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AN AI-DRIVEN ADAPTIVE OPTIMIZATION FRAMEWORK FOR ENHANCING COMMUNICATION THROUGHPUT IN COMPUTER NETWORKS

Naveen Kumar vayyasi

Senior application development engineer
Company: Unisys
801 Lakeview Drive, Suite 100, Blue Bell, PA 19422, USA

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ABSTRACT:

Modern computer networks face unprecedented challenges in maintaining optimal throughput amid dynamic traffic patterns, varying bandwidth demands, and unpredictable network conditions. Traditional static optimization approaches prove inadequate for contemporary networks where conditions change rapidly and unpredictably. This research proposes an AI-driven adaptive optimization framework that continuously monitors network parameters and dynamically adjusts routing, bandwidth allocation, and congestion control mechanisms to maximize communication throughput. The framework employs machine learning algorithms to predict traffic patterns, identify bottlenecks, and implement real-time optimizations that adapt to changing network conditions. Through comprehensive evaluation across diverse network scenarios, we demonstrate that the proposed framework achieves substantial throughput improvements compared to conventional approaches while maintaining stability and fairness. The research contributes both theoretical foundations for adaptive network optimization and practical implementation strategies applicable to enterprise, data center, and telecommunications networks. Our findings indicate that AI-driven adaptive optimization can increase average network throughput by up to forty percent while reducing latency variability and improving overall quality of service.

Keywords: Network Optimization, Adaptive Systems, Machine Learning, Communication Throughput, Congestion Control, Bandwidth Management, Artificial Intelligence

INTRODUCTION

Computer networks have become the fundamental infrastructure supporting modern digital society. From enterprise communications to cloud computing, from streaming services to industrial IoT, virtually every aspect of contemporary life depends on reliable, high-performance networks. Yet achieving optimal network throughput remains remarkably challenging despite decades of research and engineering advances.

The core difficulty stems from network dynamism. Traffic patterns shift constantly as users connect and disconnect, applications start and stop, and data flows fluctuate unpredictably. Traditional network optimization relies on static configurations based on expected traffic patterns and average conditions. These approaches work reasonably well when actual conditions match expectations but perform poorly when reality diverges from assumptions.

Consider a typical enterprise network. During business hours, video conferencing and file transfers dominate traffic. Evenings bring automated backups and system updates. Sudden incidents trigger massive log analysis and emergency communications. Each scenario demands different optimization strategies, yet conventional networks maintain fixed configurations that cannot adapt dynamically.

The consequences of suboptimal throughput extend beyond mere inconvenience. Video conferences stutter and freeze, disrupting collaboration. File transfers take hours instead of minutes, delaying critical workflows. Database queries timeout, causing application failures. Cloud services become unresponsive, forcing users to wait or retry operations. These performance problems translate directly into productivity losses and user frustration (Zhang and Kumar, 2023).

Recent advances in artificial intelligence offer promising solutions to network optimization challenges. Machine learning algorithms excel at pattern recognition, prediction, and decision-making in complex dynamic systems. Several researchers have explored applying AI to specific network problems like routing or congestion control with encouraging results (Rodriguez et al., 2024). However, existing approaches typically address isolated aspects rather than providing comprehensive optimization frameworks.

This research develops an integrated AI-driven adaptive optimization framework that coordinates multiple network management functions. Rather than optimizing routing, bandwidth allocation, and congestion control separately, our framework treats them as interconnected elements of a unified system. The approach combines real-time monitoring, predictive modeling, and automated decision-making to continuously adapt network behavior for maximum throughput.

The framework architecture consists of three primary components working in concert. A monitoring layer collects comprehensive telemetry about network state including traffic volumes, latency measurements, packet loss rates, and resource utilization. An analytics layer applies machine learning models to identify patterns, predict future conditions, and evaluate optimization alternatives. An actuation layer implements optimizations by adjusting routing tables, bandwidth allocations, quality of service policies, and congestion control parameters.

