University of Baghdad
College of Engineering

Journal of Engineering
journal homepage: www.jcoeng.edu.iq

Volume 31 Number 7 July 2025

Insight Thoughts for Intelligent Traffic Management-Based SDN

Sara Sadiq Jawad[1, *], **Dheyaa Jasim Kadhim**[1], **Yusmadi Yah Bt Jusoh**[2]

[1]Department of Electrical Engineering, College of Engineering, University of Baghdad, Baghdad, Iraq
[2]Department of Information Systems, College of Computer Science and Information Technology, University of Putra Malaysia, Kuala Lumper, Malaysia

ABSTRACT

The trend towards studying traffic management in software-defined networks (SDN) is increasing widely due to its great importance in enhancing the efficiency of networks and their abilities to adapt to the increasing demands on data and modern applications. What increases the importance of these studies is the integration of artificial intelligence (AI) technologies, which in turn provide intelligent analysis and response capabilities that contribute to improving quality of service (QoS), avoiding congestion, and achieving balanced load distribution across the network. Intelligent management in the SDN controller involves the use of modern algorithms and technologies that have been used previously and have given desirable results in this field to improve the control, configuration and automation of network resources in an advanced manner. As for SDN controllers, they have a key role in SDN architectures, as they are responsible for managing the flow of data to network devices in the Data Plane layer such as Switches and Routers. This paper introduces the integration of AI algorithms into the SDN controller so that you can make intelligent decisions using predictive analytics of future traffic, what it requires, and network capacity requirements. In addition to presenting a valuable comparison in this paper, which includes the approach of others followed in smart traffic management for SDN networks. The process of integrating artificial intelligence and SDN opens up prospects towards developing advanced networks that support the requirements of modern networks, such as the Internet of Things, communications, and others. The main focus is on comprehensive integration so that research is an effective contribution and keeps pace with the continuous development of smart grid management strategies.

Keywords: Software-Defined Networking (SDN), Traffic Management (TM), Artificial Intelligence (AI), Machine Learning (ML), Federated Learning (FL), Deep Reinforcement Learning (DRL).

1. INTRODUCTION

Software-defined networks (SDN) are forming a new model for networks where the control plane is separated from the data plane **(Żotkiewicz et al., 2021).** In traditional networks,

*Corresponding author
Peer review under the responsibility of University of Baghdad.
https://doi.org/10.31026/j.eng.2025.07.01

Article received: 17/11/2024
Article revised: 15/02/2025
Article accepted: 27/03/2025
Article published: 01/07/2025

switches and routers are responsible for control levels and data levels. The function of the controller is to tell the switches and routers in the network about the traffic forwarding mechanism and what to do. As for the data level, it is interested in moving packets from one place to another. The separation between the control plane and the data plane in SDN to direct network programming where it is possible to use software-based controllers or application programming interfaces (APIs) **(Isong et al., 2020).** Thus, it has been achieved network traffic management and communication with devices in the data was facilitated infrastructure layer (Data plane). One of the most important characteristics of the SDN that gave it great importance is the central control within level of control, while in conventional networks the control is device-specific, for example switches and routers that analyze and calculate routes individually and deal with network traffic flow. On the other hand, the SDN makes the calculation of traffic flows concentrated only within the control plane, so it will be simpler and more effective network traffic management **(Hasan and Kadhim, 2022; Dennis et al., 2024).**

The separation feature in SDN networks gave network administrators the ability to manage the network as well as monitor its behavior using software applications **(Khairi et al., 2021; Max et al., 2024),** speaking of traditional networks, they require a special manual configuration for each device in the network. This leads to the conclusion that any change in the network structure will require physically reconfiguring all devices, ultimately being complicated and difficult in traditional settings **(Kaczmarek and Litka, 2024; Sharma et al., 2024).** As for SDN, it has important and substantial technical features, the most considered of which is managing network traffic and configuring the policy in a new, innovative and atypical way that is highly flexible **(Ahmed et al., 2021; Mahajan et al., 2022).** Also, SDN enables how to dynamically and effectively control traffic and allocate resources. Software-defined networks can be used in different types of networks, they can be used in cloud networks, data centers, wide area networks and wireless networks **(Abbasi et al., 2021; Samiullah and Rajesh, 2024)**. The architecture of SDN consists of three layers: application plane, control plane, and data plane **(Kaczmarek and Litka, 2024).** As for the control level, it mainly consists of a central SDN controller, and this unit acts as the "brain" of the network, translating policies from the application into specific network configurations as well as managing the network through programmable servers.

