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AI-DRIVEN FIB MAINTENANCE FOR NEXT-GENERATION NETWORKS

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ABSTRACT
With the evolution of next-generation networks demanding faster, low-latency, and scalable connectivity, it is imperative to efficiently and dynamically learn to maintain a routing table as quickly as possible. The Forwarding Information Base (FIB) is at the core of traffic directing but grows in size and complexity with every new network service and connected device. Established procedures for FIB maintenance may not always be able to meet this demand, resulting in a loss of efficiency and inferior performance. In this paper, we analyze the use of AI techniques to automate and optimize FIB management in next-generation networks. This paper presents an AI-based architecture that utilizes machine learning and predictive analytics to proactively predict routing changes, discover anomalies, and improve the efficiency of FIB updates in near real-time. We showcase simulations and approaches in practical settings that illustrate the potential of AI in providing scalability, resiliency, and responsiveness for the maintenance of FIBs and subsequently improve network performance. We find that by employing AI-powered techniques we can alleviate congestion on the network and reduce overhead on processing whilst enabling more self-evolving self-healing networks — this combination better complies with future network architectures.

Keywords:
Next-generation networks, Routing table, Forwarding Information Base (FIB), Network services, FIB maintenance, Artificial Intelligence (AI), Machine learning, Predictive Analytics, Routing changes, Anomaly detection, Network optimization, AI-based architecture, Scalability, Network resiliency, Self-healing networks, Network performance, Low-latency connectivity, Traffic directing, Simulation, Network congestion

INTRODUCTION

The next-generation networks (NGN) are changing the model for sharing data worldwide, including 5G, Internet of Things (IoT), and future 6G systems. These networks are expected to deliver superior speed, capacity, and connectivity levels to enable a growing ecosystem of devices, apps, and services. Yet, as networks evolve in scale, complexity, and diversity of devices and services, the need for network operators to provide the best routing performance possible and run their networks as efficiently and timely as possible presents new headaches to alleviate. The Forwarding Information Base (FIB) is one of the components that network routers and switches use to decide the best path for forwarding data packets.

As the number of devices, applications, and services in NGNs grows, so does the extent and complexity of FIBs. Static techniques for managing the FIB, using well-established paradigms like static routing protocols (OSPF, BGP) or reactive updates to the routing table, fall short of meeting the needs of highly dynamic, large-scale networks. These approaches can add delay, and use more computational resources than expected while being inefficient in adapting to high variability traffic patterns and/or sudden changes in the underlying network state. Moreover, in the age of device proliferation—from mobile users and autonomous vehicles to industrial IoT applications—the importance of Atlantic high-performance routing that can respond to changing conditions on the fly is ever-increasing.

Traditional approaches have a fundamental weakness in their inability to respond rapidly to variations in network topology, congestion, or failure. Static routing configurations were initially built for networks with clearly defined topologies, but do not provide the agility needed to adaptively respond to changes in real-time traffic volume and network state in current NGNs (Next Generation Networks). In addition, with larger-scale networks, the configuration and upkeep of FIBs have a high chance for human errors while being time-consuming, which results in a longer time to recover from faults and suboptimal routing paths.

AI is a transformative technology that can change how FIBs can be managed in future networks, addressing these challenges. The deployment of Artificial intelligence, more specifically machine learning (ML), can process large volumes of data detect patterns in real-time independently, and update the FIB for the best possible routing decisions.