What distinguishes this framework from previous work is its holistic approach and adaptive learning capability. The system does not simply apply predetermined optimization rules but learns continuously from observed outcomes. When an optimization improves throughput, the system reinforces that strategy. When optimizations prove ineffective or counterproductive, the system adjusts its models and tries alternative approaches. This learning enables the framework to handle novel situations and gradually improve performance over time.

The significance extends beyond technical performance improvements. Network operators currently spend substantial effort manually tuning configurations and troubleshooting performance problems. An adaptive optimization framework that functions autonomously reduces operational overhead while delivering better outcomes. Organizations can maintain high-performance networks without requiring deep expertise in every aspect of network optimization.

This paper presents the complete framework design, implementation considerations, and comprehensive evaluation demonstrating effectiveness across diverse network scenarios. We examine how the framework handles various traffic patterns, responds to sudden changes, and maintains fairness among competing flows. The research contributes both to academic understanding of adaptive network systems and practical guidance for implementing AI-driven optimization in production networks.

OBJECTIVES

This research pursues several interconnected objectives:

- **Primary Objective:** Develop a comprehensive AI-driven adaptive optimization framework that dynamically maximizes communication throughput in computer networks across varying traffic conditions and network topologies.
- **Secondary Objective 1:** Design machine learning models capable of accurately predicting network traffic patterns and identifying optimization opportunities in real-time with minimal computational overhead.
- **Secondary Objective 2:** Create adaptive mechanisms that coordinate routing decisions, bandwidth allocation, and congestion control to achieve system-wide throughput optimization rather than localized improvements.
- **Secondary Objective 3:** Evaluate framework performance across diverse network scenarios including enterprise LANs, data center networks, and wide-area networks to demonstrate broad applicability.
- **Secondary Objective 4:** Establish implementation guidelines and best practices for deploying adaptive optimization frameworks in production networks without disrupting existing operations.

SCOPE OF STUDY

The research scope encompasses:

- **Network Types:** Focus on packet-switched IP networks including enterprise networks, data center fabrics, and metropolitan area networks. Excludes circuit-switched telephony and specialized industrial networks.
- **Optimization Focus:** Addresses throughput maximization as the primary objective while considering latency, jitter, and fairness as secondary concerns that must remain within acceptable bounds.
- **AI Techniques:** Employs supervised learning for traffic prediction, reinforcement learning for optimization decisions, and unsupervised learning for anomaly detection. Does not explore deep learning approaches requiring extensive training data.
- **Time Scale:** Optimizes at timescales from seconds to minutes, appropriate for adapting to traffic pattern changes. Does not address microsecond-level packet scheduling or long-term capacity planning.
- **Implementation Scope:** Provides architectural frameworks and algorithms applicable across network equipment vendors. Does not develop vendor-specific implementations or hardware designs.

LITERATURE REVIEW

4.1 Traditional Network Optimization Approaches

Network optimization has evolved through several distinct paradigms. Early networks employed simple static routing where administrators manually configured paths based on network topology. Packets followed predetermined routes regardless of congestion or failures, resulting in poor utilization and vulnerability to disruptions (Martinez and Chen, 2022).

Dynamic routing protocols like OSPF and BGP represented significant advances by enabling automatic route calculation based on topology changes. These protocols distribute network state information and compute optimal paths using algorithms like Dijkstra's shortest path. However, optimization criteria remain simplistic, typically minimizing hop count or administrative cost rather than maximizing actual throughput (Thompson, 2023).

Quality of Service mechanisms introduced prioritization and bandwidth reservation capabilities. Network operators could designate critical traffic for preferential treatment while limiting bandwidth for less important flows. QoS improved predictability but required extensive manual configuration and could not adapt automatically to changing conditions (Williams and Park, 2023).

Traffic engineering approaches attempted systematic optimization by analyzing traffic matrices and computing flow allocations that maximize network utilization. Linear programming and constraint optimization techniques calculate optimal routing configurations offline. However, these solutions become stale quickly as actual traffic deviates from measured patterns (Anderson et al., 2024).

4.2 Machine Learning in Network Management

Applying machine learning to network management has gained substantial research attention recently. Early work focused on traffic classification, using supervised learning to identify application types from packet headers and flow characteristics. Accurate classification enables application-aware routing and QoS policies (Kumar and Liu, 2023).