Connect directly to the data plane to manage network behavior via SDN controllers which represent the central intelligence of the SDN architecture **(Hodaei and Babaie, 2021)**. This in turn will simplify network programming, automation, scalability and management. Based on these data, these central software entities control the flow of data traffic in the network **(Isong et al., 2020).** What distinguishes this network is its function in stripping the network, which means that it simplifies the basic infrastructure of applications and services, thus managing the network and its components, and can dynamically manage devices such as switches and routers. SDN controllers can control flow and manage traffic **(Sharma et al., 2024)**, thereby optimizing data paths to improve performance. Traffic management has a key role in enhancing and increasing resource efficiency as it dynamically measures, analyzes, and adjusts data flow based on real-time network state and conditions. Static algorithms are considered to have a high probability of failure because they cannot adapt properly to deal with the complex and dynamic nature of modern networks **(Gunavathie, 2021).** The design of traditional static algorithms is based on fixed and predetermined rules that are not able to change or adapt in real-time to changing network conditions in certain cases such as increased traffic, link failure, or changes in the network map. This gives the impression of inflexibility and this is problematic because SDN networks are increasingly fast and high-speed networks, with changing traffic flows and rapidly evolving requests **(Al-Jamali and Al-Raweshidy, 2021; Kumar et al., 2020)**.

One of the examples that was presented is congestion control mechanisms that are concerned with managing the load of traffic across the network dynamically and variably, and on the other hand, the central controller can use flow control where individual flows are adjusted according to the suitability of real-time conditions and application requirements, thus transferring data efficiently and reliably. The process of following and defining a custom approach to these mechanisms is critical to being able to achieve effective traffic management in SDN.

The idea of integrating artificial intelligence (artificial intelligence) into traffic management within SDN leads to a new and influential transition in network management. SDN offers centralized control by separating the control plane from the data plane, so as to enable network resources to be managed more efficiently and intelligently **(Gunavathie, 2021).** As for AI algorithms, they possess powerful tools that can be acquired and developed their skills by operators and they use them to improve traffic flow, improve performance, and reduce response times **(Hodaei and Babaie, 2021).** One of the advantages of artificial intelligence is that it has the ability to analyze large amounts of data in real time, in order to perform predictive analysis, as this analysis leads to predicting routes and congestion points and adjusts traffic paths accordingly **(Guo and Yuan, 2021).** This is key as integrating AI into SDN traffic management actually helps improve the ability to make data-driven decisions **(Zhang et al., 2020).** According to what has been seen in traditional methods, they follow predetermined rules and inferences that may not adapt well to changing and modern network conditions. On the other hand, AI systems are able to learn on past traffic patterns and user behavior to identify trends and anomalies. This capability gives the ability to take proactive actions rather than feedback, thereby granting authority to use bandwidth more efficiently and improve quality of service (QoS) to end users **(Guo and Yuan, 2021).**

Automated responses that are sensed from the use of AI will significantly reduce human intervention during peak or failure scenarios, thereby reducing downtime and saving operational costs. In the future, there are beliefs that these intelligent systems will be relied upon to efficiently manage complex environments **(Belgaum et al., 2021).** The idea of integrating AI into SDN traffic management led to the transformation of regular network management into intelligent and proactive management **(Zhang et al., 2020).** Here, artificial intelligence plays an effective and essential role in improving the ability of the SDN controller to predict network conditions, interact with them dynamically, and thus improve performance, reliability and efficiency. The development and modernity of artificial intelligence technologies has led to the integration of artificial intelligence with SDN networks opening new and advanced horizons for smart grid management. The process of analyzing studies in this field led researchers to achieve significant progress in embedding artificial intelligence methods and mechanisms within SDN networks, thus obtaining intelligent and more efficient data traffic management, along with improving network performance and increasing resilience. The paper addresses many research gaps related to SDN-based intelligent traffic management, one of these gaps that have been addressed is the need to make more effective decisions in real time that in turn adapt to dynamic network conditions, all of you addressed and reviewed some solutions concerned with improving scalability for large and complex SDN environments, one of the important things that were reviewed is traffic prediction and mechanisms of progress in this field to enhance congestion forecasting and thus optimize resources. It is important to develop self-adaptive models, and in this area deep reinforcement learning (DRL) is mentioned as a good example of this topic, whose function is to adapt to changing traffic patterns and network topology. The biggest challenge in this area is to optimally and effectively integrate AI into SDN frameworks to obtain proactive and automated network management and address the complexities associated with this integration.

