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Intelligent Routing Optimization in Dynamic Network Environments: A Systematic Review of Advances and Limitations

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Abstract

This study focuses on routing optimization process using intelligent technologies such as Machine Learning, Deep Learning, and Deep Reinforcement Learning. With the widely use of Internet and online services, users expect faster, reliable, and uninterrupted network connections; therefore, routing optimization has become essential. The main objectives are to select the best paths for traffic, reduce delays, traffic congestion, increase throughput, and efficiently use network resources. Traditional heuristic and mathematical methods cannot fulfill these criteria, which has facilitated the adoption of intelligent routing optimization techniques. To understand state of the art, we conduct a systematic literature review on intelligent routing optimization. The analysis shows that intelligent routing methods can enhance network throughput, reduce delays and congestion, and provide effecient routing compared to traditional techniques. However, several challenges remain, such as intensive computation, time-consuming training, and ignoring hardware limitations which directly affect performance. Resolving these issues is critical to fulfill user expectations.

Keywords Deep Reinforcement Learning; Intelligent Routing; Machine Learning; Routing Optimization; Traffic Engineering

په خوځندو شبکوي چاپېريالونو کې د ځيرک لوري غوراوی: د پرمختګونو او محدوديتونو سيستماتيکه بياکتنه

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لنډيز

دا څېړنه د لوري غوراوي بهير د ښه والي (Routing Optimization) په اړه تمرکز کوي، چې پکې له ځيرکو ټکنالوژيو لکه د ماشين زده‌کړې (Machine Learning)، ژورې زده‌کړې (Deep Learning)، او ژوې تقويتي زده‌کړې (Deep Reinforcement Learning) څخه ګټه اخيستل شوې ده. د انټرنېټ او آنلاين خدمتونو د پراخ استعمال له کبله، کاروونکي د چټکو، باوري او بې‌وقفې اړيکو تمه لري؛ له همدې امله، د لوري غوراوي بهير ښه کول خورا مهم ګرځېدلي دي. اصلي موخه دا ده چې د معلوماتو لپاره غوره لارې وټاکل، ځنډونه او د معلوماتو ګڼه‌ګوڼه راکمه، د معلوماتو د لېږد ظرفيت زيات، او د شبکې بېلابېلې سرچينې په اغېزمن ډول وکارول شي. دوديزې Heuristic او رياضيکي طريقې دا اړتياوې نه شي پوره کولای. د اوسني پرمختللي حالت د درک لپاره، موږ د ځيرک لوري غوراوي د ښه والي په اړه د وروستيو څېړنو يوه منظمه ادبي بياکتنه ترسره کړېده. تحليل ښيي چې د ځيرک لوري غوراوي طريقو کارول کولی شي د شبکې Throughput زيات، ځنډونه او ګڼه‌ګوڼه راکمه، او د دوديزو طريقو په پرتله لا زيات باثباته او اغېزمنه نتيجه ورکړي. سره له دې پرمختګونو، لا هم ځينې ستونزې شته، لکه درونډ محاسبوي بار، د روزنې ډېر وخت نيول، او د هارډوير محدوديتونو له پامه غورځول شوې، چې دا ټول په مستقيم ډول د شبکې پر فعاليت اغېز کوي. د دغو ستونزو حل د کاروونکو د غوښتنو د پوره کولو لپاره ډېر مهم دي.

کليدي کلمې ژوره تقويتي زده‌کړه؛ ځيرک لوري غوراوی؛ ماشين زده‌کړه؛ د لوري غوراوي ښه والی؛ د معلوماتو انجنيري

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Introduction

The rapid growth of the Internet has transformed many aspects of human life, including lifestyle, business, communication, education, agriculture, and other sectors (Rahmatzai,2024; Wasi & Abulaish, 2024). According to the International Telecommunication Union (International Telecommunication Union, 2025) report, 74 percent of the world's population, approximately 6 billion people, is connected to the Internet. Through which they use various digital services. These services include cloud computing, Voice over Internet Protocol (VoIP), Internet of Things (IoT), and online media platforms for watching videos, listening to music, and browsing pictures. Furthermore, the ITU report presented in Figure 1 indicates that the number of Internet users increases each year.