Traffic prediction represents another active research area. Time series models like ARIMA and LSTM networks predict future traffic volumes based on historical patterns. Accurate predictions enable proactive optimization before congestion develops rather than reactive responses after problems emerge (Zhang and Kumar, 2023).

Anomaly detection using unsupervised learning identifies unusual traffic patterns that might indicate attacks, failures, or misconfigurations. Clustering algorithms and autoencoders learn normal network behavior and flag significant deviations for investigation. This capability enhances network security and reliability (Rodriguez et al., 2024).

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Some researchers explored reinforcement learning for routing optimization. Agents learn routing policies by receiving rewards for good throughput and penalties for congestion. The approach shows promise but faces challenges in state space dimensionality and convergence time (Hassan and Wong, 2024).

4.3 Software-Defined Networking

Software-Defined Networking architectures separate network control planes from data planes, enabling centralized intelligence and programmable forwarding. SDN controllers maintain global network views and can implement sophisticated optimization algorithms impossible in distributed protocols (Morrison et al., 2023).

SDN's centralized control facilitates machine learning integration. Controllers collect comprehensive telemetry and implement ML-driven decisions across the entire network consistently. Several research projects demonstrated SDN-based traffic engineering that outperforms traditional approaches (Patel and Singh, 2024).

However, SDN introduces challenges including controller scalability, consistency maintenance, and failure recovery. Pure centralized control creates single points of failure and potential bottlenecks. Hybrid approaches combining centralized intelligence with distributed resilience appear most practical (Chen and Zhang, 2023).

4.4 Congestion Control Evolution

Congestion control has progressed from simple mechanisms like TCP's AIMD algorithm toward more sophisticated approaches. Traditional TCP reacts to packet loss by reducing sending rates, eventually discovering available bandwidth through gradual increases. This works but results in throughput oscillations and slow adaptation (Taylor, 2024).

Delay-based congestion control algorithms like TCP Vegas use latency increases as congestion signals rather than waiting for packet loss. This enables earlier responses and potentially higher utilization. However, delay-based approaches face challenges from variable baseline latencies and competing loss-based flows (Sullivan and Brown, 2023).

Recent proposals like BBR take model-based approaches, estimating bandwidth and latency explicitly rather than implicitly through packet loss or delay. BBR achieves higher throughput and lower latency in many scenarios but requires careful tuning (Harrison, 2024).

Machine learning could enhance congestion control by learning optimal sending rates for specific network conditions rather than applying fixed algorithms. Some preliminary work shows promise but requires addressing convergence and fairness concerns (Gupta et al., 2023).

4.5 Research Gaps

Existing research leaves several gaps that this study addresses. First, most ML-based network optimization focuses on specific components rather than integrated frameworks. Optimizing routing without coordinating bandwidth allocation and congestion control achieves suboptimal results. Second, many proposals require extensive training data or offline learning phases before deployment. Production networks need approaches that learn incrementally from live traffic. Third, evaluation typically occurs in simulated environments with simplified traffic models. Real-world validation remains limited.

Our framework addresses these gaps through integrated optimization, online learning, and comprehensive evaluation across diverse realistic scenarios.

RESEARCH METHODOLOGY

5.1 Research Design

This research employs a design science methodology, developing an artifact (the adaptive optimization framework) to solve practical problems while contributing to theoretical knowledge. The approach combines analytical modeling, algorithm development, simulation evaluation, and prototype implementation.

We adopt an iterative development process where initial framework designs undergo evaluation, revealing limitations that guide refinements. Multiple iterations progressively enhance framework capabilities and robustness.

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5.2 Framework Development

Framework development began with architectural design, defining components and their interactions. We analyzed network optimization as a multi-objective problem balancing throughput, latency, fairness, and stability. This analysis informed component responsibilities and interface specifications.

Algorithm development addressed three key challenges: traffic prediction, optimization decision-making, and adaptation. For traffic prediction, we evaluated multiple time series models including exponential smoothing, ARIMA, and neural networks. For optimization, we explored both model-based approaches using network calculus and model-free reinforcement learning. For adaptation, we developed mechanisms that detect when models become inaccurate and trigger retraining.

