ENHANCING ROUTING AND FORWARDING IN ETHERNET/IP NETWORKS WITH MACHINE LEARNING

by

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Enhancing routing and forwarding in Ethernet/IP networks with machine learning

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Abstract

Enhancing routing and forwarding in Ethernet/IP networks using modern machine learning addresses critical challenges in modern network environments. This systematic literature review examines recent advancements in applying machine learning techniques to improve network performance and adaptability. Analyzing methodologies such as neural networks and deep reinforcement learning, the study highlights their impact on routing efficiency and scalability. Key challenges, including computational complexity and integration with existing infrastructures, are identified. The review synthesizes findings from various studies, offering insights into practical applications and future research directions. This work contributes to the field by providing a comprehensive understanding of how machine learning enhances routing and forwarding in Ethernet/IP networks, informing academic research and industry practices.

Keywords: Ethernet/IP networks, machine learning in network routing, deep reinforcement learning for Ethernet/IP networks, forwarding algorithms, neural networks in routing algorithms, deep reinforcement learning.

Introduction

Routing and forwarding in Ethernet/IP networks face significant challenges in modern networking. Increasing data traffic and dynamic network conditions demand more intelligent and adaptive routing solutions. Traditional algorithms lack scalability and fail to adapt to real-time changes effectively (Gilsdorf & Brauer, 1999; Kojić et al., 2005, 2006). Integrating machine learning (ML) techniques to enhance routing and forwarding in Ethernet/IP networks offers promising avenues to overcome these limitations. While earlier research, such as Rauch and Winarske's (1988) work on using neural networks (NNs) to determine optimal routing paths, laid a foundational understanding of ML's role in network optimization, modern technological advancements such as high-performance parallel computing offer new opportunities to enhance these systems further.

Problem statement

Ethernet/IP networks require efficient routing and forwarding to handle growing complexity and dynamic conditions. Traditional methods fail to meet scalability and real-time decision-making requirements (Gilsdorf & Brauer, 1999; Kojić et al., 2005, 2006). ML techniques, including neural networks and deep reinforcement learning, offer the potential to enhance the efficiency of these algorithms. However, these techniques' practical application and effectiveness in real-time Ethernet/IP environments remain insufficiently understood.

Purpose of the study

This study conducts a narrative literature review to determine the validity of ML as a solution, assessing the current research on enhancing routing and forwarding in Ethernet/IP networks, analyzing current methodologies, and identifying challenges to validate the effectiveness of these techniques. The analysis of the literature will offer insights into future developments and practical applications, enabling the researcher to address the following question.

Research question

What key findings emerge from the literature regarding using machine learning to enhance routing and forwarding in Ethernet/IP networks?

Research objectives

The primary objectives of this research focus on analyzing the current state of ML techniques in network routing and forwarding. The research seeks to identify key challenges and limitations associated with implementing these techniques within Ethernet/IP networks, highlighting potential barriers to adoption. To establish an understanding of current network routing and forwarding ML solutions, a comprehensive literature review will synthesize significant findings, providing a cohesive overview of existing knowledge and insights. Based on these analyses, the research will conclude by recommending future directions and practical strategies for further exploration and application.

Review of the literature

ML integration into Ethernet/IP network routing addresses significant challenges in dynamic and complex environments. The rapid growth of data traffic and the increasing complexity of network topologies demand intelligent routing solutions adapt in real-time. As a result, researchers explore how NNs leveraging deep reinforcement learning (DRL) enhance routing efficiency and network performance. This review focuses on key themes emerging from the literature, including early NN applications, traffic prediction methodologies, reinforcement learning (RL) integration, and generalization and scalability challenges.