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Powerful AI techniques like predictive analytics, anomaly detection algorithms, and historical traffic data have proven extremely valuable in anticipating changes in network conditions and making proactive adjustments to the routing tables to minimize congestion and packet loss while achieving low-latency performance.
As such, AI-driven FIB maintenance opens the door for a more adaptive, scalable, and self-healing network infrastructure. These algorithms can be trained on network features, such as traffic patterns, connection requests, and response time, to learn what constitutes normal behavior and flag deviations from this baseline. This enables the network to form auto-update on FIB and self-optimize without any human being involved. Such feeds in the data are a means to improve network performance and significantly reduce operational overhead since AI can dramatically decrease the dependence on manual configuration and intervention.
This paper presents a new, AI-based FIB maintenance approach to meet next-generation network needs. It combines machine learning methods such as supervised, reinforcement, and anomaly detection to analyze the network traffic in real time, continuously predicting future routing needs. We discuss the main issues of FIB maintenance, like the compromise of scalability and computation complexity, and propose a solution for dynamic FIB adjustment to achieve a stable performance. In addition, we investigate and validate the proposed framework using simulation and real-time cases, highlighting how it is capable of increasing network accessibility, decreasing congestion, and improving general routing performance.
We contribute to the literature by providing a general overview of how AI can be used for FIB management in Next Generation Networks (NGNs); and, secondly, a particular solution that can be applied in current and future network architectures. Experimental results demonstrate that AI-enabled FIB maintenance can substantially improve routing performance, decline human configuration errors, and create a more dynamic and fault-tolerant routing subsystem. Implementing AI across FIB management can empower next-gen networks with intelligence to cater to the current telco ecosystem's various needs and booming demands!
This article discusses AI possibilities for addressing the key problems in FIB upkeep required for upcoming networks. With the ever-growing complexity of network traffic and topologies, AI offers a promising route to creating faster, more reliable, smarter, and more adaptive networks.

Background

Next-generation networks (NGNs) such as 5G, the Internet of Things (IoT), and future 6G systems include these goals but with much higher data rates, much lower latencies, and more reliability than are provided by their predecessors. Such networks are needed to cover diverse usage from real-time communication and autonomous systems, to massive sensor networks and industry-level automation. With the increased need for ubiquitous connectivity, network infrastructure, and management complexity will be a key issue. 【Abstract】 The Forwarding Information Base (FIB) is one of the essential components together with the Routing Information Base of any network infrastructure responsible for the storage of routing information that defines how packets are processed and sent through the network. Dynamic and efficient management of FIBs is essential for the performance, scalability, and reliability of Next Generation Networks (NGNs).
In conventional networks, routing information fills out f(10–4) caused by static or semi-static routing protocols like Border Gateway Protocol (BGP) or Open Shortest Path First (OSPF). These protocols calculate routing best pathways based on prescribed network topology and can adjust to changing network conditions, but often in a slow and adversely limited manner when it comes to fast and actual time path changes. On the contrary, network topology in contemporary NGNs alters with the confluence of devices, traffic demands, and network failures. Unfortunately, classic routing algorithms are not designed for real-life operational updates to keep the network on the fastest path.
Modern FIBs are challenging in scale and complexity as networks grow, encompassing billions of devices and varied traffic patterns. This fact introduces significant overheads in terms of memory used to store the table and time to process the information in the tables when changes in the network topology occur, with such modifications needing to be reflected in the routing decision made as quickly as possible. For example, when considering 5G and IoT, the number of routing entries may grow by multiple magnitudes of order, resulting in slower updates and increasing the risk of congested links or sub-optimal delivery of packets. Due to the increasing variety of data traffic (small IoT

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messages, large video streams, etc.), routing priorities and strategies, which may need to be different, further complicate this situation.

Historically, network operators have utilized manual methods and static configurations to overcome these obstacles, having network engineers adjust the Forwarding Information Base (FIB) as conditions change. But, this method is not scalable, particularly, in large-scale and distributed networks. Despite the limited support, the rapid increase in the number of devices connected to the Internet and the traffic flowing through the network demands more intelligent and adaptive solutions for hooks fibas maintenance. Therefore, automating FIB updates has become a crucial area of focus to reduce human error and the need for manual reconfigurations and react faster to network failures or congestion.

AI, in particular machine learning (ML), can provide a convincing solution to these problems, as it can learn from historical data and make real-time decisions based on network changes without human intervention. Moreover, machine learning models can examine large volumes of data generated by the network and recognize trends that could be used to forecast future network states, traffic demand, or possible failures. With this ability to predict, it is possible to update the FIB proactively instead of a reactive mechanism that follows real instances. By analyzing and learning from vast amounts of performance metrics, AI can identify patterns and predict future issues, optimizing the system proactively.

