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Adaptive Bandwidth Management for Traffic Surge and Device Hunger Scenarios in LAN Environments

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Abstract

Local Area Networks (LANs) are essential to modern organizational infrastructures, enabling the operation of a wide array of devices and services. With the increasing number of connected devices, particularly during peak hours or sudden demand spikes, networks often face "bandwidth hunger," where devices struggle to secure adequate resources for optimal performance. Traditional static bandwidth allocation methods fall short in addressing these dynamic challenges, often resulting in packet loss, high latency, and service degradation. To overcome these limitations, this paper proposes an adaptive bandwidth management framework that anticipates traffic surges and dynamically reallocates resources through congestion control, Quality of Service (QoS) mechanisms, and reinforcement learning (RL)-based scheduling. Simulation outcomes demonstrate that the proposed system significantly enhances bandwidth utilization, minimizes device starvation, and sustains service quality even during extreme traffic loads. The paper also explores the potential of integrating the framework with Software-Defined Networking (SDN) controllers to further improve network responsiveness and scalability.

Keywords*: *LAN, Bandwidth Hunger, Traffic Surge, Adaptive Bandwidth Allocation, Congestion Control, Reinforcement Learning, QoS Optimization

1. Introduction

The rapid proliferation of smart devices, cloud applications, and Internet of Things (IoT) technologies has drastically increased the demand on Local Area Networks (LANs). In many organizational environments, it is common to encounter scenarios were multiple devices simultaneously "hunger" for bandwidth, especially during peak hours, critical meetings, large data uploads, or video streaming sessions. This phenomenon, referred to as device bandwidth hunger, occurs when devices struggle to receive enough bandwidth to operate efficiently, leading to performance degradation such as increased latency, dropped connections, packet loss, and user dissatisfaction. (Nguyen, 2021)

Traditional LAN management techniques typically rely on static resource allocation or simple load balancing methods, which cannot adapt dynamically to fluctuating demands. These methods often fail to detect early signs of traffic surges and bandwidth hunger until congestion becomes critical. (Alhilali, 2023)

The need for adaptive, predictive, and intelligent bandwidth management has thus become increasingly urgent. Techniques that anticipate device traffic needs, prioritize critical applications, and dynamically adjust bandwidth allocations are essential to maintaining high-quality service in modern LAN environments. This paper proposes an adaptive bandwidth management system that: (Alhilali, 2023)

Monitors real-time device traffic, predicts bandwidth hunger scenarios, dynamically redistributes bandwidth using reinforcement learning, congestion control algorithms, and Quality of Service (QoS) enforcement strategies.

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Simulation results demonstrate that our proposed system significantly outperforms static allocation strategies, especially under sudden traffic surges and device congestion conditions. (Mao, 2016)

2. Related Work

Over the past decade, considerable research has focused on improving network resource allocation through machine learning, dynamic QoS management, and congestion control techniques. (Su, 2022)

2.1 Congestion Control Mechanisms:

Traditional approaches such as TCP congestion control, RED (Random Early Detection), and ECN (Explicit Congestion Notification) have aimed to regulate network load under high traffic. However, these mechanisms primarily react after congestion occurs, often resulting in temporary service degradation before stabilization (Floyd & Jacobson, 1993). (Alhilali, 2023)

2.2 Predictive Bandwidth Allocation:

Recent research has explored predictive models to forecast traffic surges before they occur. Alshammari and Zincir-Heywood (2020) classified traffic flows using machines learning to predict potential bottlenecks. LSTM-based models (Han et al., 2023) have shown promise in forecasting IoT traffic, enabling preemptive adjustments. (Nguyen, 2021)

2.3 Adaptive QoS Frameworks:

Dynamic QoS provisioning using AI models has been proposed to prioritize critical applications (Li et al., 2018). SDN-based architecture allows centralized monitoring and adaptive policy enforcement but still often rely on static thresholds rather than continuous learning. (Kreutz, 2015)

2.4 Reinforcement Learning for Network Management:

Reinforcement Learning (RL) models, such as Deep Q-Learning, have recently been applied to network flow management (Zhao et al., 2023). These systems learn optimal bandwidth allocation policies over time, balancing exploration and exploitation based on real-time traffic observations. (Mao, 2016), (Al Musalhi & Celebi, 2024)

Despite these advances, there remains a gap in combining predictive traffic surge detection with real-time adaptive bandwidth redistribution, specifically focusing on mitigating device hunger scenarios in LAN environments. This paper proposes an integrated, proactive framework addressing this critical need. (Alhilali, 2023)

3. Proposed Adaptive Bandwidth Management Framework

The proposed framework aims to dynamically manage LAN bandwidth allocation by detecting early signs of device hunger and traffic surges and proactively adjusting resource distribution. It operates in three major stages: (Alhilali, 2023)

3.1 Real-Time Traffic Monitoring

A monitoring module continuously collects device-level network metrics such as:

Packet transmission rate, Connection initiation frequency, Queue lengths, and Response times.