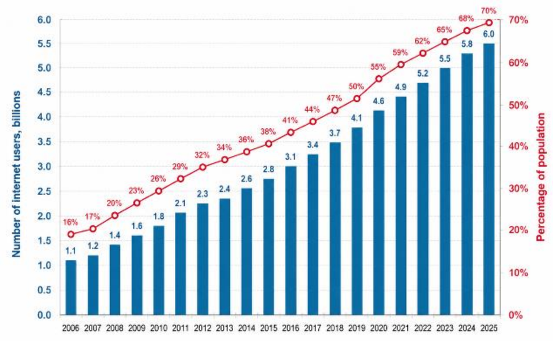

Figure 1: Online population percentage (International Telecommunication Union, 2025)

Access to online services depends on various networking hardware, including computers, mobile devices, wireless access points, switches, routers, etc. Each of these components require appropriate software to operate its functions effectively. Among them, routers play a particularly crucial role, as they forward data packets from a source to their destination across different networks using various routing protocols (Forouzan, 2022).

Routing protocols are a set of instructions that direct routers to forward packets from source to destination. Generally, routing protocols are divided into two main categories: static and dynamic. Each of these categories is further divided into several subcategories, as illustrated in Figure 2 (Abadin et al., 2021; Yousif, 2025).

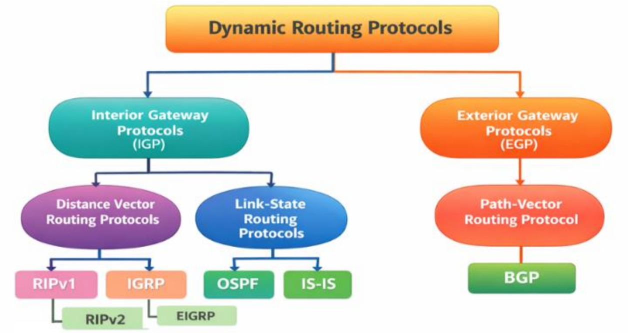

Figure 2: Categories of Routing Protocols (Abadin et al., 2021; Yousif, 2025)

Among link-state routing protocols, Open Shortest Path First (OSPF) is the most widely used in modern Internet Protocol (IP) networks due to its open-standard nature, broad multi-vendor support, scalability, and efficient shortest-path computation. Intermediate System to Intermediate System (IS-IS) is another link-state routing protocol. However, it is less commonly deployed in enterprise environments and is more frequently used in large-scale service provider networks (Kurose & Ross, 2021).

The use of the Internet and online services in daily activities has also significantly increased users' expectations for fast, reliable, and uninterrupted network access. As a result, optimizing network performance has become a critical concern, particularly regarding routing efficiency, optimal path selection, topology convergence speed, and resource utilization. These performance characteristics are strongly influenced by the design and operation of routing protocols, which play a central role in determining how traffic is forwarded across different networks (Jiang et al., 2024).

Traditional routing optimization methods are generally divided into two main categories: heuristic methods and mathematical optimization-based methods. Heuristic approaches produce results quickly, but they depend on expert knowledge and manual configuration. Generally, it is used for shortest-path routing and load balancing. As a result, it often struggles to handle changing network environments rapidly. In contrast, mathematical optimization-based methods rely on general-purpose solvers, such as IBM ILOG CPLEX, which provide flexibility but require high computational time, making them unsuitable for real-time routing decisions (Almasan, 2021). These limitations have motivated the networking research community to investigate alternative methods and emerging technologies that better accommodate the adaptability, scalability, and responsiveness required by modern, network-changing environments (Liu et al., 2025).

Emerging intelligent technologies, particularly Artificial Intelligence (AI) and Machine Learning (ML), have introduced new and effective approaches to enhance the optimization of traditional routing protocols. In contrast to static routing methods, these technologies can adapt to real-time network conditions, learn from historical traffic patterns, and efficiently utilize available network resources to improve routing decisions and overall network performance (Alam & Thottan, 2024). As a result, intelligent techniques have created significant opportunities for routing optimization across various network environments and routing protocols, including Software-Defined Networking (SDN) and OSPF. A wide range of techniques, models, and optimization methods have been proposed to enhance routing performance in various areas (Amin, 2025; Chen et al., 2024). Therefore, this study aims to identify the key factors influencing routing optimization and to identify underexplored parameters that may further improve routing efficiency. To achieve this aim, the following research objectives are defined:

RO1. To identify intelligent techniques used for dynamic routing optimization and their network environments. RO2. To examine objectives, performance metrics, and evaluation methods of intelligent routing approaches. RO3. To compare intelligent routing methods with traditional routing protocols in terms of adaptability, scalability, efficiency, convergence speed, and real-time decision-making in dynamic network conditions. RO4. To identify limitations and research gaps in AI-based routing optimization.