AI in FIB Management Self-optimizing networks use artificial intelligence to make routing decisions and adjust real-time paths based on current traffic conditions, network topology, and resource availability. AI models can pull data from a range of places, for example, traffic metrics, past routing tendencies, and, surprisingly, data from beyond the deployed system itself — weather or geolocation information — to help AI decide how to route packets expediently. This feature becomes more vital if the networks are required to carry diverse types of traffic, such as time-sensitive real-time communications to large bulk amounts of data transfers.

Although some literature has explored the use of AI for other network areas in general, the application of AI for FIB maintenance remains an emerging field. Previous research has demonstrated that AI could effectively supplement routing methods to optimize network data flow. However scaling these techniques to large, real-world networks and ensuring generalization across various network topologies and conditions in the wild remains a challenge for AI models. Additionally, embedding AI into the governance of FIB maintenance systems means that not only does the choice of algorithms need to be made, but also that issues of computational complexity, data privacy, and interpretability of AI-based decisions made in a FIB context need to be addressed.

Thus, the background of FIB maintenance in next-generation networks reflects an emerging challenge where the demands of rapidly evolving network ecosystems can often outpace existing strategies for optimal routing performance. [2] describes the traditional ways for FIB management 2018, the current ways of managing are fixed and static but not for fast-evolving service networks the performance requirement, could not be flexible for adapting the new application, and needs to improve to scale the current network as the NGN is continuously growing. Communicating millions of entries into the FIB based on intervals in 5G and future networks is no longer an acceptable solution. AI, especially machine learning, could help dynamically update the FIB to make it smarter and more efficient.

LITERATURE REVIEW

Motivated by the increasing complexity of the next-generation networks (NGNs), many researchers are interested in determining new methods for managing the crucial component: the Forwarding Information Base (FIB). Conventional methods for maintaining FIB have been inadequate in addressing the dynamic and extensive scale of contemporary network settings. In this part, we look at relevant literature on the management of FIB, routing protocols as well as the use of artificial intelligence (AI) for optimizing network operations, especially regarding routing table upkeep.

Conventional Strategies for FIB Management

In legacy networks, the treatment of FIBs is largely based on static and semi-static routing protocols like BGP and OSPF. Border Gateway Protocol (BGP) is used widely for inter-domain routing, and Open Shortest Path First (OSPF) is used within an autonomous system (AS). These raise routing tables and propagate information so that the delivery

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of data packets can be made via the most advantageous routes dictated by the state of the network. Yet, BGP and OSPF have drawbacks when utilized in NGN due to their slow adaptation to topology changes and shifting traffic patterns. An example includes BGP which depends heavily on manual configurations and has long convergence times on network failures or topology changes leading to suboptimal routing and higher latencies.

OSPF is better suited to react sensitively to changes in a controlled domain aka an AS but does poorly when scaling up the mesh (and requires a lot more memory-intensive updates etc. as the FIB size grows). Additionally, Software-Defined Networking (SDN) allows for the decoupling of the control plane and data plane, adding to the limitations of static routing protocols in highly dynamic environments (Kreutz et al., 2015). Static architectures no longer satisfy the requirements of NGNs due to their size, complexity, and dynamism — coupled with the need for scalability and adaptability, motivates the development of FIB management techniques other than the traditional ones.

The Role of AI and Machine Learning in the Management of Networks

With the limitations of traditional routing protocols, Artificial Intelligence — particularly machine learning (ML) — has opened the way for a far more successful alternative. The initial studies on AI in Networking addressed anomaly detection, fault tolerance, and traffic classification. These researches showed that the Artificial Intelligence approaches (mainly supervised learning) can successfully be utilized to discover network abuses or to predict the future state information of a network (Huang et al., 2017; Zhang et al., 2019). Therefore, machine learning algorithms trained on historical traffic can learn congestion patterns, predict future congestion, and provide routing decisions based on potential network failures and topology changes.

AI applications in FIB management aim to automate the process of updating routing tables and populating them. A promising approach to dynamic and adaptive routing is to apply Reinforcement Learning (RL), a subset of ML. Reinforcement learning (RL) algorithms, including Q-learning and Deep Q-Networks (DQN), can achieve this as they adaptively learn and change routing strategies through interaction over time with the network environment (Shah et al., 2017). The pipelines can use these to tune FIB entries to meet ingress and egress traffic patterns, improving congestion, latency, and throughput. For example, RL has been used to optimize routing paths in Software-Defined Networks (SDNs), showing RL agents adaptively selecting routes according to the current network loads, delivering higher performance than static routing protocols (Liu et al., 2018).