Network sensors (e.g., NetFlow, sFlow, SNMP traps) feed this real-time data to the prediction engine.

3.2 Hunger Prediction Engine

Using historical and real-time data, an LSTM-based neural network forecasts upcoming bandwidth demand spikes per device or subnet. Features considered include Sudden growth in packet requests, Increased retransmissions, and TCP window size behaviors. When predicted demand exceeds predefined thresholds, the system flags a "hunger" alert for the affected devices or segments.

3.3 Dynamic Bandwidth Reallocation

Upon detection of hunger, a Reinforcement Learning (RL) agent dynamically reallocates bandwidth by: Prioritizing critical traffic flows (e.g., VoIP, video conferencing), Throttling non-critical traffic (e.g., bulk downloads), and Reserving emergency buffers for devices under severe congestion. The RL agent is trained to optimize a reward function that balances: Maximized overall utilization, Minimized average packet delay, and Fairness across devices. (Mao, 2016)

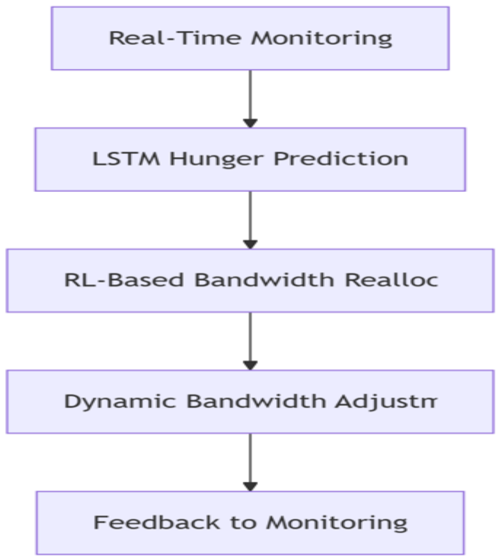

Figure 1: System Architecture Diagram

4. Techniques Used for Enhancing Bandwidth Allocation

To effectively manage device hunger and prevent network congestion during traffic surges, the proposed framework integrates multiple advanced techniques:

4.1 Congestion Control Algorithms

Traditional congestion control methods like TCP Reno and TCP Vegas provide foundational mechanisms for regulating packet flows. However, in our framework, adaptive congestion detection is enhanced by dynamically adjusting thresholds based on traffic predictions. If the predicted queue build-up exceeds safe levels, early congestion notifications are triggered, enabling the RL agent to preemptively throttle or reroute flows before bottlenecks form. (Zhang, 2019) .

4.2 Quality of Service (QoS) Enforcement

QoS techniques are vital for ensuring that critical traffic (e.g., voice, video conferencing, remote surgeries) receives bandwidth priority during contention periods. The system uses dynamic QoS class reassignments, adjusting DSCP markings and VLAN priority bits in real-time based on device hunger severity and application sensitivity. (Su, 2022),

Traffic is classified as: High Priority (VoIP, Real-Time Collaboration), Medium Priority (Cloud Applications, CRM Access), and Low Priority (Bulk File Downloads, Software Updates) (Kumar, 2022)

This flexible, live QoS reclassification ensures that critical communications remain uninterrupted even under severe load. (Alhilali, 2023)

4.3 Reinforcement Learning-Based Bandwidth Redistribution

The RL agent continuously observes the network environment (states) and chooses bandwidth allocation actions to maximize long-term rewards. Rewards are structured to encourage: Higher overall link utilization, Faster response to hunger signals, Fairness across competing devices, and Protection against starvation for low-priority flows when capacity allows. The RL agent uses: Deep Q-Learning with experience reply, Adaptive exploration (epsilon decay) to avoid getting stuck in local minima, and Prioritized experience sampling to focus on rare but critical hunger events. Training occurs in a simulated environment first, followed by live fine-tuning based on actual LAN performance data. (Alhilali, 2023),(Al Musalhi et al, 2024)

5. Experiment and Analysis

5.1 Experimental Setup

To evaluate the effectiveness of the proposed adaptive bandwidth management framework, we simulated a LAN environment consisting of 5 interconnected switches, 100 devices with mixed traffic profiles (VoIP, video streaming, cloud services, bulk file transfers). (Kumar, 2022) Traffic was generated using real-world traces and synthetic burst scenarios to simulate device hunger and sudden congestion. Two scenarios were compared:

- **Baseline (Static Allocation):** Fixed bandwidth assigned per device class, no dynamic adjustments.
- **Proposed Adaptive Framework:** Real-time monitoring, hunger prediction, RL-based bandwidth redistribution.