Early neural network applications in routing

Early attempts applying ML to network routing demonstrated significant potential, laying the groundwork for later developments. Rauch and Winarske (1988) pioneered NNs in routing communication traffic, targeting reduced network delays through adaptive routing. Their findings highlighted NNs' ability to adapt effectively to dynamic conditions and complex network topologies. Soon after, Ali and Kamoun (1993) employed Hopfield networks for shortest-path computations in packet-switched networks, emphasizing flexibility in managing changing network conditions and minimal path delays. To preserve the quality of transport networks, Gilsdorf and Brauer (1999) combined NNs with fuzzy logic to improve route assignments.

Researchers increasingly recognized neural architectures' value for real-time route selection, contributing to ongoing exploration and growth in this research area. Continued research expanded on early findings, applying NNs to complex routing computations and congestion management. Using NNs, Kojić et al. (2005) adjusted traffic flows adaptively to address symmetrical and non-symmetrical links. As a follow-up to this, Kojić et al. (2006) introduced a Hopfield-based method aimed at reducing packet loss and balancing link loads.

Traffic prediction and congestion management

Traffic prediction and the application of multipath routing and congestion management represent an evolving focus on enhancing network efficiency. Barabas et al. (2011) proposed a multipath routing framework based on NN-driven traffic prediction. By anticipating congestion and dynamically adjusting routes, Barabas et al.'s (2011) work demonstrated how predictive models could reduce network delays and enhance Quality of Service (QoS). Later, L. Xu et al. (2020) presented Active Buffer Queueing (ABQ), an approach for managing congestion within data center networks by directly adjusting packet flow at the switch level. Pham et al. (2019) employed DRL to implement QoS-assigned routing for latency-sensitive flows. Almasan, Xiao, et al. (2022) integrated WAN traffic optimization with DRL-trained models, dynamically reducing overhead during changing link states. Although focused on traffic prediction and congestion control, such research offers relevant insights into managing dynamic conditions in Ethernet/IP networks.

Reinforcement learning for adaptive routing

The integration of DRL has emerged as a significant trend, with DRL models providing adaptive, intelligent routing in complex network scenarios. Valadarsky et al. (2017) addressed the challenges of implementing ML for network routing by proposing a DRL model tailored for adaptive routing. In their research, Stampa et al. (2017) examined the use of DRL agents, their adaptability to changing network traffic, and their ability to reduce network delays by autonomously adjusting routing configurations. Amin et al. (2021) surveyed supervised, unsupervised, and RL-based methods for Software-Defined Networking (SDN) routing and forwarding. Test observations indicated such ML-driven traffic optimization frameworks increased average throughput, though implementations require robust hardware acceleration to handle inference loads (Żotkiewicz et al., 2021).

Continuing DRL research saw additional frameworks with advanced capabilities. Almasan, Suárez-Varela, et al. (2022), B. Chen et al. (2022), X. Xu et al. (2022), and He et al. (2024) explored DRL models integrated with Graph Neural Networks (GNNs), which combine topology learning and decision-making capabilities. Such models leverage GNNs to represent the network state, improving routing efficiency and scalability under fluctuating conditions. The ability of DRL to autonomously learn optimal routing strategies aligns with Ethernet/IP networks' need for continuous adaptation to real-time changes.

Security and data-driven assurance

Security concerns emerged in ML-driven enhanced routing and forwarding. Bhavanasi et al. (2022) demonstrated how adversarial traffic patterns disrupted learning in multi-agent DRL, revealing how partial data—resulting from malicious flows manipulating queue levels—caused agent confusion. Additionally, attackers could exploit DRL training phases by injecting incorrect states, resulting in scenarios where agents might adopt suboptimal routes (Almasan, Suárez-Varela, et al., 2022). To address concerns, Amin et al. (2021) recommended secure data channels for training feedback, and Almasan, Suárez-Varela, et al. (2022) suggested robust anomaly detection to quarantine harmful data. Overall, research favored frameworks that maintained secure local models while exchanging summarized parameters, an approach that preserved privacy and accuracy (Y.-R. Chen et al., 2020; Tayeen et al., 2022).