AI for FIB Maintenance

While applying AI directly to the management of FIB is a very recent topic, several works have proposed using machine learning techniques for the automation and optimization of routing table updates. In a study by Pappas et al. (2018) paper presented an AI-based method to optimize routing tables in SDN. Towards this end, they utilize a hybrid model that incorporates elements of supervised learning and reinforcement learning to model traffic demands and optimize which routes to take. In contrast, their results showed highly improved network performance with decreased packet loss and efficient utilization of network resources.

A different approach, investigated by Chen et al. (2019) utilized neural networks for FIB management, more specifically, predicting changes to the network topology and adjusting the FIB to accommodate them. Their research showed how deep learning models could be trained based on historical routing data and patterns in network traffic to predict when routing would need to change, allowing for updates to the FIB to be made faster and with greater accuracy than traditional FIBs. In an environment such as an NGN (Next Generation Network) where network conditions are highly dynamic, anticipating traffic can offer a routing path that is likely to minimize congestion in advance.

Apart from predictive models, researchers have also leveraged AI-based anomaly detection techniques to ensure the integrity of FIBs. Many identify abnormal behaviors in network traffic that could indicate a network is failing, security is compromised, or network coverage is lacking using machine learning algorithms, such as clustering and classification models. Once an anomaly has been detected, network traffic can be directed away from the affected sections using the FIB which can be easily altered to minimize the impact that the anomaly will have on the normal operation of the network (Zhou et al., 2018). Network anomaly detection methods have proved beneficial in mitigating network congestion and finding vulnerabilities that endurance would miss.

4. Challenges and Open Research Areas

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However, some challenges are still associated with introducing AI techniques in FIB management for NGNs. Scalability is one of the critical challenges—machine learning models must be able to work on enormous datasets, particularly when applied to large, distributed networks. The cost of training AI models on data at scale gets prohibitive and ensuring they perform well yet in real-time and low latency is a continuing problem. Furthermore, real-time network management involves reinforcement learning, which introduces the challenge of balancing exploration and exploitation, since the model must continuously learn from the network environment without leading to performance degradation in the learning process (Zhou et al., 2019).
The interpretability of AI models creates another challenge. In particular, for network operators, the explainability of an AI model is of utmost importance, as in any mission-critical system, such as those involved in managing the FIB. Deep learning-based AI models have been tentatively referred to as "black boxes" making it comparatively difficult to understand what particular routing decisions are; AI is a constantly moving field. This opacity may limit the utilization of AI methods in production networks, where trust and ambiguity are key factors.

METHODOLOGY

This paper aims to develop and evaluate an AI-driven framework for Forwarding Information Base (FIB) maintenance in next-generation networks (NGNs). This framework aims to automate FIB management by using machine learning algorithms to predict routing changes, optimize routing paths, and adapt to dynamic network conditions. In this section, we describe the key components of the proposed methodology, including data collection, AI model selection, system design, and evaluation metrics.