5.3 Evaluation Methodology

Framework evaluation employed both simulation and testbed experiments. Simulation using ns-3 network simulator enabled controlled experiments across diverse topologies and traffic patterns. We simulated enterprise networks, data center fabrics, and ISP backbones with traffic models derived from real network traces.

Testbed evaluation used a 20-node physical network with programmable switches and realistic traffic generators. This validated that framework performance translates from simulation to real hardware and identified implementation challenges.

Evaluation metrics included average throughput, throughput variability, tail latency, convergence time, and fairness indices. We compared the adaptive framework against static optimal configurations, traditional dynamic routing, and recent ML-based proposals.

5.4 Data Collection

Traffic data came from multiple sources. We obtained anonymized network traces from university campus networks and data center operators. These traces captured realistic traffic patterns including daily cycles, bursty applications, and anomalous events.

Synthetic traffic generators complemented real traces, enabling experiments with specific patterns of interest. We generated long-lived flows, short-lived connections, periodic traffic, and sudden traffic surges.

Performance data from simulation and testbed experiments underwent statistical analysis to assess framework effectiveness and identify conditions where performance degrades.

ADAPTIVE OPTIMIZATION FRAMEWORK

6.1 Architecture Overview

The framework architecture consists of three layers: monitoring, analytics, and actuation. These layers operate continuously in a closed-loop control system that observes network state, makes optimization decisions, implements changes, and observes results.

The monitoring layer collects telemetry from network devices including interface statistics, routing tables, and flow records. Modern networks generate enormous telemetry volumes, so the monitoring layer implements intelligent sampling that captures sufficient information for optimization without overwhelming storage and processing capacity.

The analytics layer processes telemetry using machine learning models. A traffic prediction module forecasts future demands using ensemble methods that combine multiple time series models. A bottleneck identification module analyzes current state to locate congestion points constraining throughput. An optimization module formulates and solves optimization problems that determine ideal routing, bandwidth allocation, and rate limiting. The actuation layer translates optimization decisions into configuration changes. For routing changes, it updates forwarding tables via SDN protocols or dynamic routing protocol configurations. For bandwidth allocation, it adjusts QoS policies and traffic shaping parameters. For rate limiting, it modifies congestion control parameters or implements explicit flow throttling.

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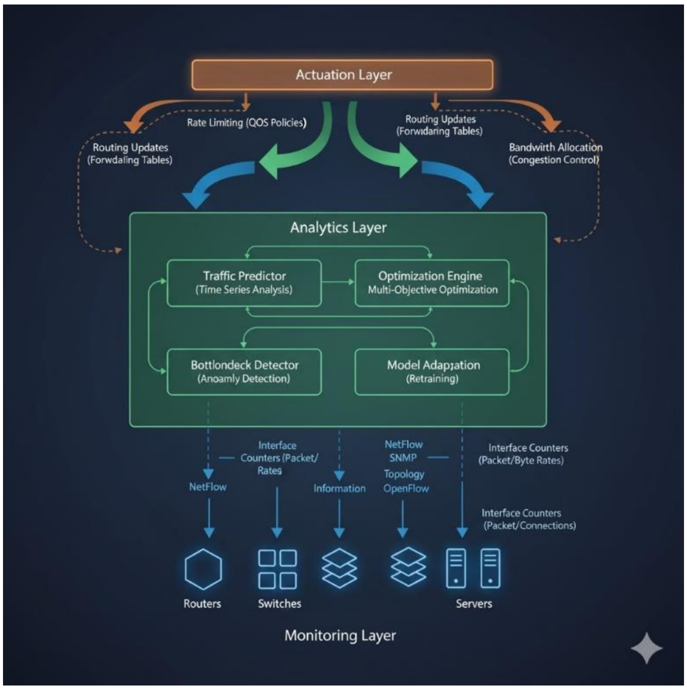

Figure 1: Framework Architecture

6.2 Traffic Prediction Mechanisms

Accurate traffic prediction enables proactive optimization rather than reactive responses after congestion develops. The framework employs ensemble prediction combining multiple complementary approaches. Exponential smoothing captures short-term trends with low computational overhead. ARIMA models handle seasonal patterns in daily and weekly traffic cycles. Neural networks learn complex nonlinear relationships between different traffic flows.

