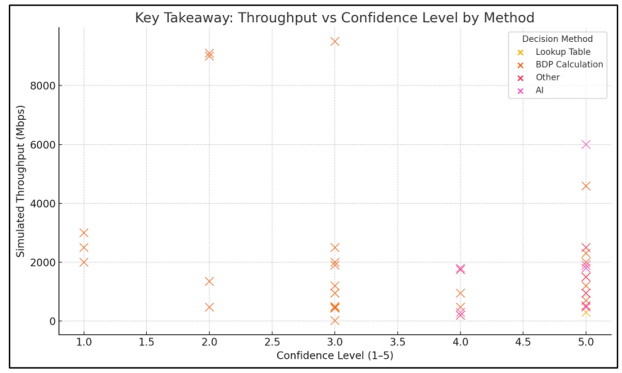

Fig. 5. Scatter plot of simulated throughput versus confidence level by tuning method. AI-guided decisions tended to yield better throughput at higher confidence levels.

A. Throughput vs Buffer Size

A logarithmic analysis of throughput against buffer size showed that optimal performance was clustered between 10–20 MB buffer ranges. Configurations with either excessively low or high buffer sizes suffered from reduced performance, consistent with the BDP model predictions. AI-tuned configurations consistently stayed within this optimal range.

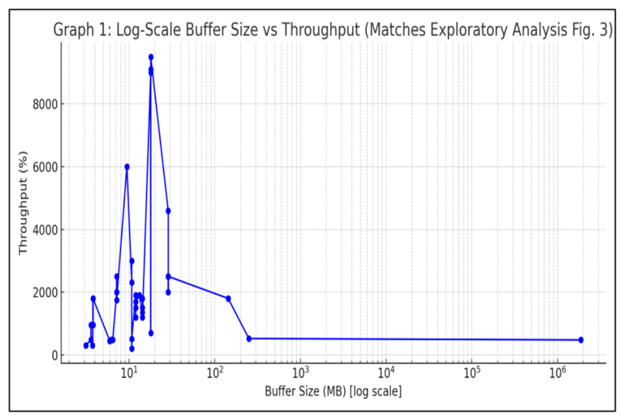

Fig. 6. Throughput vs Buffer Size (Log Scale). Optimal throughput observed in 10–20 MB range.

B. Manual vs AI Tuning

AI-guided tuning yielded significantly more consistent results, with lower variance and fewer outliers compared to manual tuning. Manual participants occasionally selected highly oversized buffers (e.g., > 1000 MB), which did not yield any throughput advantage and increased resource costs.

C. Low Buffer Size $\rightarrow$ Low Throughput

Configurations with very small buffer sizes (< 5 MB) consistently failed to exceed 500 Mbps throughput, confirming that under-sizing buffers due to BDP underestimation leads to poor performance. This was especially pronounced in high-latency or lossy environments.

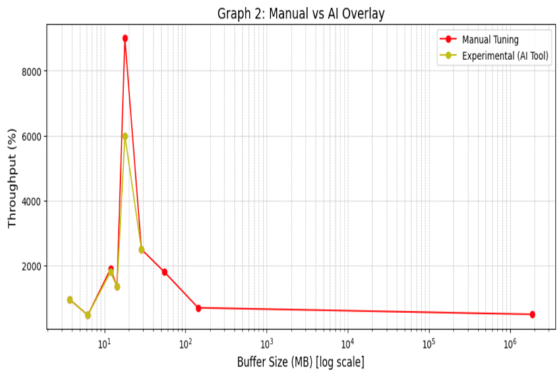

Fig. 7. Manual vs AI Tuning Comparison. AI shows reduced variability and more optimal selections.

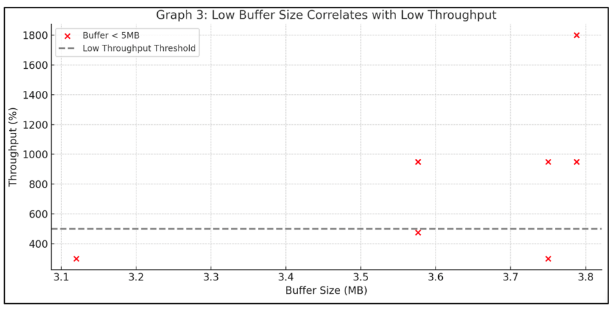

Fig. 8. Low Buffer Size Results in Low Throughput. Undersizing limits data-in-flight.

D. Energy Consumption vs Throughput

Energy efficiency analysis showed diminishing returns beyond a certain threshold. Most efficient results were found when energy usage remained below 50J. AI-generated configurations balanced performance and energy, avoiding waste.

