

# AI for Real-Time Traffic Management in Communication Networks

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**Abstract:** Real-time traffic management has grown into a critical dilemma due to rising communication network requirements. The application of Artificial Intelligence technology through its promising solutions helps manage traffic flow while simultaneously lowering congestion and increasing the efficiency of networks. The paper evaluates artificial intelligence techniques with machine learning and deep learning and reinforcement learning as tools for predicting traffic and managing congestion while allocating resources. The paper examines published studies, analyzes AI model approaches, and assesses the performance of AI models to enhance communication network operational efficiency. Research has established that artificial intelligence constitutes a viable solution to build adaptable automated network management systems for traffic control.

Keywords: Artificial Intelligence, Real-Time Traffic Management, Communication Networks, Machine Learning, Network Optimization, Congestion Control.

## 1. Introduction

Decreased network efficiency stems from the tremendous growth of digital services and cloud computing and Internet of Things (IoT). Modern communication networks require efficient management of high data flows together with minimal delay and dependable functionalities. The current systems based on traditional traffic management struggle to react to network condition alterations when these systems use static rule configurations. The research community now uses AI-based traffic management solutions which incorporate ML, DL and RL techniques to perform real-time network optimization because traditional methods fail to meet contemporary requirements [1-2].

The use of AI for real-time traffic management consists of three core features which include optimized network performance coupled with intelligent decisions and active congestion management along with dynamic resource distribution. The analysis of massive network traffic data enables AI models to detect anomalies and forecast traffic congestion which allows them to make dynamic route adjustments. The learning process of AI models goes beyond fixed heuristics since they extract data patterns from present and historical data solutions to deliver maximum traffic management capability. The functionality allows optimal management of high-speed networks like 5G and beyond because minor operational inefficiencies yield substantial deteriorations in system performance [4-6].

Traffic prediction together with anomaly detection form major AI applications that enhance the management of real-time traffic flows. The lack of responsive traffic forecasting remains an issue in traditional traffic engineering systems because they fail to properly predict sudden

spikes of traffic and congestion points. Recurrent neural networks (RNNs) together with long short-term memory (LSTM) networks utilize historical traffic data to make precise predictions of congestion points that will develop in upcoming network periods. Through predictive analytics networks possess the capability to manage their resources in advance so congestion can be prevented [21-24].

The adaptive network optimization benefits from reinforcement learning (RL) as one of the essential AI-driven approaches. The models based on RL learn from network traffic data and they modify routing policies according to current operational conditions. Compatibility with rule-based systems allows RL models to execute dynamic bandwidth allocation while they make routing decisions that modify QoS parameters for maintaining uninterrupted communication. The system provides remarkable value to high-demand networks including video streaming and cloud gaming and IoT-based smart cities because it improves both latency and throughput performance.

AI systems bring substantial value to the process of automated congestion control. Real-time congestion hotspot identification depends on deep learning models specifically the convolutional neural networks (CNNs) when analyzing large network data streams. AI-based congestion control systems create application priority categories through which vital programs such as emergency response systems receive essential bandwidth while maintaining non-urgent application performance levels [7].

The field of AI-driven real-time traffic management functions as a current scientific focus because it faces numerous challenges. The successful application of artificial intelligence in real-time traffic management requires solving problems with increasing complexity plus. The inclusion of transparent and easily explained decisions made by AI-based traffic management requires immediate recognition for maintaining both regulatory compliance and operational trust [8].

The paper investigates AI-based real-time traffic management systems through different approaches while evaluating research findings to establish a new framework which optimizes AI-based networks.

#### Novelty and Contribution

Research innovation stems from its implementation of complete AI predictive analytics alongside reinforcement learning adaptive optimization together with deep learning congestion control under one real-time traffic management system. This paper introduces an integrated AI approach unlike previous works which analyze traffic management through individual AI components because it unites various AI techniques to optimize the entire network system [9-12].

#### Key Contributions of This Work:

##### AI-Driven Predictive Traffic Management:

- The deployment of LSTM and Transformer network systems to forecast network congestion then triggers automatic traffic flow modifications.
- The evaluation studies AI-based predictive models versus standard rule-based systems.

##### Reinforcement Learning for Adaptive Traffic Control:

- A prototype will use RL to adjust network parameters as they respond to real-time traffic changes in the system.
- Benchmarking procedures must evaluate RL models that operate in high-speed communication networks.