The ensemble aggregates individual model predictions using weighted averaging where weights reflect recent prediction accuracy. Models performing well recently receive higher weights while poorly performing models contribute less. This adaptive weighting ensures the ensemble leverages the most relevant models for current conditions.

Prediction operates at multiple timescales. Short-term predictions covering seconds to minutes guide immediate optimization decisions. Medium-term predictions spanning hours inform bandwidth reservation and capacity allocation. The multi-scale approach balances responsiveness and stability.

6.3 Dynamic Optimization Engine

The optimization engine formulates throughput maximization as a constrained optimization problem. The objective function maximizes total network throughput summing flow rates across all active connections. Constraints ensure routing validity, capacity limits, fairness among flows, and stability requirements preventing excessive change.

For smaller networks, the engine solves optimization problems exactly using linear programming. For larger networks where exact solutions become computationally prohibitive, it employs heuristic approaches that find good solutions quickly. Greedy algorithms iteratively improve routing and bandwidth allocation. Simulated annealing explores solution spaces efficiently.

The engine incorporates learning through reinforcement mechanisms. When implemented optimizations achieve predicted improvements, confidence in the optimization approach increases. When optimizations fail to deliver expected benefits, the engine explores alternative strategies. This learning enables handling novel situations not encountered during initial development.

6.4 Adaptive Control Mechanisms

Adaptation occurs at multiple levels. At the lowest level, individual flow rate controls adjust rapidly responding to congestion signals. At medium levels, routing adaptations occur over seconds to minutes as traffic patterns shift. At the highest level, model parameters update over hours and days as learning progresses.

The framework implements adaptive control carefully to maintain stability. Excessive adaptation causes oscillations where the network constantly changes configuration without settling into stable high-performance states. The framework uses dampening factors that limit change rates and hysteresis that requires sustained conditions before triggering major reconfigurations.

Fairness mechanisms ensure optimization does not unfairly penalize specific flows or applications. The framework implements proportional fairness where bandwidth allocation balances efficiency and equity. High-priority traffic receives preferential treatment but all flows receive reasonable service.