Scalability and resource challenges

Implementing ML techniques, especially DRL, involves significant computational complexity. Amin et al. (2021) raised concerns regarding computational overhead during route calculations. As overhead complicated real-time responses, traditional protocols occasionally overshadowed ML solutions when hardware constraints limited feasible application at scale (Singh et al., 2021). B. Chen et al. (2022) explained complexity and overhead may hinder scalability across large, distributed networks. Addressing such scale demanded parallel computing resources, as indicated by Lupión et al. (2023), whose research revealed detailed HPC-type parallel computing neural architecture searches to speed ML model training. While parallelization accelerated training, applying HPC-based architectures and methodologies at scale for real-time decision-making in network routing and forwarding continued to pose difficulties.

Despite advancements, challenges remain. The ability to generalize across diverse topologies remains a primary challenge. Almasan et al. (2021) and You et al. (2019) noted DRL models perform well on specific topologies but struggle with generalizing to unseen network configurations. Despite earlier research by Gilsdorf and Brauer (1999) pointing out complexities when merging neural-based algorithms with existing routing and forwarding methods, little has been accomplished since to overcome such complexities. Partial observability of network states and the need for compatibility with legacy infrastructure present practical barriers to deploying ML-based solutions effectively (Almasan et al., 2021).

Methodology

This study adopted a qualitative, narrative literature review approach to examine ML-based enhancements to routing and forwarding in Ethernet/IP networks. Kitchenham and Charters (2007) established guidelines that structure the review process and promoted thorough examination of relevant publications. The systematic methodology collected, analyzed, and interpreted existing evidence regarding routing and forwarding improvements under ML paradigms. This approach supported a comprehensive investigation of prior research on NNs, DRL, and other ML methods.

Defining the approach

The decision to pursue a systematic review rather than an empirical study was driven by several considerations. First, the inherent complexity and multifaceted nature of ML applications, encompassing NNs, DRL, and other emerging techniques, necessitates an approach capable of synthesizing diverse findings from a wide array of studies. This comprehensive synthesis unifies disparate methodologies and results, highlighting critical challenges such as computational complexity, scalability, and interoperability constraints, which might be overlooked in a single empirical investigation. By reviewing existing literature, the study identifies research gaps and future directions. Due to the continuous development of ML techniques and Ethernet/IP network technologies, employing a systematic review proves a resource-efficient and feasible alternative to initiating new experimental studies. Finally, the use of a rigorous, transparent protocol ensures data collection and analysis remain methodologically sound and reproducible, minimizing bias and enhancing the validity of the conclusions.

Planning and conducting the review

The relevance of Kitchenham and Charters' (2007) work provided the foundation on which the protocol that guided the entire review was based. The protocol described the research question, search strategy, inclusion and exclusion criteria, and data extraction procedures. The question targeted ML-based enhancements to routing and forwarding in Ethernet/IP networks, focusing on demonstrated efficiency and scalability. A complement to the employed protocol saw a typology derived from the work of Grant and Booth (2009) that clarified the review approach, which centered on the critical appraisal of findings from relevant sources.

A structured plan that targeted publications released within the past decade was adhered to for this study. IEEE Xplore, ACM Digital Library, ScienceDirect, ResearchGate, and Semantic Scholar served as search venues. Queries included "machine learning in network routing," "deep reinforcement learning for Ethernet/IP networks," and "neural networks in routing algorithms." These terms aligned with the focus on NN-based techniques that address scalability, congestion management, and real-time decision-making in complex network environments.

Selection of primary studies and quality assessment

Inclusion criteria favored articles that clearly examined ML-based routing or forwarding within Ethernet/IP networks. Studies that presented empirical evidence or simulations demonstrating improved routing performance received the highest priority. Studies that addressed unrelated protocols or theoretical proposals without experimental results were excluded. This practice produced a concise set of publications for further examination and analysis.

Each publication was evaluated on methodological soundness, clarity of objectives, and strength of findings. That process drew on guidelines from Kitchenham and Charters (2007) along with additional best practices from Templier and Paré (2015). Each study received a quality rating based on transparency in data collection and thoroughness in analysis. Hazzan et al. (2006) highlighted qualitative research criteria that guided additional scrutiny regarding validity and trustworthiness.