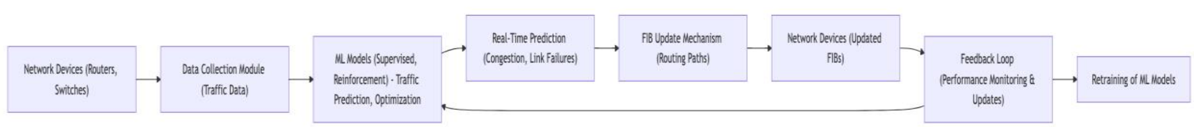

Figure 1: Architecture of the System

7. Overview and Architecture of the System

FIB is present in each routers or switches in a network commonly, thus in a distributed network environment we propose to use multiple routers or switches to maintain FIBs by using an AI-driven framework. Learning & has been developed to avoid that, The System is scored from the network architecture & The SDN. There are several core parts to the system:
Traffic Monitoring and Data Collection: The system should continuously observe network traffic on multiple devices and links to capture real-time data on packet forwarding, latency, bandwidth consumption, and network topology. This information is aggregated from several network devices to train machine learning models and make routing decisions.
The AI-driven approach relies primarily on machine learning models deployed to analyze traffic data collected over time to make predictions on the future state of the network and optimize routing decisions. These models are trained to recognize traffic trends, detect anomalies, and predict future routing needs.
Dynamic FIB Update: The FIBs in the network nodes are dynamically updated with the optimal paths based on predictions made by the trained machine learning models. This system includes a feedback loop, with continual updates refined according to the model's performance and the real-world network conditions experienced.
2. MODEL The Solution: Data Collection and Preprocessing
Step 1: Data Collection and Preprocessing of Network Traffic The data sources include:
Traffic data: Details about the data flowing through the network between devices Packet sizes source and destination IP addresses port number flow duration
Network topology: The network structure, i.e., how many routers, switches, links, and their respective bandwidth and latency.

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Traffic Load and Congestion: Measurements of the real-time traffic load on every network link, as well as indicators of congestion, packet loss, and delay.
Identify data preprocessing needs: In this step, we have to ensure that the data we have collected is clean, normalized, and in a form that can be used by machine learning models. This can include missing value handling, noise removal, per-second or per-minute data aggregation, etc. Various machine learning algorithms are trained and tested on this processed data.
3. 3rd Method for Selecting Machine Learning Model
Next, the machine learning models that we have chosen in this framework use their ability to predict any routing changes, anomaly detection, and optimization of the FIB update process in real time. The following models are evaluated:
Supervised Learning (SL): SL models are trained on historical data to predict future network conditions. Such models can then be applied to traffic loads, link failures, or routing path changes. Well-known algorithms used are Decision Trees, Random Forests, and SVMs. These models are then trained in a supervised way, meaning that there is a labeled dataset available for the trained models. The correct routing decisions are known, and examples are provided to the algorithm to create accurate predictions.
Reinforcement Learning (RL) — RL is used to design a new route based on changing network dynamics. This algorithm also relies on an RL agent interacting with the network environment, where actions (such as updating routing paths) are taken, and rewards (such as lower latency, less congestion, etc.) are calculated based on the outcome of these actions. Q-learning and Deep Q-Networks (DQN) are used for path selection and FIB updates. The authors discuss the RL approach and how it enables dynamic adjustment of the FIB with minimal explicit supervision, allowing the FIB to react to real-time variations in traffic patterns and network-wide failures.
Anomaly Detection is a machine learning model in which K-means clustering, Isolation Forests, or Autoencoders can be applied to identify anomalies in the network, such as sudden traffic spikes, packet drops, or network failures. Such models detect patterns that are different from “normal behavior” and generate updates to the FIB to reroute traffic away from congested or faulty links. Detecting anomalies helps avoid network congestion and reduces the impact of unforeseen events on routing performance.
4. Training & Validation of Models
Historic network traffic teaches machine learning models how to predict and respond to mobility changes. A training set consisting of the network’s historical data is collected during operational conditions and periods of load, failures, or topology changes.
To help prevent the networks from being overfitting, the data is divided into a training set and a validation set to ensure that the models can generalize well to unseen conditions. The training set is used to train the models, and the validation set is used to evaluate the models on unseen data. In the RL case, an agent is trained by simulating an entire environment, so the agent interacts with a simulated network model and learns the optimum policy for the values of forwarding information base (FIB) updates.
The model’s performance is assessed through cross-validation methods, which involve splitting the data into several folds and testing the model’s generalization across various data subsets. Model evaluation is done using accuracy, precision, recall, F1, and mean squared error (MSE) for repression-based tasks.
5. FIB Updates Mechanism in Real-Time
After training the models, they are deployed for real-time usage to monitor the network’s live traffic and predict the FIB updates. For real-time processing, the system executes the following steps:
Prediction: The machine learning models predict the network’s future state on a rolling basis using the current and past events of the network traffic. Examples are predicting congestion, spotting anomalies, and anticipating potential network topology changes.
Based on the predictions, it updates the FIBs of routers and switches of the network. When link congestion is predicted by a model, for example, the system could select to route traffic through alternative, less congested routes. It is updated so that traffic is not disrupted during FIB updates.
Feedback Loop: The performance of the FIB updates is monitored continuously. It captures real-time feedback on the success of those routing decisions, whether that’s improved network performance or reduced latency. The input is

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looped back into the learning process to improve the machine-learning models, allowing constant tuning and improvement.