Considering the objectives of this study, the following research questions are addressed: RQ1. What kind of intelligent techniques are used for dynamic routing optimization, and in which types of network environments are they implemented? RQ2. What are the objectives, key performance metrics, and evaluation methods of assessing intelligent routing optimization approaches? RQ3. How do intelligent routing optimization methods perform compared to traditional routing protocols in terms of adaptability, scalability, efficiency, convergence speed, and real-time decision-making in dynamic network conditions? RQ4) What are the main limitations and unexplored areas of AI-based routing optimization in the literature?

To achieve the above objective, we conduct a systematic literature review to analyze existing research on OSPF performance optimization and the integration of machine learning techniques into routing protocols.

Literature Review

Amin (2025) indicated that traditional dynamic routing protocols like OSPF calculate the best path from source to destination using factors such as interface cost, hop count, etc., without considering real-time factors such as latency, congestion, or link stability. These calculations cannot account for the above-mentioned factors, which eventually lead to latency that is not suitable for peak-time network traffic, making the network unstable.

To improve OSPF performance, the researchers have used ML models and techniques for traffic forecasting, anomaly detection, failure prediction, and dynamic cost optimization. Supervised learning models, such as Random Forest and XGBoost, were used to predict network states and dynamically assign routing costs based on traffic utilization and real-time performance metrics. Time series forecasting models, including Auto Regressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM), were applied to forecast traffic patterns and proactively adjust routing paths before congestion occurs. In addition, Random Forest and logistic regression were also used to predict link and node failures. Their results show that integrating ML models into OSPF can reroute traffic, improving latency and throughput by 30%. (Amin, 2025; Abulaish et al., 2024).

Almasan et al. (2021) and Wasi and Abulaish (2023) focus on ML unseen features and DRL-based routing in Software-Defined Networking (SDN) environments to enhance routing optimization. They proposed a DRL routing framework that combines Proximal Policy Optimization (PPO) with Graph Neural Networks (GNNs). Their framework dynamically selects paths to minimize maximum link utilization and congestion. Their findings show that this approach performs better than traditional OSPF routing and other heuristic methods, achieving results close to those of optimization-based techniques with much lower computational time. Further, the graph-based learning model enables the system to operate effectively across diverse, previously unseen network topologies.

Etengu et al. (2022) introduced a DL-based traffic prediction framework for hybrid SDN/OSPF backbone networks. Researchers used LSTM and Gated Recurrent Unit (GRU) along with Principal Component Analysis (PCA) and Canonical Correlation Analysis (CCA) to improve prediction accuracy and computational efficiency. Real traffic traces have been used from the Gigabit European Academic Network Technology (GEANT) backbone network, and their results show that the proposed models achieve low prediction errors, approximately 0.0114–0.0118, with Root Mean Square Error (RMSE) values, indicating very good prediction accuracy compared to traditional ML approaches. In particular, the CCA-based LSTM model demonstrated strong multi-step traffic-prediction capability, thereby improving throughput and delay performance.

Similarly, Li et al. (2023) proposed a novel intelligent routing algorithm, called DRL-PPONSA, for software-defined wireless networks (SDWNs) that integrates network situational awareness with PPO-based DRL. The global network state information—such as bandwidth, delay, packet loss, and wireless node distance — is collected through an SDWN controller and further improved using a GCN–GRU-based traffic prediction model to capture spatiotemporal traffic dynamics. The predicted traffic matrices and topology information are then used as the environment state for a DRL agent, which selects next-hop nodes to optimize routing decisions. The experimental results show that the proposed algorithm outperforms traditional routing algorithms in terms of shortest path, throughput, delay, and packet loss. In addition, it achieves faster, more stable convergence than DQN-based methods.

In addition to DRL, metaheuristic optimization has also been implemented. El-Hefnawy et al. (2021) introduced a Hybrid Ant Colony Optimization (HACO) algorithm for large-scale SDNs. The researchers combined ACO with mutation operators and employed box-covering and k-means clustering techniques to partition the network into smaller logical subnets. The results show that the proposed approach reduced computational complexity, the routing search space, and improved routing efficiency in dynamic topologies. Finally, HACO outperforms OSPF in terms of delay and packet loss, but remains limited to centralized SDN environments.