Data extraction and thematic synthesis

The data extraction phase focused on identifying recurring themes, challenges, and contributions across studies. Following methodologies outlined by Hazzan et al. (2006), Grant and Booth (2009), and Templier and Paré (2015), thematic coding was applied iteratively to extract insights related to computational complexity, scalability, adaptability, and performance enhancements. The extracted data were categorized into predefined themes, with emerging themes identified through an open-coding process.

The thematic synthesis process followed an inductive approach to generate overarching patterns from the collected studies. Studies were compared and contrasted based on methodologies, objectives, and reported outcomes. Each study was reviewed, and key phrases or concepts were highlighted and assigned preliminary codes. Recurring patterns and relationships among codes were identified, allowing for broader theme categorization. Themes were refined and structured based on their relevance to applications in network routing and forwarding. Finally, a narrative synthesis was developed, presenting a comprehensive view of how machine learning enhances routing and forwarding performance in Ethernet/IP networks.

Analysis

Selection of primary studies

Following the inclusion and exclusion criteria discussed in the methodology, twenty-seven peer-reviewed studies were chosen based on their focus on ML-driven routing or forwarding strategies in Ethernet/IP or closely related IP-based networks. To qualify, each study provided simulation or empirical evidence of enhanced routing or forwarding under ML-based methods or offered significant insights into ML approaches (e.g., DRL, NNs) that could be applied in Ethernet/IP contexts.

Studies focusing exclusively on unrelated protocols or presenting purely theoretical proposals without simulation or real-world testing were excluded. Table 1 summarizes the final set of publications, including each paper's main objective, ML techniques, and overall contribution to Ethernet/IP network routing and forwarding.

Table 1: Overview of selected studies

Study/Studies	Objective	ML Technique(s)	Primary Contribution
Almasan et al. (2021)	Investigate ML-based solutions for real-time, dynamic routing	DRL	Highlights potential for real-time ML-driven routing
Almasan, Suárez-Varela, et al. (2022) and Almasan, Xiao, et al. (2022)	Ensure QoS with DRL + GNN; address real-time WAN routing	DRL, GNN	GNN-DRL approach for WAN routing, QoS
Amin et al. (2021)	Survey ML in SDN routing (supervised, unsupervised, RL)	Supervised, Unsupervised, RL	Comprehensive classification of ML for SDN routing
Barabas et al. (2011)	Develop NN-based multipath routing framework with traffic prediction	Neural Networks	Predictive routing, improves QoS
Bhavanasi et al. (2022)	Investigate ML to automate network routing with multi-agent learning	Graph Convolutional Networks, RL	Routing that addresses dynamic conditions without retraining
Y.-R. Chen et al. (2020)	Introduce a DRL agent for SDN routing	DRL	DRL approach for minimizing network delay in SDN

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Table 1: Overview of selected studies ***(Continued from previous page)***