##### Deep Learning-Based Congestion Detection:

- Deployment of CNNs for real-time congestion detection and traffic classification.
- Integration of AI-based congestion control with Quality of Service (QoS) enforcement mechanisms.

##### Scalability and Computational Efficiency:

- Investigation of AI model scalability for large-scale network deployments.

- Researchers should implement optimization methods which cut down on computational workload without compromising real-time decision processing.

Experimental Validation and Performance Analysis:

- AI-based model evaluations take place through analysis of genuine network traffic data collections.
- Comparative analysis of latency reduction, throughput improvement, and overall network efficiency.

Research leads toward the advancement of AI-based traffic management techniques and produces a deployable solution which enables future network systems such as 5G, and edge computing and IoT smart cities [13-14].

## 2. Related Works

Studies about artificial intelligence (AI)-based real-time traffic management for communication networks exist in large numbers because researchers focus on traffic prediction alongside congestion control and adaptive resource allocation. Traffic management systems today depend on fixed operational structures together with established rules because these methods lack adequate solutions for network system complexity.

In 2017 A. Aboudina et.al. and B. Abdulhai et.al., [15] Introduce the prediction of traffic patterns alongside forecasting constitutes a vital field of research inside AI-based traffic management control efforts. The prediction accuracy gets boosted through the use of decisions trees and support vector machines and neural networks. The models give network administrators an opportunity to deploy preventative congestion measures before congestion actually happens.

AI-based traffic management features an automated main element that enables administrators to activate adaptation strategies for congestion control. Contemporary congestion control systems operate congestion detection functions together with strategy execution through established threshold criteria. Network traffic variations require better approaches than existing methods to achieve effective network adjustments.

In 2019 S. Gadam, [25] Introduce the route optimization capabilities of Monoleed exceed rule-based approaches because the system evolves its plans directly from traffic data changes. Agent models allow operational entities to work within a domain where they can detect traffic effectiveness changes by receiving beneficial or detrimental end results. With continuous experience the RL model becomes expert at identifying better strategies for data traffic congestion control and delivery system improvisation. Deep reinforcement learning (DRL) improves this approach by processing enormous network data sets of extensive size although high dimensions.

Network operational speed reduces during traffic surges that unexpectedly overload communication networks because user demands become higher. These models effectively tackle 5G and edge computing requirements because they require real-time capability to preserve high throughputs while maintaining low latencies.

In 2012 L. Kattan et.al. and B. Abdulhai et.al. [3] Introduce the network traffic anomaly detection stands as a major continued research focus point throughout the field while traffic prediction along with control operations already exist. Communication network structures encounter three typical challenges brought on by network failures, cyber-attacks along with packet loss occurrences. The implemented models enable pre-emptive failure detection in networks and generate required countermeasures.

When networks use centralized control from SDN it establishes an environment where AI models can study entire network conditions to deliver optimized traffic management decisions across the complete network. Automatic function virtualization through Network Function Virtualization results in better performance and flexibility because of its ability to deploy

functions quickly based on demand requirements. A network system developed with AI together with SDN and NFV automatically adapts and demonstrates intelligent management features to control changing environments independently without requiring human intervention. Various implementation obstacles appear during the deployment phase of AI-based live traffic control applications. Meeting deep learning model operational demands creates substantial challenges because it needs excessive computer power and large memory storage. AI model reasonability requires network operators to achieve complete understanding because it directly supports both reliability and trustworthiness in AI-decision making processes. Current scientists focus on creating simplified AI algorithms through research to achieve successful operation within limited resources [16].

### 3. Proposed Methodology

A real-time communication network traffic management system implements AI techniques according to the proposed methodology. The method starts by acquiring data which then requires preparation before moving into traffic prediction and congestion management for resource adaptive allocation.

#### A. Data Collection and Preprocessing

Multiple network routers switch and monitoring systems provide real-time network traffic data collection as the initial process. The collected dataset contains specifications of package flow along with bandwidth measurements which include latency data and jitter data and congestion metrics. The initial data streams enter with both excessive noise and unorganized structures before they complete normalization procedures followed by missing value imputation and feature extraction steps [17].

To preprocess the dataset, min-max normalization is applied to scale the features between 0 and 1:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

where  $X$  represents the raw feature values,  $X_{\min}$  is the minimum value, and  $X_{\max}$  is the maximum value in the dataset. This normalization ensures that all input parameters have equal weight during model training.