To improve the generalization capability of DRL, Almasan et al. (2022) integrated Deep Q-Networks (DQNs) with GNNs, thereby overcoming the limited generalization of traditional DRL-based routing solutions. The researchers treated the routing problem in optical transport networks as a sequential decision-making task, in which traffic requests are assigned routes dynamically without rerouting previously established connections. A DQN is used, where the Q-value is computed by a GNN that learns from the network’s graph structure. The model uses link information such as available capacity and path importance to make routing decisions. It also uses routing actions as graph features to work correctly on different network topologies. Experimental results on unseen simulated and real-world topologies demonstrate that the proposed DRL+GNN model outperforms existing DRL methods with strong generalization and millisecond decision latency.

Wu et al. (2020) introduced the idea of cognitive routing to improve traditional routing methods that rely solely on basic rules, such as shortest path, and ignore network quality in modern high-traffic networks. The author’s model routing as a DRL problem, using the network as the environment, traffic patterns as states, link weights as actions, and negative end-to-end delay as the reward. Their Deep Deterministic Policy Gradient (DDPG)-based algorithm, tested in the RL4Net simulator, shows that it learns efficient routes and reduces packet delays compared to OSPF and random routing.

To improve scalability in large-scale SDNs, Ye et al. (2024) proposed a multi-agent DRL-based cross-domain routing framework (MDRL-TP). This framework addresses the scalability and slow convergence issues encountered in traditional SDN routing methods. In their approach, the network is divided into multiple subdomains, each managed by a local controller. A root controller supervises communication between these subdomains using a hierarchical structure. The system combines Dueling DQN with a GRU-based traffic-prediction model to create adaptive routing paths within and between domains in real time. Experimental results show that the proposed approach significantly improves network throughput and reduces delay and packet loss compared to traditional routing algorithms such as OSPF.

To address distributed optimization, Bernárdez et al. (2023) explored the limitations of traditional TE methods, which depend on centralized optimization and suffer from long execution times and poor scalability. To solve these issues, the authors proposed MAGNNETO, a fully distributed TE framework based on multi-agent reinforcement learning (RL) and GNNs. In this framework, agents are placed on network links and cooperatively adjust OSPF link weights using local information and communication with neighboring agents. The results show that the framework enables fast, parallel decision-making without a central controller. It also performs well across different network sizes and remains compatible with traditional OSPF.

Integrating AI-driven optimization with practical, real-world routing, Al-Najjar et al. (2024) explore the gap between AI-based TE research and real-world deployment. ML can optimize traffic and predict congestion. Earlier studies mainly used simulations, but this work uses Hecate, an AI system that decides the best paths for network traffic, together with PolKA. This routing system ensures traffic actually follows those paths. Using real-time network data and path-quality predictions, the system calculates the best routes and applies them directly. The findings show how networks can operate like self-driving systems, automatically directing traffic, reducing congestion, and making better use of available resources.

To handle hardware constraints, Wang et al. (2020) propose a framework that jointly optimizes Traffic Matrix Measurement (TMM) and TE in SDN switches with limited Ternary Content-Addressable Memory (TCAM) capacity. In SDN, both traffic measurement and routing require installing flow rules in TCAM, which is a limited, expensive memory resource. Allocating TCAM separately for TMM and TE reduces network performance. The authors formulated a Mixed Integer Linear Programming (MILP) model to maximize directly measured traffic for improved accuracy and minimize maximum link utilization for better load balancing. Since this problem is very hard to solve (NP-hard), they use approximate methods: Maximum Load Rule First (MLRF) for initial estimation, Traffic Matrix Measurement First (TMMF), which prioritizes measuring large flows, and Traffic Engineering First (TEF), which prioritizes routing optimization. Their results show that jointly optimizing TMM and TE works much better than handling them separately, highlighting the significant impact of limited TCAM capacity on SDN performance.