Study/Studies	Objective	ML Technique(s)	Primary Contribution
B. Chen et al. (2022)	Combine GNN & DRL for auto-generation of routing policies	GNN, DRL	Improved end-to-end delay, robust to topology changes
Fang et al. (2019)	Apply Q-learning & Deep Q-learning to SDN routing	RL, Deep Q-Learning	RL-based routing algorithm for SDN
He et al. (2024)	Develop MPDRL using GNN for dynamic routing under Knowledge-Defined Networking	DRL, GNN	Enhanced link utilization, load balancing in dynamic networks
Kojić et al. (2005, 2006)	Propose Hopfield NN-based routing for packet-switched networks	Hopfield Neural Network	Optimization approach balancing shortest path, traffic constraints
Liu et al. (2021)	Classify ML-based online routing for multi-QoS in SDN	Supervised, Unsupervised, DRL	Comprehensive approach for multi-type traffic flows
Lupión et al. (2023)	Automate NN design via meta-heuristics & HPC for specialized tasks	Parallel NN architecture search	Accelerates neural architecture design; relevant to routing tasks
Obukhov and Krasnyanskiy (2020)	Automate data forwarding decisions in Adaptive Information Systems	Neural Networks	Minimizes execution time for forwarding tasks
Pham et al. (2019)	Use DRL to improve QoS routing in Knowledge-Defined Networking	DRL	Boosts multi-flow, QoS-constrained routing performance
Singh et al. (2021)	Propose Trailnet for DRL-based forwarding table replacement	DRL	ANN-based forwarding, reduces large table reliance
Stampa et al. (2017)	Develop DRL agent for adaptive SDN routing	DRL	Reduces network latency through automated traffic engineering
Tayeen et al. (2022)	Evaluate independent Q-learning for packet forwarding in ISP-scale networks	Multi-agent RL (IQL)	Multi-agent RL approach for large-scale forwarding
Valadarsky et al. (2017)	Explore data-driven routing with DRL	DRL	Early demonstration of data-driven routing viability
L. Xu et al. (2020)	Develop real-time congestion control in data center networks	ABQ	Proposes switch-level adjustments to packet flow, improving throughput, lowering latency
X. Xu et al. (2022)	Optimize network routing with GNN-based DRL under topology changes	GNN, DRL	Introduces GRL-NET for adaptive routing
You et al. (2019)	Multi-agent distributed routing with LSTM-based DRL	Multi-agent DRL, LSTM RNN	Balances shortest paths, congestion avoidance
Żotkiewicz et al. (2021)	AI logic for intent-based routing in SDN	Deep Q-Learning, ANN	Resource allocation approach ensuring QoS in next-gen networks

Quality assessment

To assess the methodological rigor of each source, criteria recommended by Kitchenham and Charters (2007) and Templier and Paré (2015) was applied, examining each study for methodological soundness (whether robust experimental or simulation methods were employed and results presented transparently), clarity of objectives (clearly stated goals or research questions), transparency in data collection and analysis (level of detail provided about data sets, tools, reproducibility, or simulation environments), and strength and applicability of findings (alignment of conclusions with empirical results and relevance to Ethernet/IP scenarios).

Table 2 synthesizes the assessments using a qualitative scale of *Low*, *Medium*, or *High*. Most studies were rated *Medium* or *High*, indicating generally robust methods and clear objectives, but varying degrees of real-world validation.

Table 2: Quality assessment of primary studies

Study	Methodological Soundness	Clarity of Objectives	Transparency in Data	Strength of Findings	Overall
Almasan et al. (2021)	High	High	Medium	High	High
Almasan et al. (2022)	High	High	High	High	High
Amin et al. (2021)	High	High	Medium	Medium	Med-High
Barabas et al. (2011)	High	High	Medium	High	High
Bhavanasi et al. (2022)	Medium	High	Medium	Medium	Medium
Chen et al. (2020)	High	High	Medium	High	High
Chen et al. (2022)	High	High	High	High	High
Fang et al. (2019)	Medium	Medium	Medium	Medium	Medium
He et al. (2024)	High	High	Medium	High	High
Kojić et al. (2005)	Medium	High	Medium	Medium	Medium
Kojić et al. (2006)	Medium	Medium	Medium	Medium	Medium
Liu et al. (2021)	High	High	Medium	Medium	Med-High
Lupión et al. (2023)	Medium	High	Medium	Medium	Medium
Obukhov & Krasnyanskiy (2020)	Medium	High	Medium	Medium	Medium
Pham et al. (2019)	High	High	Medium	High	High
Singh et al. (2021)	High	High	Medium	High	High
Stampa et al. (2017)	High	High	Medium	High	High
Tayeen et al. (2022)	Medium	Medium	Low	Medium	Med-Low
Valadarsky et al. (2017)	Medium	Medium	Medium	Medium	Medium
You et al. (2019)	High	High	Medium	High	High
Żotkiewicz et al. (2021)	High	High	Medium	High	High

Data extraction

In line with Hazzan et al. (2006) and Templier and Paré (2015), data extraction targeted computational complexity (algorithmic overhead, hardware requirements), scalability and adaptability (support for large-scale or real-time changes), performance enhancements (reduced latency, higher throughput, better QoS), and key challenges (partial observability, overhead, integration barriers). Open-coding identified recurring patterns and relationships. Table 3 offers illustrative examples of how codes were assigned.