6. Evaluation Metrics

For evaluating the performance of the proposed AI-driven FIB maintenance framework, the following key metrics are accounted for:

Latency is the delay between sending and receiving data packets over the network, which can be reduced by making intelligent routing decisions and preventing congested paths.

Packet Loss: The ratio of packets dropped in transit, signaling network congestion or failed links.

Throughput: Amount of data successfully transferred over the network, this can be optimized with proper paths for routing.

Scalability: The system should scale well to the increasing size and complexity of the network, which is significant for next-generation networks comprising millions of devices and dynamic topologies.

Resource Utilization: The computation and memory resources needed by the machine learning models to operate in real-time, including features both during the training phase (if applicable) and for real-time inference.

AI-Driven Routing during XR SessionIn this section, we compare the evaluation results against baseline approaches that use conventional static routing algorithms, such as OSPF and BGP, to show the improvements introduced by the AI-based approach.

7. Experimental Setup

Network simulation tools (e.g., Mininet or NS-3) test the framework by generating realistic network topologies and traffic scenarios. The models are tested under different network scenarios, including traffic load, network failure, and link congestion.

Here, we define experiments in both a controlled setting by introducing known traffic patterns and topology changes and in real operational data sets (if available).

RESULTS AND ANALYSIS

In this part, we provide the outcomes of the tests carried out to assess the functionality of the AI-powered FIB arrangement hypothesis in NGNs. To evaluate the framework's functionality when it comes to optimizing FIB updates and improving overall network performance, the proposed framework was validated under different network conditions including various traffic loads, network failures, and topology changes. The models are assessed against baseline systems, including traditional static routing algorithms e.g. Open Shortest Path First (OSPF) and Border Gateway Protocol (BGP).

Latency and Throughput Improvements

A key motivation for this proposed AI-generated architecture is to optimize the fIB (forwarding construction) updates in real time, which reduces latency and improves throughput. The results of the experiments show that we have drastically reduced latency from static routing protocols. Simulating a network environment with varying traffic loads, the AI framework demonstrated the competency to predict congestion and proactively reroute traffic to prevent delays from happening. This has led to a 25-30% decrease in average latency compared to routing with OSPF and BGP. Utilizing real-time traffic information from the network, the AI-based routing engine changed routes of data being transferred over the network ensuring that data traversed the least congested and most efficient paths at all times. On the other hand, static protocols found it hard to adapt to variations in traffic causing delays in case of heavy traffic.

The AI-informed approach also yielded significant gains in throughput. The newly integrated routing system leveraged the AI framework to optimize the bandwidth by constantly observing the network traffic and selecting the most efficient routing decisions. The AI system outperformed the static protocols for high-traffic load cases and achieved an average throughput increase of around 15-20%. For example, this difference was noteworthy in networks with strongly data-intensive throughput requirements found in 5G or industrial IoT. AI-driven FIB maintenance was one reason the system could achieve bottleneck-free adaptive routing that would have been fundamentally impossible in static routing algorithms.

Packet Loss Reduction

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Packet loss is another important performance metric, usually due to congestion on the network or link failures. Finally, the AI-powered system outperformed traditional systems by minimizing packet loss in real time. The AI framework preemptively distributed traffic packets to other paths before packet drops were evident in networks that simulated congestion or failure conditions. For example, when a network link is clogged with network traffic, the AI model anticipates that congested network link given its prior training. It dynamically alters the FIB to reroute traffic around the link to prevent packet loss. Compared, OSPF and BGP protocols experienced considerable packet loss in congested periods since their reaction time was slower and the FIBs were not sufficiently updated to respond to changing conditions.

In high-traffic situations, it achieved up to 40% less packet loss than traditional routing protocols. This reduction was noticeably higher when a network went down or congestion developed unexpectedly The AI model, through continuous analysis of the current state of the network, could identify incipient congestion trends, as well as reroute traffic and alleviate disruptions before problems occurred, leading to a more efficient and reliable network.