Lightweight-RL approaches have also been explored. Nemoto & Matsutani (2022) propose a method called Online Sequential Extreme Learning Machine Q-Network (OS-ELM-QN). This approach is a fast, simple network routing method that uses a lighter model that trains more quickly and requires less computing power than complex deep neural networks like DQN. The researcher’s findings show that the OS-ELM-QN method adapts better to network congestion than traditional routing protocols like OSPF and avoids the massive training cost of deep reinforcement learning. In addition, OS-ELM-QN trains approximately twice as fast as DQN and reduces packet delay under heavy traffic. Finally, this method offers a good balance between speed, efficiency, and accuracy.

Yi et al. (2025) proposed a novel routing method, Adaptive Predictive Multi-Metric (APMM), for UAV swarm networks. This method was generally used in dynamic environments where drones move quickly and network connections change frequently, because traditional routing methods cannot maintain stable, fast communication in such environments. The authors designed a system that predicts the future positions and speeds of drones to estimate how long communication links will remain stable. They use this predicted link stability, along with queue length and transmission distance, to choose the best route using a Max-Min Ant Colony System (MMAS). The simulation results show that combining movement prediction with multi-metric optimization improves communication reliability and quality in UAV swarm networks. APMM achieves a higher packet delivery ratio and maintains competitive delay compared to DSR, traditional ACO, and LSTM-based methods, especially under high mobility.

Serag et al. (2024) explore the use of ML for traffic classification in SDN environments, focusing on the limitations of traditional classification methods such as port-based techniques and deep packet inspection. The researchers claim that conventional methods suffer from low accuracy, high computational cost, and poor scalability. They analyze various machine learning approaches, including supervised, unsupervised, semi-supervised, reinforcement, and ensemble learning. The study shows that supervised algorithms, such as Random Forest and Support Vector Machine, achieve the best performance, and integrating ML with SDN significantly improves traffic classification, Quality of Service (quality of service), and network security.

Finally, Casas-Velasco et al. (2021) introduce a routing framework for SDN based on DRL to address the limitations of traditional static routing algorithms, which are unable to adapt to changing network conditions. The authors develop an intelligent routing agent based on a Deep Q-Network, integrated into the SDN controller. The model represents routing as a decision-making process in which network parameters, such as link utilization and delay, serve as inputs, and routing decisions are guided by a reward mechanism that minimizes delay and congestion while maximizing throughput. Experimental results show that the approach, called Deep Reinforcement Learning-based SDN Intelligent Routing (DRSIR), improves load balancing, reduces packet loss, and enhances overall network performance compared to traditional routing methods.

The comparative analysis of the above-reviewed literature considers evaluation factors such as the applied algorithms, optimization objectives, key performance metrics, and the analysis of congestion causes. These criteria provide a structured framework for assessing how prior research addresses routing efficiency and congestion reduction, with the results summarized in Table 1 to highlight the strengths and limitations of existing approaches.

Table 1: Summary of Implemented Intelligent Technologies for Routing Optimization

No	Study	Applied Algorithms	Optimization Objectives	Key Performance Metrics	Congestion cause analysis
1	Amin (2025)	RF, XGBoost, ARIMA, LSTM	Dynamic cost optimization	Delay, Throughput	No congestion root-cause analysis
2	Almasan et al. (2021)	PPO + GNN	Minimize link utilization	Link utilization	–
3	Etengu et al. (2022)	LSTM, GRU	Traffic prediction	RMSE, Delay	–
4	Li et al. (2023)	PPO + GCN-GRU	Multi-metric routing	Bandwidth, Delay, Loss	–
5	El-Hefnawy et al. (2021)	HACO	Delay reduction	Delay, Loss	–
6	Almasan et al. (2022)	DQN + GNN	Traffic allocation	Capacity utilization	–
7	Wu et al. (2020)	DDPG	Delay minimization	End-to-end delay	–
8	Ye et al. (2024)	Multi-agent DRL + GRU	Cross-domain TE	Throughput, Delay	–
9	Bernárdez et al. (2023)	Multi-agent RL + GNN	Distributed TE	Link utilization	–
10	Al-najjar et al. (2024)	Supervised ML	AI-driven TE	Bandwidth, Latency	–
11	Wang et al. (2020)	MILP + Heuristics	Joint TMM & TE	Link utilization	Only TCAM constraint modeled
12	Nemoto & Matsutani (2022)	OS-ELM Q-learning	Latency reduction	Packet delay	No congestion root-cause analysis
13	Yi et al. (2025)	Diffusion + MMAS	Multi-metric routing	PDR, Delay	–
14	Serag et al. (2024)	Supervised/Unsupervised ML	Traffic classification	Accuracy	–
15	Casas-Velasco et al. (2021)	DQN	Congestion minimization	Delay, Loss	–