Table 3: Example of data extraction and coding

Study	Key Concepts	Codes
Almasan et al. (2022)	DRL + GNN approach for QoS and SLA compliance; robust, scalable operation.	*Scalability, QoS, GNN, DRL*
Barabas et al. (2011)	Multipath routing with NN-based prediction for congestion avoidance.	*Predictive Routing, Congestion Management, QoS*
Chen et al. (2022)	AutoGNN for adaptive topology changes; DRL-based.	*Topology Adaptability, GNN, DRL*
Singh et al. (2021)	ANN to replace IP forwarding tables, reduce latency.	*Forwarding Table Replacement, Latency Reduction, ANN*
Pham et al. (2019)	DRL for QoS-aware multi-flow routing; improved performance.	*QoS, Multi-flow, DRL*
Tayeen et al. (2022)	Independent Q-Learning for ISP-scale forwarding.	*Multi-agent, Scalability, Independent Q-Learning*

Results

Thematic synthesis

Synthesizing these codes via an inductive approach yielded four major themes: (1) Real-time adaptability—many studies demonstrated an emphasis on adaptive and online decision-making to accommodate fluctuating traffic volumes (Almasan et al., 2021; Stampa et al., 2017), with approaches leveraging DRL agents showing particular promise for continuous route updates under dynamic conditions; (2) Topology awareness via GNNs—GNNs significantly enhance generalization and scalability (Almasan, Suárez-Varela, et al., 2022; B. Chen et al., 2022), allowing routing solutions to handle variations in network architectures more gracefully than traditional fully connected or convolutional architectures; (3) Predictive and proactive routing—several works (Barabas et al., 2011; Pham et al., 2019) deployed NNs for forecasting traffic congestion or queue lengths, enabling proactive route selection before bottlenecks arise, resulting in improved QoS and reduced latency; and (4) Scalability and complexity barriers—while ML-driven routing exhibits strong potential, researchers frequently highlight computational overhead and training complexity as obstacles (Amin et al., 2021; B. Chen et al., 2022), since large-scale Ethernet/IP networks can pose high demands on memory, compute resources, and real-time inference speeds.

Interpretation of findings

Overall, the synthesis confirms the efficacy of ML-based techniques for enhancing routing in Ethernet/IP networks by providing adaptive routing, where agents respond to congestion and topology changes in real or near-real time; predictive control, where NNs forecast traffic trends to enable proactive rerouting; and scalability with cautions, as GNN-based models scale better to larger network topologies, although training overhead remains a bottleneck. As such, the selected literature provides strong evidence ML—especially DRL combined with GNNs—can significantly improve routing and forwarding in Ethernet/IP networks when carefully implemented. Even so, further investigations into hardware acceleration, more efficient training mechanisms, and real-world validations are necessary to establish these approaches as real-world solutions and implementations.

Discussion of findings

The findings reveal a variety of outcomes regarding techniques for improving Ethernet/IP routing and forwarding. Multiple studies (Almasan et al., 2021; Amin et al., 2021; B. Chen et al., 2022) share a central observation that methods are suitable for scenarios where dynamic traffic conditions require continuous and efficient decision-making. Several core themes emerge from those studies. One central theme is real-time adaptability, which refers to routing frameworks that adjust forwarding paths almost instantly in response to new congestion data or shifting flow patterns. Work by Stampa et al. (2017) and Valadarsky et al. (2017) exemplifies this, demonstrating agents can autonomously identify routes that provide greater throughput and reduce overall latency.