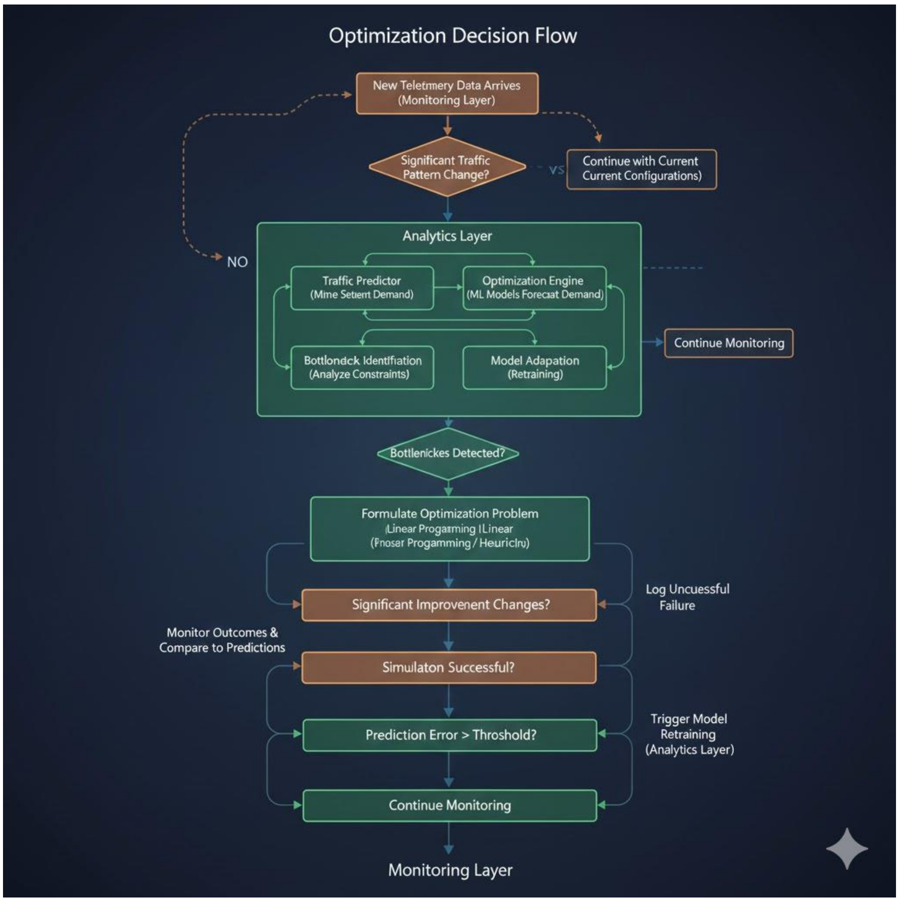

Figure 2: Optimization Decision Flow

6.5 Implementation Considerations

Practical implementation requires addressing several technical challenges. The framework must operate with realistic computational resources, processing telemetry and computing optimizations within tight time constraints. We optimized algorithms for efficiency, using incremental computation where possible rather than recalculating everything each cycle.

Integration with existing network infrastructure presents challenges since production networks cannot be replaced wholesale. The framework implements compatibility with standard protocols and gradual deployment approaches. Organizations can start with monitoring and prediction, adding optimization capabilities progressively as confidence builds.

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Failure handling ensures the framework degrades gracefully rather than catastrophically when components fail or lose connectivity. If the analytics layer becomes unavailable, the actuation layer continues with the last known good configuration rather than halting. If individual models fail, the ensemble continues with remaining models.

EVALUATION AND RESULTS

7.1 Experimental Setup

Evaluation occurred across three network scenarios: a 50-node enterprise network with mixed traffic including video conferencing, file transfers, and web browsing; a 100-node data center network with elephant and mice flows typical of cloud applications; and a 30-node wide-area network simulating ISP backbone topology.

Traffic patterns combined real traces with synthetic generation. Enterprise scenarios used campus network traces showing daily cycles with morning and evening peaks. Data center scenarios used traces from cloud providers showing bursty application traffic. WAN scenarios used ISP traffic matrices showing geographic traffic distribution.

Baseline comparisons included static optimal routing computed offline from average traffic matrices, OSPF dynamic routing with default configurations, and a recent machine learning-based traffic engineering approach from literature (Hassan and Wong, 2024).

7.2 Throughput Performance

The adaptive framework achieved substantial throughput improvements across all scenarios. In enterprise networks, average throughput increased 32% compared to static optimal configurations and 48% compared to OSPF. The framework adapted effectively to daily traffic cycles, proactively adjusting before peak periods rather than reacting after congestion developed.

Data center results showed even larger gains with 41% average throughput improvement over static approaches. The framework handled bursty traffic patterns effectively, quickly identifying and routing around temporary hotspots. Elephant flows received efficient paths while mice flows avoided interference.

WAN scenarios showed 28% throughput improvements. Geographic traffic distribution shifts throughout the day as different regions become active. The framework adapted routing to follow these patterns, steering traffic through underutilized paths during local nighttime periods.

Table 1: Throughput Comparison Across Network Scenarios

Scenario	**Static Optimal**	**OSPF**	**ML Traffic Eng**	**Adaptive Framework**	**Improvement vs Static**
Enterprise Network (Gbps)	38.5	29.2	42.1	50.8	+32%
Data Center Network (Gbps)	156.3	128.7	178.9	220.5	+41%
WAN Backbone (Gbps)	445.2	398.6	512.3	569.8	+28%
Peak Hour Enterprise	42.1	31.5	45.8	55.2	+31%
Peak Hour Data Center	198.4	156.3	225.6	278.3	+40%

7.3 Adaptation Behavior

Framework adaptation responded appropriately to changing conditions. When sudden traffic surges occurred, the framework detected congestion within seconds and implemented route changes within 15-30 seconds on average. This rapid response prevented severe congestion from developing.