Note: RF = Random Forest, XGBoost = Extreme Gradient Boosting, ARIMA = AutoRegressive Integrated Moving Average, LSTM = Long Short-Term Memory, PPO = Proximal Policy Optimization, GNN = Graph Neural Network, GRU = Gated Recurrent

Unit, GCN = Graph Convolutional Network, HACO = Hybrid Ant Colony Optimization, DQN = Deep Q-Network, DDPG = Deep Deterministic Policy Gradient, DRL = Deep Reinforcement Learning, TE = Traffic Engineering, MILP = Mixed Integer Linear Programming, TCAM = Ternary Content Addressable Memory, OS-ELM = Online Sequential Extreme Learning Machine, MMAS = Max-Min Ant System, PDR = Packet Delivery Ratio.

Methodology

This systematic literature review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, which comprise four principal phases: identification, screening, eligibility, and inclusion. The workflow corresponding to these phases is illustrated in Figure 3.

In the identification phase, we considered all papers published from 2020 to 2025, resulting in 80 articles. After identifying the articles, the title, abstract, and keywords are reviewed in the screening phase, and 26 articles are included that mention “routing optimization”, “traffic engineering”, “intelligent routing”, or “optimal routing” in the title, abstract, or keywords. The complete paper is read during the eligibility phase, and a decision is made on whether to keep it based on the inclusion/exclusion criteria listed in Table 2. In this phase, 11 records are eliminated. The remaining 15 papers that pass this stage are eligible and included for the final detailed analysis as shown in Figure 3.

IDENTIFICATION	Google Scholar	Initial Search	27	Impurity Removal	13	Duplicate Removal N=11	Total Records Remaining N=32
	ACM		30		15		
	IEEE Explore		15		5		
	Science Direct		8		4		
	Total		**80**		**37**		
SCREENING	Total Records Passed Through the 1st Phase N=32	Filtered by Title & Abstract	Records Removed Based on the Inclusion / Exclusion Criteria N=6				Total Records Remaining N=26
ELIGIBILITY	Total Records Passed Through the 2nd Phase N=26	Filtered by Eligibility Criteria	Records Removed Based on the Inclusion / Exclusion Criteria N=11				Total Records Remaining N=15
INCLUDED	All the Articles that passed the 3rd Eligibility Phase are included in the Final in-Depth Analysis for this Study.						Total Records Selected N=15

Figure 3: A step-by-step process and flow diagram indicating the identification and selection of the articles

Table 2: Inclusion and Exclusion Criteria

Inclusion Criterion	Exclusion Criterion
Articles focusing on routing optimization, traffic engineering, intelligent routing, and optimal routing using machine learning and deep learning techniques	Articles addressing routing optimization, traffic engineering, intelligent routing, and optimal routing without the use of machine learning or deep learning
Articles published or made available between 2020 and 2025	Articles published or made available before 2020
Articles explicitly addressing optimization problems in routing	Articles focusing on routing-related topics without an optimization perspective (e.g., fake news propagation, security attacks, or social network analysis)
Studies that analyze routing optimization, traffic engineering, intelligent routing, and optimal routing from a machine learning or deep learning perspective, including relevant optimization factors	Studies that discuss routing optimization, traffic engineering, intelligent routing, and optimal routing without involving machine learning or deep learning methods
Articles presenting theoretical models, practical frameworks, or experimental implementations related to routing optimization, traffic engineering, intelligent routing, and optimal routing using machine learning and deep learning	Articles that are purely descriptive, conceptual, or unrelated to machine learning–based routing optimization, traffic engineering, intelligent routing, and optimal routing

Findings

In this section, we systematically address the four research questions. The analysis begins by identifying and examining the key aspects of routing optimization, traffic engineering, intelligent routing, and optimal routing. It also reviews the research methodologies employed in this domain, as well as the principal theories and frameworks that provide the theoretical foundation for routing optimization studies.

A. RQ1. What kind of intelligent techniques are used for dynamic routing optimization, and in which types of network environments are they implemented?