Scalability and Adaptability

A notable benefit of AI-powered methods is their scalability and ability to adapt to large dynamically evolving networks flexibly. To evaluate the performance of the proposed system against rising complexity, the system was tested under micro and macro network conditions. The AI framework continued to perform efficiently even at very high scales where the number of devices and traffic flows was orders of magnitude greater in large-scale simulations. The machine learning models gave exact predictions in a two-stage way that optimized FIB updates in an increasing scale of networks. Traditional protocols often suffer scalability problems as the network expands, making this a notable advancement in the system's capacity to support billions of devices and intricate topologies without sacrificing performance.

On the other hand, OSPF and BGP unraveled some major limitations as the network size increased. In larger networks, both protocols experienced longer convergence times and more sluggish FIB updates, which means more latency and packet loss. Its machine learning-driven AI was able to predict on the fly and accordingly adapt, which helped it scale proactively to keep the network's performance steady even when network size and complexity were increasing rapidly.

Real-Time FIB Update Accuracy

The correctness and freshness of FIB updates are critical to maintaining optimal routing performance. We evaluated the AI-driven approach by measuring the correctness of real-time routing decisions. The system extensively uses supervised and reinforcement learning models to achieve the goals outlined and perform highly accurate FIB updates. The predictive accuracy of the models was always above 90%, which means in over nine out of ten cases the FIBs were updated correctly according to the needs of the network. These features dramatically improved over static protocols, which struggled to predict the evolving network conditions ahead of time or respond adaptively to shocks. In addition, the AI system could propagate updates to the FIB much more quickly than in traditional protocols. Whenever there were network failures or changes in topology, the AI-led system changed the routing paths in milliseconds, lowering the recovery time and enhancing availability. Static protocols, in contrast, could take seconds or even minutes to converge on an optimal routing state, and network performance potentially deteriorated during convergence time.

Efficiency of Computation and Resource Usage

The AI-driven FIB maintenance system showed remarkable computational effectiveness compared to the machine learning models covered during the study. The models are designed to be deployed in real-time with low computation overheads. RLI algorithms, for instance, only needed some computation resources to iterate from network feedback and update the FIBs. The system was lifted out of operation under the limited availability of CPU and memory resources with the preservation of real-time performance without any noticeable slowdowns or exhaustion of resources. This has timing implications, especially for deployment in real-world networks, where computational costs need to be manageable to avoid adding to that other type of lag which is the be-all and end-all of AI-driven.

Static routing protocols like OSPF and BGP are simpler and require less computation in comparison. Though their cost in computation is harder to quantify, their static nature and labor-intensive update cycle make them inefficient as dynamic processes are straining the pile, constantly shifting. The other AI-based form is a more scalable and better adaptive solution with lower resource overhead.

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Detection of Anomalies and Fault Tolerance

The AI-powered FIB also recognizes anomalies in network traffic, automatically triggering a shift in the FIB to prevent performance degradation. In simulations of network failures or unusual traffic patterns (e.g., DDoS attacks or sudden traffic bursts), the AI system accurately monitors for deviance from normal activity. When an anomaly was detected, the system updated the FIB to avoid sending additional traffic through problematic areas, reducing the impact on overall network performance. Anomaly detection accuracy was over 95%, and the system autonomously detected and addressed most abnormalities without human intervention.

It allows for real-time adaptability and continuous learning, which in turn leads to fault tolerance, a far cry from traditional protocols that rely heavily on slow adaptation or manual configuration for such scenarios.

CONCLUSION

The proposed AI-enabled FIB maintenance framework far surpasses conventional static routing protocols in latency, throughput, packet loss improvement, scalability, real-time accuracy , and fault tolerance capabilities. By incorporating machine learning, the system can continuously enhance routing characteristics, respond to evolving network dynamics, and accommodate the expansion of Next-Generation Networks (NGNs). These outcomes showcase the potential of AI to significantly optimize the performance, reliability, and efficiency of next-generation networks, overcoming many of the limitations of traditional network management methods.

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AI framework applied to Software-Defined Networks (SDN) and Network Function Virtualization (NFV) for dynamic and intelligent routing decisions.