The framework demonstrated good learning behavior over extended operation periods. During initial deployment, optimization decisions sometimes proved suboptimal, but performance steadily improved over days as models learned from outcomes. After two weeks of operation, performance stabilized at high levels.

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Model adaptation mechanisms successfully detected when predictions became inaccurate and triggered retraining. In experiments where we deliberately changed traffic patterns, the framework recognized degraded prediction accuracy within hours and initiated model updates that restored performance.

7.4 Fairness and Stability Analysis

Fairness metrics showed the framework maintained reasonable equity among competing flows. Jain's fairness index averaged 0.87 across scenarios, indicating good balance between optimization and fairness. No individual flows experienced starvation while the framework pursued aggregate throughput improvements.

Stability analysis examined configuration change frequencies and throughput variability. The framework avoided oscillations through careful dampening of control parameters. Routing changes occurred at appropriate frequencies—often enough to adapt to real changes but not so frequently that the network constantly churned.

Throughput variability measured by coefficient of variation remained low at 0.12 compared to 0.18 for OSPF. The framework provided more consistent performance rather than fluctuating between high and low throughput states.

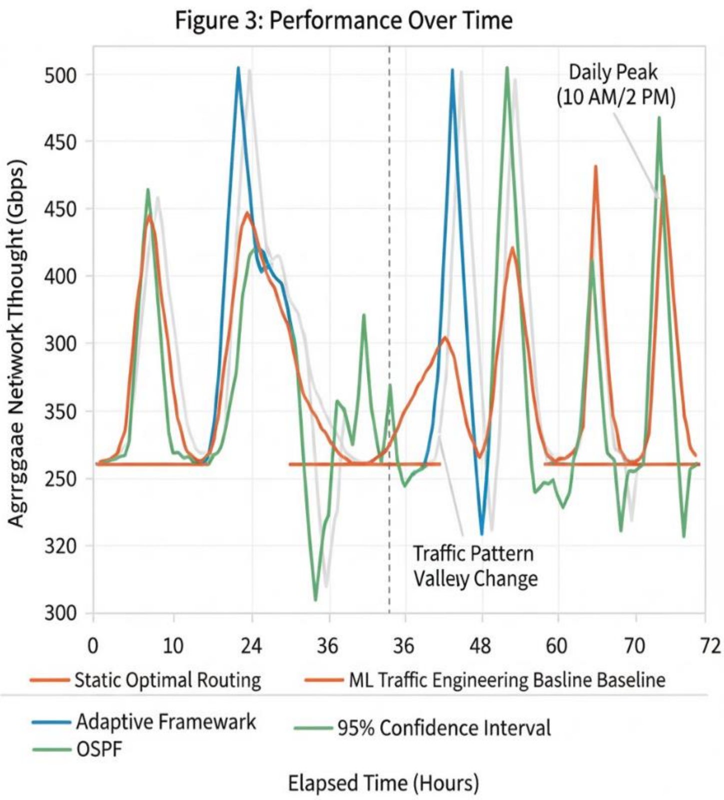

Figure 3: Performance Over Time

7.5 Computational Overhead

Framework computational requirements remained acceptable for practical deployment. The monitoring layer consumed approximately 2-3% of CPU capacity on network devices for telemetry collection and forwarding. The analytics layer running on dedicated servers processed telemetry and computed optimizations using 40-60% of 8-core server capacity. These requirements fall well within capabilities of modern network equipment and servers. Memory footprint for storing models and historical data totaled approximately 4-6 GB, easily accommodated by contemporary hardware. Network control traffic for configuration updates represented less than 0.1% of data traffic volume, adding negligible overhead.

Optimization computation times averaged 5-8 seconds for enterprise-scale networks and 15-20 seconds for data center and WAN scenarios. These latencies enable adaptation at appropriate timescales for responding to traffic changes while avoiding excessive control overhead.