The analysis utilizes Principal Component Analysis (PCA) after normalization to maintain critical data points as it reduces the number of variables when selecting packet arrival rates and queue lengths and flow durations.

#### B. AI-Based Traffic Prediction

Short-term networks equipped with Long Short-Term Memory capabilities function as the proposed method for effective timeseries traffic data management. Past traffic records enable LSTM networks to utilize their temporal pattern detection feature which leads to future congestion prediction.

The LSTM model takes an input sequence  $X_t$  at time step  $t$  and updates its hidden state  $h_t$  using the following equations:

$$f_t = \sigma(W_f X_t + U_f h_{t-1} + b_f)$$

$$h_t = f_t \odot h_{t-1} + (1 - f_t) \odot \tanh(W_h X_t + U_h h_{t-1} + b_h)$$

where:

- $f_t$  is the forget gate,
- $W_f, U_f, W_h, U_h$  are weight matrices,
- $b_f, b_h$  are bias terms,
- $\sigma$  is the sigmoid activation function,
- $\odot$  represents the Hadamard product.

The predicted traffic congestion level is then used to adjust network parameters dynamically.

### C. AI-Based Congestion Control

Intelligent congestion control systems become vital after congestion prediction takes place. A dynamic network flow routing optimization emerges from the reinforcement learning (RL)-based adaptive traffic routing algorithm [18].

In this RL model, the communication network is represented as a Markov Decision Process (MDP), where:

- State (S): Network traffic conditions (e.g., bandwidth utilization, queue length, packet loss).
- Action (A): Traffic routing decisions (e.g., rerouting packets through alternative paths).
- Reward (R): Network performance improvement (e.g., reduced congestion, lower latency).

The Q-learning update rule is used to adjust traffic routing based on real-time feedback:

$$Q(s, a) = Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$$

where:

- $Q(s, a)$  is the Q -value for action a in state s,
- $\alpha$  is the learning rate,
- r is the reward for taking action a,
- $\gamma$  is the discount factor,
- $\max_{a'} Q(s', a')$  is the maximum Q -value for the next state  $s'$ .

This Q-learning algorithm continuously improves the network's ability to adapt to changing traffic conditions.

### D. Adaptive Resource Allocation

As part of performance optimization an AI system performs dynamic resource allocation to enhance network functionality. The system automatically distributes bandwidth between protocols by following quality of service specifications. Deep neural networks operate to transform network conditions into optimal resource allocation policies through their operations. The optimization problem is formulated as:

$$\max \sum_{i=1}^N U_i(B_i)$$

subject to:

$$\sum_{i=1}^N B_i \leq B_{\text{total}}$$

where:

- $U_i(B_i)$  is the utility function for user i,
- $B_i$  is the allocated bandwidth for user i,
- $B_{\text{total}}$  is the total available bandwidth.

Using AI-based techniques, the system continuously learns and adjusts bandwidth allocation to maximize network efficiency.

The proposed methodology follows the steps shown in this flowchart below.