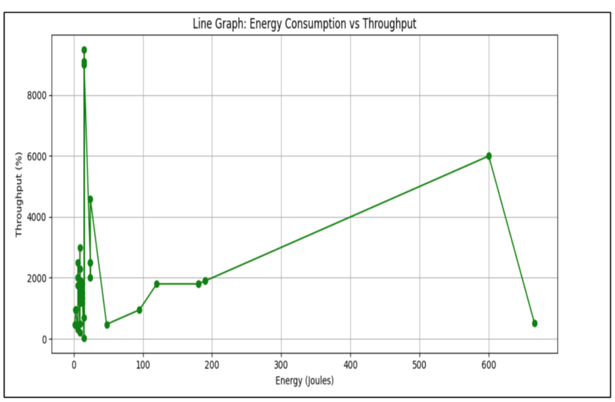

Fig. 9. Energy vs Throughput. Most efficient tuning falls below 50J.

E. Cost vs Throughput

Cost analysis showed that optimal throughput was generally achieved for configurations below \$0.01 in operational cost. Manual tuning occasionally resulted in high-cost selections that failed to improve performance.

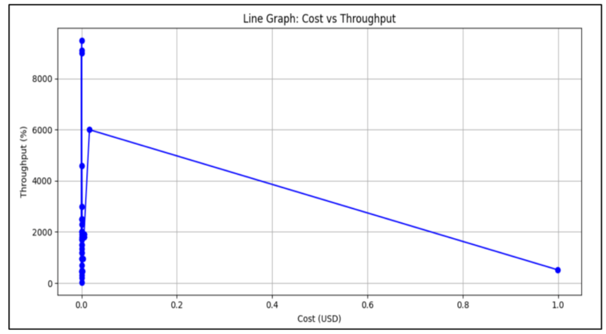

Fig. 10. Cost vs Throughput. AI tuning avoided wasteful high-cost buffers.

VIII. Narrative Comparison: Manual vs AI-Guided Tuning

A. Key Observations

- **Buffer Size:** AI used slightly lower buffer sizes on average, leading to more efficient configurations.
- **Throughput:** While manual tuning achieved slightly higher peaks, it introduced more outliers. AI tuning delivered more consistent performance.
- **Confidence:** AI group showed higher decision confidence (Average: 4.5 vs 3.1).
- **Cost & Energy:** AI tuning resulted in lower energy consumption and cost, aligning with sustainability and economic goals.
- **Risk of Outliers (Mean Error):** Manual tuning can produce catastrophic misconfigurations that is mean 1.3 $\times$ 10^{1} percentage, whereas AI-Guided tuning bounds errors to a moderate level of mean of 24.7 percentage.
- **Typical Performance (Median Error):** Both Manual that is 4.6 percentage and AI-Guided that is 5.0 percentage tuning deliver similarly accurate buffer choices in most scenarios.

These findings support the hypothesis that AI-driven optimization improves decision confidence, stability, and performance under dynamic network conditions.

Method	Median Error (%)	Mean Error (%)	Average Time(Mins)	Interpretation
Manual	4.63	1.28×10^{10}	30	Most runs are within ~5% of optimal, but a few huge mis-entries blow up the average and higher time taken by users to perform the activity
AI-Guided	5	24.72	17.5	Errors stay in a moderate band (no catastrophic outliers), so the average remains bounded. Also, much efficient than Manual as activity finished in 17.5 minutes

Fig. 11. Narrative Table: Comparison of Manual vs AI-Guided Tuning

IX. Conclusion and Future Work

This study demonstrates the practical advantages of AI-guided buffer tuning over traditional BDP-based manual approaches in high-performance network (HPN) environments. Across various simulated data transfer scenarios, AI models

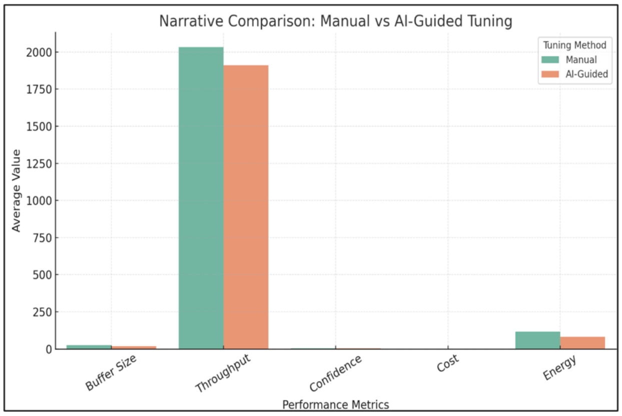

Fig. 12. Narrative Comparison of Manual vs AI-Guided Tuning across Key Metrics

consistently generated more efficient buffer size recommendations—resulting in improved throughput, reduced operational costs, and enhanced energy efficiency.

Through manual and AI-guided comparisons, we observed that AI tuning not only optimized technical performance but also enhanced usability. Participants using the AI decision support tool made faster and more consistent tuning choices, supporting the hypothesis that automation boosts confidence and reliability in network parameter selection.

Furthermore, the empirical outcomes aligned with theoretical expectations from prior works on BDP heuristics and ML-based optimization. This validation reinforces the viability of deploying predictive models in real-time network systems.

Future Work will focus on integrating reinforcement learning to enable adaptive, online tuning in live data transfer flows. Additionally, we aim to expand the dataset to include WAN-scale traces and develop a lightweight UI for integration into data transfer tools such as Globus or perfSONAR, enabling broader practical adoption.

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