The reviewed studies show that routing optimization based on intelligent technologies is increasingly used in different network environments. Traditional ML algorithms such as Random Forest, XGBoost, and Support Vector Machine (SVM) are mostly used to improve OSPF by predicting traffic, failures, and congestion in traditional IP networks (Amin, 2025; Serag et al., 2024; Wasi & Abulaish, 2020).

DL models such as *LSTM* and *GRU* are mainly used for traffic prediction in backbone and hybrid SDN/OSPF networks to prevent traffic congestion (Etengu et al., 2022).

DRL methods such as *PPO*, *DQN*, *DDPG*, and *multi-agent RL* are widely used for fully dynamic routing, particularly in SDN, optical, and large-scale programmable networks, where they enable real-time optimal path selection (Almasan, 2021; Almasan et al., 2022; Bernárdez et al., 2023; Casas-velasco et al., 2021; Nemoto & Matsutani, 2022; Wu et al., 2020; Ye et al., 2024).

Many recent studies combine DL prediction with DRL decision-making for better scalability and adaptability, particularly in software-defined wireless networks and cross-domain SDNs (Li et al., 2023; Ye et al., 2024).

In addition, metaheuristic methods such as Ant Colony Optimization are used in highly dynamic network environments, including large-scale SDNs and UAV swarm networks (El-Hefnawy et al., 2021; Yi et al., 2025).

In conclusion, the research demonstrates that ML, DL, and DRL methods can quickly adapt to dynamic network environments.

B. RQ2. What are the objectives, key performance metrics, and evaluation methods of assessing intelligent routing optimization approaches?

Increasing throughput, decreasing packet loss and latency, improving link stability, ensuring QoS, and enabling scalable routing in large-scale networks are among the most popular optimization objectives (Almasan, 2021; Ye et al., 2024; Yi et al., 2025).

End-to-end delay, throughput, packet delivery ratio, link utilization, congestion levels, prediction accuracy, and convergence time are the most common performance metrics used in routing optimization processes (Etengu et al., 2022; Li et al., 2023; Nemoto & Matsutani, 2022).

Simulation-based testing, experimental deployment in SDN, comparative analysis of intelligent routing with traditional routing protocols, multi-agent frameworks, and multi-metric optimization for DRL methods were used for the evaluation process (Al-Najjar et al., 2024; Bernárdez et al., 2023; Casas-velasco et al., 2021).

Finally, the reviewed studies demonstrate that integrating predictive and reinforcement learning models enables adaptive routing, improving throughput, reducing delay and packet loss, and maintaining stable and efficient network performance compared to classical approaches (Amin, 2025; Li et al., 2023; Wu et al., 2020).

C. RQ3. How do intelligent routing optimization methods performs compare to traditional routing protocols in terms of adaptability, scalability, efficiency, convergence speed, and real-time decision-making in dynamic network conditions?

The reviewed research indicates that AI-based routing, especially DRL-based routing methods, outperforms the traditional routing approach. The reason is that AI-based methods can effectively respond to real-time congestion, latency variations, or link instability, compared to traditional routing protocols such as OSPF, shortest path routing, and ACO, in dynamic network environments (Amin, 2025).

In contrast, ML and DL approaches are generally used to forecast traffic, predict failures, and dynamically adjust routing costs, with studies reporting notable improvements in latency and throughput. Based on PPO, DQN, and DDPG methods, DRL provides the greatest improvements in real-time decision-making and convergence speed. Multi-agent RL continuously learns from network conditions and produces faster, more stable routing decisions across different topologies (Almasan, 2021; Li et al., 2023; Wu et al., 2020).

AI-driven techniques generally achieve better throughput, lower delay, and reduced packet loss than metaheuristics such as ACO or HACO, while multi-agent and cross-domain DRL frameworks further enhance scalability in large-scale networks (Bernárdez et al., 2023; Ye et al., 2024).

D. RQ4. What are the main limitations and unexplored areas of AI-based routing optimization in the literature?

The literature shows that although AI-based routing methods achieve strong performance, several important challenges remain, as identified by various researchers. One major issue is the high computational complexity and training cost of deep, multi-agent DRL models, which can limit real-time use; however, lightweight approaches such as OS-ELM-QN aim to reduce this load while maintaining acceptable performance (Nemoto & Matsutani, 2022).

The second issue is the generalization to unseen network topologies. Although GNN-enhanced DRL models improve cross-topology performance, many solutions are still primarily implemented in simulation rather than in real operational environments (Al-najjar et al., 2024; Almasan et al., 2022).