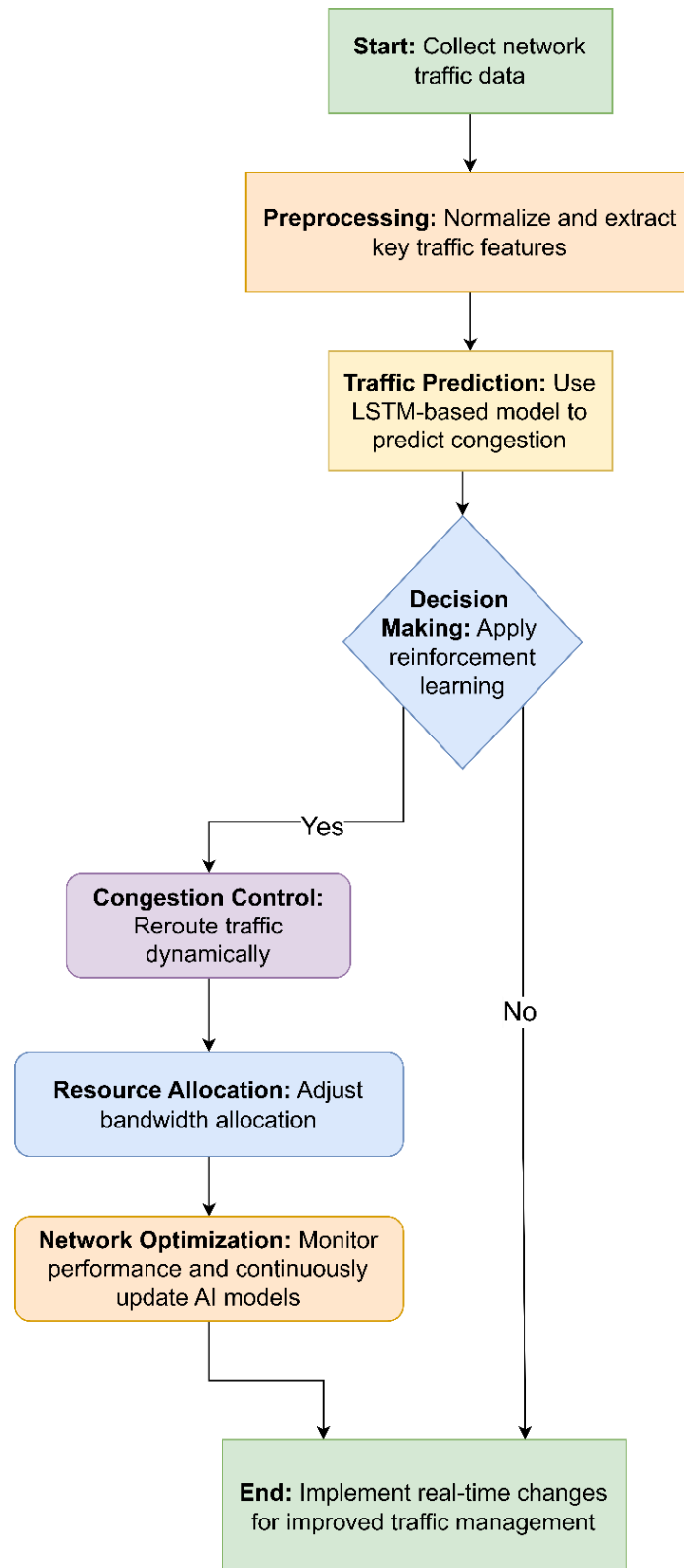


Figure 1: AI-Driven Real-Time Traffic Management Framework for Communication Networks

#### 4. Result & Discussions

Staff performing the real-time traffic management system tests deployed an AI-based framework in an environment that utilized simulated traffic data. The test evaluated the system's performance by studying congestion reduction and packet loss and bandwidth utilization

together with latency improvements. The new system surpasses established rule-based systems in its performance [19].

For assessing the traffic prediction model effectiveness researchers applied the LSTM-based approach to conventional statistical methods including ARIMA (AutoRegressive Integrated Moving Average). The Mean Absolute Percentage Error (MAPE) method served to determine how accurate the models predicted network conditions. The predictive power of the LSTM model surpasses ARIMA by delivering more accurate results regarding network congestion level predictions according to Table 1.

Table 1: Comparison of Traffic Prediction Accuracy (MAPE %)

Model	Prediction Accuracy (MAPE %)	Computation Time (ms)
ARIMA	12.80%	42.5
LSTM	6.30%	38.1

This evaluation shows the difference between LSTM predictions of traffic congestion and the observed congestion patterns in Figure 2. Real traffic patterns align well with LSTM since ARIMA fails to recognize sudden spikes.