Another essential discovery involves applications of NNs, including GNNs. These structures offer richer representations of network topologies, replacing older approaches reliant on standard feedforward or convolutional neural network models. GNNs capture link relationships in detail, aiding the model's capacity to operate on unseen topologies (Almasan, Suárez-Varela, et al., 2022; B. Chen et al., 2022). The capacity to generalize—crucial for Ethernet/IP networks—as operators frequently upgrade infrastructures or switch to new configurations that differ from training conditions. When GNN modules join with DRL, researchers have shown promising outcomes in controlling route assignments even when incoming traffic volumes fluctuate. In addition, proactive routing frameworks (Barabas et al., 2011; Pham et al., 2019) offer early identification of possible congestion hotspots, supporting decisions that preempt bottlenecks and distribute loads effectively.

The review also reveals certain persistent impediments. Some research sources (Amin et al., 2021; Kojić et al., 2006) indicate complex overhead and hardware constraints still slow widespread adoption, especially when real-time inference at large scale is necessary. Others (Lupión et al., 2023) emphasize parallel computing can mitigate training delays, although inference complexity in production environments might still be substantial. Another recurring issue is partial observability, where local routing and forwarding platforms have incomplete data regarding global network states. Such gaps reduce the accuracy of predictions or route decisions, especially in multi-agent designs that attempt to coordinate decisions across multiple nodes. Security concerns add an extra challenge, as deceptive traffic patterns can derail training or manipulate congestion signals (Bhavanasi et al., 2022). Collectively, these findings point to meaningful progress yet highlight persistent barriers to be addressed before large-scale commercial deployment is fully achieved.

Implication of findings

The studies analyzed in this review signify that data-driven models, including RL and DRL methods, hold promise for optimizing Ethernet/IP routing and forwarding. As traffic grows and becomes more unpredictable, the requirement for automated solutions at scale increases (Almasan, Xiao, et al., 2022). Adaptive agents based on DRL exhibit robust performance when altering forwarding rules based on real-time measurements, showing clear potential for network operators responsible for mission-critical services. Traditional routing paradigms grounded in static or heuristic approaches may be unable to accommodate bursts of traffic or sudden link failures with the same level of efficiency (B. Chen et al., 2022).

In addition, GNN-enhanced DRL stands out for its capacity to process changing network topologies. This approach permits a universal, topology-agnostic framework that can adjust if links are added or removed (B. Chen et al., 2022). In practical contexts, that adaptability aligns with the reality of networks where expansions, device substitutions, and reconfigurations are common. Operators might integrate GNN-DRL agents to handle route decisions without continuously redesigning ML models each time a node is decommissioned or newly installed. This lowers the operational burden associated with repeated retraining phases (Obukhov & Krasnyanskiy, 2020).

Despite these possibilities, multiple aspects will govern how far these findings influence real-world

Ethernet/IP networks. For example, hardware overhead emerges when many routers or switches need inference capabilities. While specialized hardware such as GPUs can reduce processing time, the deployment costs may be formidable for smaller organizations (Almasan, Suárez-Varela, et al., 2022). Some investigations (Singh et al., 2021) suggest that table replacement via NNs is appealing only when a strong match exists between hardware constraints and system objectives.

The security implications cannot be overlooked. Adversarial manipulation can distort traffic features, mislead agents, and result in inefficient routing decisions (Bhavanasi et al., 2022). Researchers have suggested robust anomaly detection and parameter exchange frameworks (Almasan, Suárez-Varela, et al., 2022; Tayeen et al., 2022) to help counter these risks, but additional research is needed to refine these protective measures. While the evidence indicates that RL and DRL solutions improve adaptability and predictive control, so exists the demand to strike a careful balance between performance gains and exposure to security vulnerabilities.