In addition, the practical implementation remains challenging due to interoperability issues with existing protocols and the overall system complexity (Al-Najjar et al., 2024). Scalability in large or cross-domain networks and coordination overhead in multi-agent systems are further concerns despite recent progress (Bernárdez et al., 2023; Ye et al., 2024).

All the above-mentioned challenges are highlighted by various researchers. But none of the researchers focused on hardware resources. For example, when a router receives packets from a source, it first checks the destination IP address in the packet against the routing table. If the destination IP address exists, the router DE encapsulates the Layer2 header of the incoming packet, processes the packet, and then RE encapsulates and adds new source and destination physical addresses to the frame before forwarding it to the next router.

If router continuously receives a huge number of packets with limited resources such as limited processing power, buffer space, queue size, and memory capacity, it may be unable to process all packets efficiently without delay, which can lead to traffic congestion. As shown in Table 1, most reviewed studies focus primarily on mitigating congestion, minimizing delay, and reducing packet loss; however, they rarely address the root cause of congestion, namely hardware resource limitations. An exception is Wang et al. (2020), who examined the limited capacity of TCAM memory in SDN switches, which restricts scalability and efficient deployment.

Discussion

The review studies explore recent research on intelligent techniques for dynamic routing optimization, focusing on network environments, evaluation methods, performance, and limitations.

Generally, traditional ML methods are used in non-intelligent networks to support existing routing protocols by predicting traffic and failures (Amin, 2025; Serag et al., 2024). This strongly supports earlier research that view ML as suitable for environments with limited programmability. In contrast, DL models are more common in backbone and hybrid SDN networks for traffic prediction and proactive congestion prevention (Etengu et al., 2022).

DRL methods dominate fully programmable and large-scale networks because they enable real-time decision-making and can be adopted quickly in high-dynamic environments (Amin, 2025; Li et al., 2023; Wu et al., 2020).

Regarding performance evaluation, most studies focus on delay, throughput, packet loss, and convergence time. These findings are compatible with earlier research that prioritizes user-level performance metrics (Etengu et al., 2022; Li et al., 2023; Nemoto & Matsutani, 2022).

Compared to traditional routing protocols, AI-based routing, especially DRL, usually adapts better, learns faster, and works more efficiently when network conditions change frequently (Almasan, 2021; Amin, 2025; Bernárdez et al., 2023; Li et al., 2023; Wu et al., 2020; Ye et al., 2024).

This aligns with previous studies that highlight the advantages of learning-based routing over static or heuristic approaches. At the same time, this review shows that these benefits often come with increased computational cost and system complexity, which is not always sufficiently discussed in earlier work.

A key finding of this study, which differs from the existing research, is the limited attention to hardware resource constraints. While many studies focus on reducing congestion, delay, and packet loss, they rarely consider hardware limitations such as *processing capacity*, *buffer size*, *queue length*, and *memory*. These constraints are a root cause of congestion in real networks, yet they are largely ignored in routing optimization models. Only one study explicitly addresses hardware limitations, such as TCAM capacity in SDN switches (Wang et al., 2020), indicating a clear gap in the literature.

Conclusion

The findings of the review show that AI-based routing methods, especially DRL and multi-agent approaches, significantly improve routing performance, particularly in changing network environments. Compared to traditional routing protocols, these methods adapt well, learn faster, and make routing decisions more efficiently in real time. As a result, they increase throughput and reduce delay and packet loss across different network types.

The findings also show a comprehensive move from basic ML and DL models, which generally predict traffic, toward DRL-based routing systems that make routing decisions automatically. Combining traffic prediction with learning-based routing further improves scalability and network response, making these approaches more suitable for large and complex networks.

In conclusion, to fully benefit from intelligent routing, future research should focus more on hardware-aware routing and real-world use. Solving these problems is important to make AI-based routing reliable and usable in real networks.

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Authors Contributions

Sibghatullah Rahmatzai conducted the literature search, conceptualization of the study, study selection, data extraction, analysis, and prepared the original draft of the manuscript. Nesar Ahmad Wasi contributed to the methodology, provided supervision, validated the findings, and reviewed and edited the manuscript. Both authors have read and approved the final version of the manuscript.

Conflict Of Interest Statement

The authors declare that no financial, personal, or professional conflicts of interest exist regarding the publication of this manuscript.

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