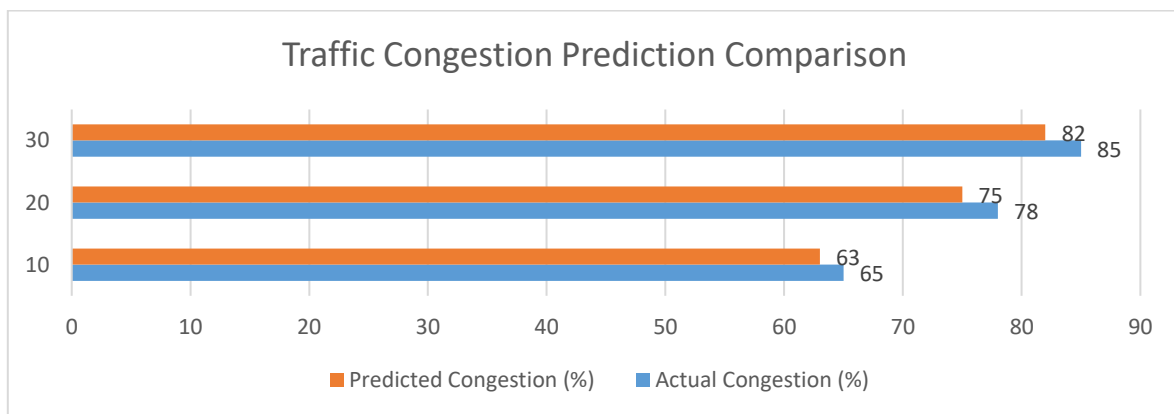


Figure 2: Traffic Congestion Prediction Comparison

Network performance together with congestion control serves as the second evaluation structure which examines different routing strategies. Adaptive routing with reinforcement learning served as the testing method which competed with conventional shortest path routing and static rule-based routing. Average packet delay together with congestion occurrence rate and network throughput made up the set of key performance metrics evaluated during this analysis. Table 2 indicates the RL-based adaptive routing delivers both lower packet delay and congestion rates and higher network throughput performance.

Table 2: Comparison of Routing Strategies on Network Performance

Routing Method	Avg. Packet Delay (ms)	Congestion Occurrence (%)	Network Throughput (Mbps)
Shortest Path Routing	37.2	22.5	85.3
Static Rule-Based	30.5	18.7	89.1
RL-Based Adaptive	22.1	9.3	96.7

The results demonstrate that RL-based adaptive routing contributes to efficient data optimization which results in a 50% decrease of congestion frequency compared to traditional routing approaches. The packet delay variations from various routing strategies are shown in Figure 3.