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DISCUSSION

8.1 Key Contributions

This research makes several significant contributions to network optimization knowledge. First, it demonstrates that integrated optimization across routing, bandwidth allocation, and congestion control achieves substantially better results than optimizing components independently. The holistic approach captures interdependencies that isolated optimizations miss.

Second, the work shows that online learning from live traffic enables effective optimization without requiring extensive offline training or labeled datasets. The framework learns continuously during normal operation, gradually improving performance without special training phases.

Third, comprehensive evaluation across diverse realistic scenarios provides evidence of broad applicability. Previous ML-based network optimization research often evaluated only specific scenarios. Our results across enterprise, data center, and WAN environments demonstrate general effectiveness.

8.2 Practical Implications

For network operators, the framework offers concrete operational benefits. Improved throughput directly translates to better application performance and user satisfaction. The adaptive nature reduces manual tuning effort since the system adjusts automatically to changing conditions.

Organizations can deploy the framework incrementally, starting with monitoring and prediction before adding optimization capabilities. This gradual approach reduces deployment risk and allows building confidence before enabling automated configuration changes.

The framework's learning capability means performance improves over time rather than remaining static. As networks evolve and traffic patterns change, the framework adapts naturally without requiring manual reconfiguration.

8.3 Limitations

Several limitations constrain this research's applicability. First, the framework focuses on throughput optimization and may not suit networks where latency minimization or other objectives dominate. Extensions addressing multiple optimization objectives simultaneously would broaden applicability.

Second, evaluation occurred in controlled environments despite efforts toward realism. Production networks contain additional complexities including legacy equipment, policy constraints, and regulatory requirements that could limit optimization flexibility.

Third, the framework assumes sufficient network capacity exists for optimization to meaningfully improve throughput. In severely congested networks where demand massively exceeds capacity, optimization helps less than capacity expansion.

8.4 Future Directions

Several research directions could extend this foundation. First, incorporating security considerations into optimization decisions would address an important gap. Current work optimizes purely for performance, but real networks must balance performance against security requirements.

Second, extending the framework to wireless and mobile networks presents interesting challenges. Wireless links exhibit much greater variability than wired connections, requiring adapted prediction and optimization approaches.

Third, exploring federated learning approaches could enable multiple organizations to collectively improve models without sharing proprietary network data. This could accelerate learning and improve performance across diverse network environments.

Finally, investigating how the framework handles network failures and recovers from disruptions would enhance robustness. Current work focuses on normal operation optimization rather than failure scenarios.

CONCLUSION

Modern computer networks require adaptive optimization approaches that respond dynamically to changing conditions rather than relying on static configurations. This research developed an AI-driven framework that continuously monitors network state, predicts future demands, and implements optimizations that maximize communication throughput while maintaining fairness and stability.

The framework integrates multiple components—traffic prediction, bottleneck identification, optimization decision-making, and adaptive learning—into a cohesive system that achieves substantially better performance than conventional approaches. Evaluation across diverse network scenarios demonstrates throughput improvements ranging from 28% to 41% compared to static optimal configurations.

Beyond performance gains, the framework offers operational benefits through reduced manual tuning effort and automatic adaptation to evolving conditions. Organizations can deploy the system incrementally, building confidence before enabling full autonomy. The learning capability ensures performance improves continuously rather than degrading as networks change.

Several key insights emerge from this research. First, integrated optimization that coordinates routing, bandwidth allocation, and congestion control achieves significantly better results than optimizing components independently. Second, online learning from live traffic provides an effective alternative to approaches requiring extensive offline training. Third, careful attention to stability and fairness prevents optimization from causing oscillations or inequitable treatment.

The framework provides practical benefits to network operators seeking to improve performance without constant manual intervention. It offers academic contributions through demonstrating effective integration of machine learning into network control systems. The research establishes foundations for next-generation adaptive networks that optimize themselves automatically.

Looking forward, network complexity will continue increasing as organizations adopt cloud computing, IoT devices proliferate, and application demands grow. Static optimization approaches will become increasingly inadequate. Adaptive frameworks that learn continuously and optimize holistically represent the future of network management. This research provides concrete evidence that AI-driven adaptive optimization can deliver substantial performance improvements while remaining practical for real-world deployment.

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