Conclusion

Limitations of the study

This study adopted a narrative review structure guided by works such as Kitchenham and Charters (2007), which means certain constraints may limit overall generalizability. Many of the original research articles rely on simulation-based experiments, as opposed to real-world implementations. Although simulation helps explore routing strategies at scale, simulation alone cannot fully reflect the influence of hardware limitations, manufacturing variations, or environmental conditions that might occur in live Ethernet/IP networks (Amin et al., 2021; Fang et al., 2019). Consequently, real-world factors such as abnormal network events, rogue traffic patterns, and external hardware failures may produce unexpected results outside the scope of simulation.

Additionally, there exists an inherent challenge in comparing papers that differ in objectives, metrics, or testbed environments presents an inherent challenge. Various authors define throughput, latency, or congestion indicators differently, complicating direct comparisons. The field would benefit from standardized definitions and consistent methods for performance measurement. Without consistent benchmarks or uniform datasets, the relative gains reported in isolated experiments may be less straightforward to interpret across different platforms (Templier and Paré, 2015).

Another point to highlight concerns the limited body of large-scale, field-deployed analyses. While certain studies incorporate mid-size topologies or advanced parallelized training pipelines, wide-scale experimentation in an operational setting remains sparse (Y.-R. Chen et al., 2020). This means potential bottlenecks—such as resource contention on shared infrastructure or dynamic interactions across multiple administrative domains—might not be captured thoroughly. As a result, real deployments could demand more robust fallback mechanisms and validated modeling for partial observability than what is addressed in the literature surveyed.

The selection of publications for review potentially introduces its own biases. The focus on articles that present empirical or simulated data about solutions for Ethernet/IP routing could overlook conceptual studies or methods that have been tested only on proprietary platforms. While the intent was to emphasize reproducible findings, it remains possible certain in-house industrial developments or private standards were not fully covered.

Recommendations for future research

Research pathways emerge from the analysis of challenges and gaps highlighted by this review. One direction relates to cross-topology generalization, an issue repeatedly cited in GNN-based studies (Almasan, Suárez-Varela, et al., 2022; B. Chen et al., 2022; He et al., 2024; X. Xu et al., 2022). While some initial outcomes (Almasan, Suárez-Varela, et al., 2022; B. Chen et al., 2022) show GNNs learn robust policies for multiple networks, more systematic validations in larger, heterogeneous topologies would clarify how consistently these models perform as network sizes grow or node and link properties vary. Collaborative research efforts aimed at curating openly shared topological datasets, along with standardized evaluation protocols, could reduce fragmentation among competing methods.

Another open question is real-world validation at a greater scale. Although parallelized training reduces overhead for preparing advanced models (Lupión et al., 2023), operational networks still require near-instant inference and stable responses to link failures. Exploration of hardware accelerators embedded in routers or switches could potentially address these latency demands, but thorough cost-benefit analyses would be needed. Controlled pilots on production networks with mid-range scales might offer insight into how ML-based routing and forwarding copes with abrupt surges in traffic flows, legitimate or malicious. Comprehensive defenses against adversarial patterns also demand further attention, supported by the concerns of Bhavanasi et al. (2022).

Finally, interdisciplinary collaboration across distributed systems and network operations stands to improve the reliability and interpretability of ML-driven routing and forwarding approaches. Possibly, some advanced neural models made available may act as "black boxes," generating route decisions that can be hard to justify when traffic anomalies occur. Researchers could investigate model-agnostic explanation tools—originally conceived for image recognition—and adapt them for network route selection. Such efforts would equip operators with interpretive frameworks to examine routing proposals and detect unintended behaviors more quickly. Ensuring the explainability of real-time routing systems might raise trust among network operators who otherwise remain cautious about adopting complex algorithms without transparent rationales.

These suggested research directions should help consolidate ongoing explorations of ML-based routing into unified frameworks. They would strengthen ties between academic research and industry practice, aligning theoretical concepts with practical operational needs. Over time, narrowing the gap between simulation results and reliable, secure real-world deployments will prove essential for further research and development of ML-enhanced Ethernet/IP routing and forwarding.

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