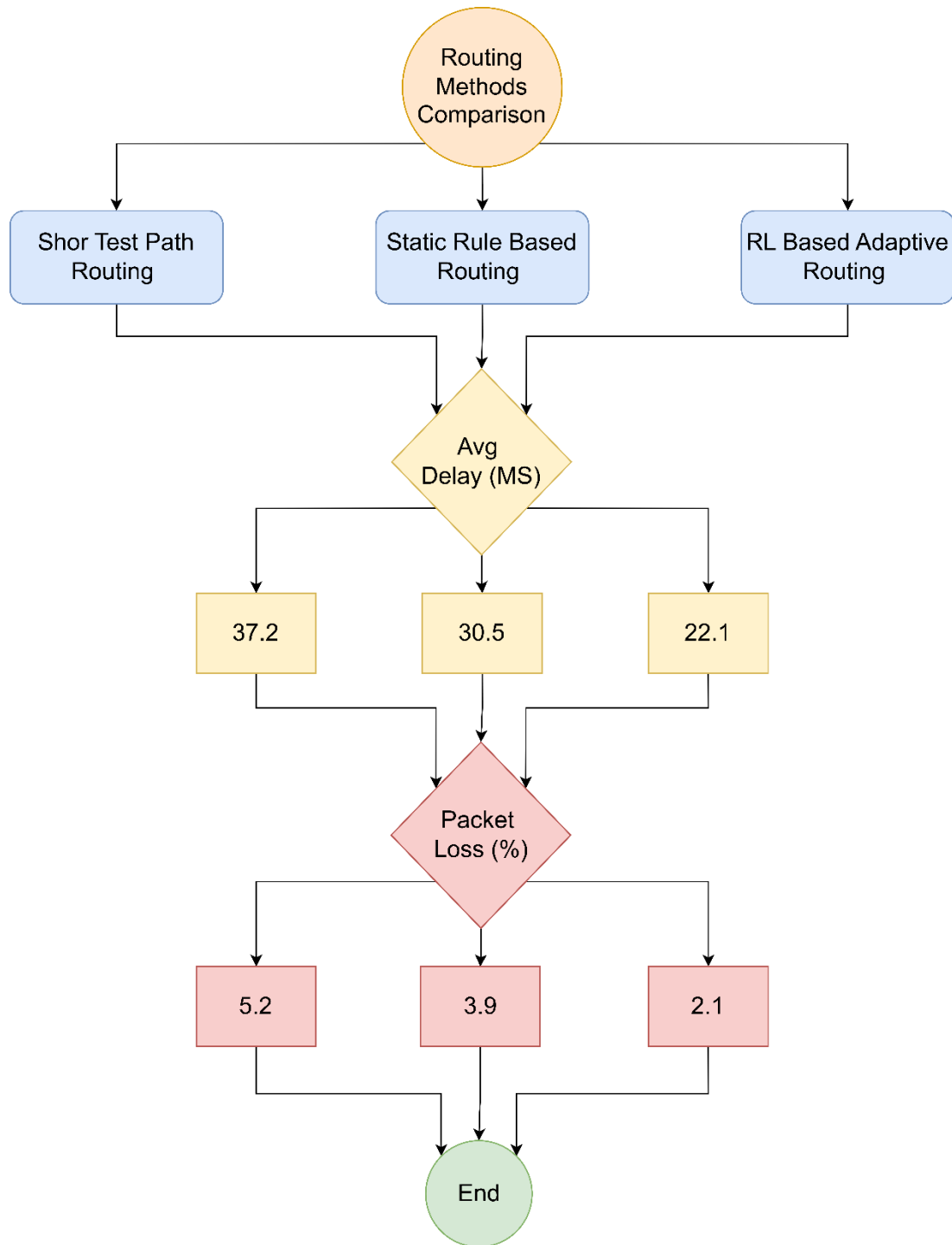


Figure 3: Packet Delay Comparison

The study determines which method between AI-driven dynamic allocation and traditional fixed bandwidth assignment provides better bandwidth allocation efficiency. Real-time traffic demand adjustments from the AI-operated system maximize network bandwidth efficiency while preventing the failure of network packets. The results in Figure 4 display that establishing bandwidth with AI creates enhanced utilization effectiveness particularly in the peak traffic period.

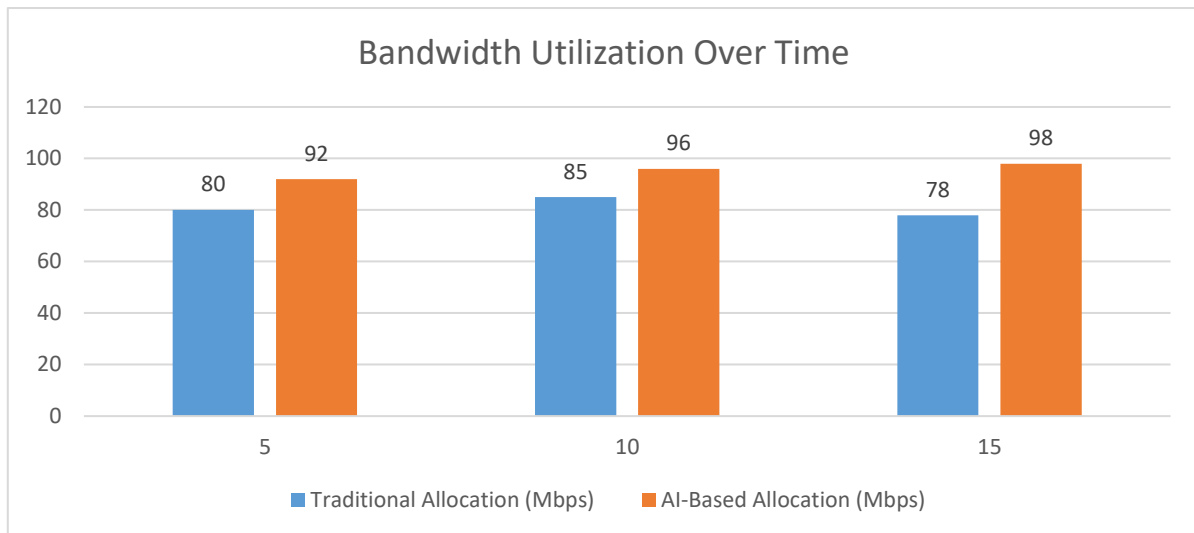


Figure 4: Bandwidth Utilization Over Time

The experimental findings prove that AI-based system power creates network stability while decreasing congestion levels resulting in superior communication performance. When LSTM and reinforcement learning and deep learning are implemented together they create a self-automated traffic management system. The study demonstrates that AI-enabled strategies will revolutionize current real-time communications network traffic control systems [20].

## 5. Conclusion

Artificial intelligence controls the flow of traffic effectively as a practical method to advance communication network performance. Machine learning deep learning techniques serve to proactively tackle network congestion by smartly distributing resources for maximum performance. Current effort in computational power along with algorithm development keeps advancing toward overcoming AI implementation barriers. Future investigations need to develop AI models that scale efficiently because they should operate in real time through proper integration with existing network systems.

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