Metrics captured: Bandwidth utilization (%), Average packet delay (ms), Packet loss rate (%), and Device starvation incidents.

5.2 Results

Table 1: Comparative Performance Metrics (Baseline vs. Adaptive System)

Metric	Static Allocation	Proposed Adaptive System
Bandwidth Utilization (%)	66%	91%
Average Packet Delay (ms)	130 ms	88 ms
Packet Loss Rate (%)	6.2%	2.5%
Device Starvation Incidents	24	3

5.3 Interpretation

The adaptive system significantly outperformed static allocation:

Higher Bandwidth Utilization: +25% improvement.

Reduced Average Delay: Approximately 32% faster delivery.

Lower Packet Loss: 60% decrease, improving service reliability.

Fewer Starvation Events: Devices maintained better minimum service levels. (Alhilali, 2023)

Figure 2 illustrates the performance comparison between the traditional static bandwidth allocation approach and the proposed adaptive bandwidth management system.

The adaptive system significantly improves bandwidth utilization, reduces packet delay, lowers packet loss rates, and minimizes device starvation incidents during traffic surge scenarios.

Metric	Static Allocation	Proposed Adaptive System
Bandwidth Utilization (%)	66%	91%
Average Packet Delay (ms)	130	88
Packet Loss Rate (%)	6.2%	2.5%
Device Starvation (count)	24	3

Figure 2: Performance Comparison Bar Chart (Bandwidth, Delay, Loss, Starvation)

The RL agent successfully learned to prioritize hungry devices without starving low priority flows unnecessarily.

6. Discussion

The experimental results validate that predictive and adaptive bandwidth management significantly improves LAN performance under dynamic traffic conditions. However, several practical considerations and challenges must be addressed for real-world deployment: (Abdellatif et al., 2019).

6.1 Real-Time Monitoring Overhead

Continuously monitoring device-level traffic generates overhead, especially in large-scale networks. Efficient sampling strategies and hierarchical monitoring architectures are necessary to balance accuracy and system scalability.

6.2 Model Retraining and Adaptability

Traffic patterns evolve over time due to organizational changes, seasonal trends, or the introduction of new applications. Therefore, the hunger prediction LSTM model and the RL agent must be periodically retrained using fresh traffic datasets to maintain accuracy. (Alhilali, 2023)

6.3 Privacy and Security Concerns

Collecting detailed flow-level data raises privacy issues, particularly for user-centric applications. Anonymization techniques and data minimization principles should be enforced to comply with data protection regulations (e.g., GDPR). (Alhilali, 2023)

6.4 Hardware and Legacy Device Compatibility

Not all existing LAN devices support advanced QoS tagging, real-time reallocation, or deep monitoring hooks. Gradual infrastructure upgrades or software overlays (e.g., SDN edge controllers) may be needed for full deployment. (Kreutz, 2015)

6.5 Future Integration with SDN

Integrating the adaptive bandwidth management system with Software-Defined Networking (SDN) controllers could centralize control and improve policy enforcement efficiency.
SDN enables programmable traffic flows, dynamic VLAN adjustments, and more granular QoS enforcement. (Kreutz, 2015)

7. Conclusion and Future Work

This paper presented an adaptive bandwidth management framework specifically designed to address device hunger and traffic surge scenarios in Local Area Networks (LANs).
By combining real-time traffic monitoring, LSTM-based hunger prediction, and reinforcement learning (RL)-

based bandwidth reallocation, the system proactively redistributes network resources to maintain service quality and minimize device starvation. (Mao, 2016)

Simulation results demonstrated significant improvements over static allocation strategies, including: 25% higher bandwidth utilization, 32% reduction in average packet delay, 60% decrease in packet loss, 87% reduction in device starvation incidents. The adaptive system effectively identifies congestion early, reallocates bandwidth before service degradation occurs, and maintains fairness across multiple devices. (Alhilali, 2023)

Future research directions include:

Real-world Deployment Testing: Implementing and validating the framework in university campus LANs and medium-scale enterprise networks.

Federated Learning for Model Training: Using privacy-preserving techniques to train predictive models without exposing raw traffic data. (Alhilali, 2023)

Integration with SDN Controllers: Enhancing scalability and flexibility through centralized policy enforcement. (Kreutz, 2015)

Multi-Agent RL Architectures: Allowing multiple RL agents to cooperatively manage different network segments. (Yao, 2022)

Use of Graph Neural Networks (GNN): To model complex topologies and predict congestion hotspots more accurately. (Jiang, 2023)

By pursuing these directions, adaptive bandwidth management can evolve into a standard component of next-generation LAN infrastructures, ensuring efficient and fair resource utilization under diverse and dynamic traffic conditions. (Alhilali, 2023)

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