This article provides highly valuable, forward-looking research guidelines. It identifies and discusses potential issues in SDN traffic management, then outlines mechanisms for integrating artificial intelligence into SDN traffic management, presenting the latest solutions and approaches adopted by researchers in this field. This paper focuses on the most current contributions in intelligent traffic management for SDNs, thoroughly analyzing recent studies relevant to this area. Furthermore, it addresses the main current gaps, the methods used to identify and resolve these gaps in intelligent management, examining and analyzing these solutions along with the metrics and mechanisms implemented, as well as the notable results achieved in this regard. This research paper raises the critical challenges facing researchers in the field of SDN-based intelligent traffic management and offers several recommendations that open up opportunities for researchers in this area, serving as a reference and guide to the latest developments in SDN-based intelligent traffic management. This work reviews the main objectives and challenges to predict the traffic in the network to perform intelligent management-based SDN, especially in dynamically changing network environments where real-time performance is critical, with challenges around real-time decision-making and network scalability. SDN allows for dynamic traffic routing and real-time adjustments based on network conditions, improving bandwidth utilization, reducing congestion, and optimizing network performance. This approach leads to intelligent traffic management for SDN networks. The process of exploring self-adaptive DRL models increases the power of management to adjust learning rates and required goals based on real-time network conditions. These include self-tuning algorithms that optimize model parameters based on changes detected in traffic patterns or network topology.

2. TRAFFIC MANAGEMENT-BASED SDN (TM-SDN)

Network traffic management is of great importance because it controls the flow of data and optimizes it so that the efficient use of bandwidth is reliable and secure, thus significantly reducing the chances of congestion while maintaining high quality of service. Effective strategies such as load balancing and traffic formation and analysis are catalysts at different levels **(Sharma et al., 2024),** including coding, segmentation to improve user experience and possible resource optimization and cost reduction are all illustrated in **Fig. 1**. Priority can be given by Quality of Service (QoS) management and is dedicated to critical traffic, to ensure and ensure adequate bandwidth as well as ensure that latency is low and ensure reliability. In traffic management (TM) in SDN there is an emphasis on optimizing data transmission over the network to get performance boosters, increase resource efficiency and do the fulfillment of specific SLAs **(Samiullah and Rajesh, 2024).** This centralized control and centralized programming in SDN gives an ideal platform to help implement advanced traffic management technologies. One of the main aspects of traffic management in SDN is to maintain a centralized view of the network, as SDN controllers can broadly understand network topology and understand and analyze the status of links and traffic patterns that exist. Here better decisions can be made compared to traditional distributed systems **(Huang et al., 2021).**

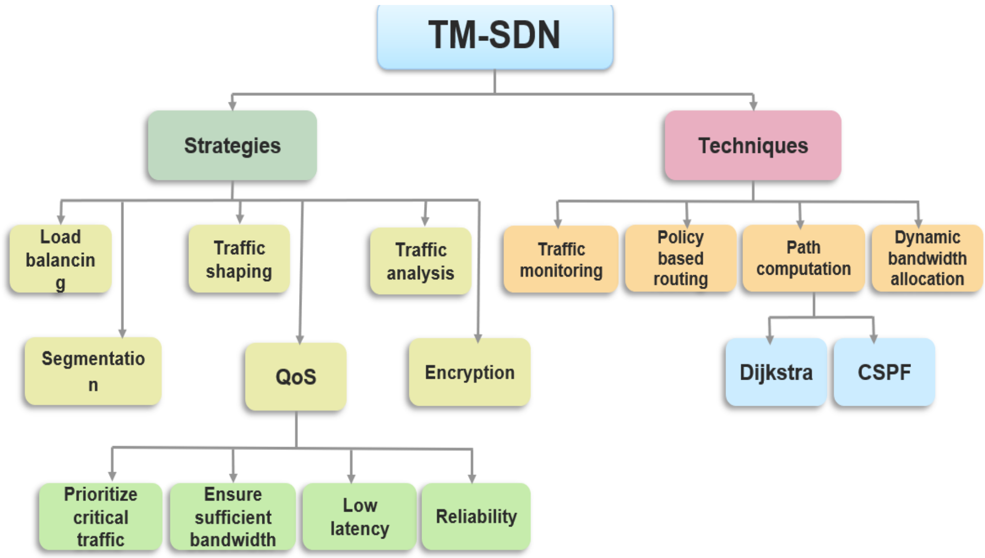

Figure 1. Components of TM-SDN.

Speaking of SDN controllers, they are represented by a number of technologies that are responsible for calculating the path of intelligent decision-making using algorithms, examples of which include Dijkstra's or Open Shortest Path First (OSPF) **(Casas-Velasco et al., 2021)**, the best paths are determined based on several specific criteria, including bandwidth or latency. In terms of traffic monitoring and analysis, the SDN controller is responsible for monitoring network conditions continuously and periodically and has the authority to make real-time adjustments according to the traffic patterns being worked out **(Wu et al., 2020).** Policy-based directive empowers network administrators to set rules to prepare them to work with different types of traffic, to ensure priority for critical applications or to avoid congestion, which is important **(Faezi and Shirmarz, 2023).** As shown, dynamic bandwidth allocation ensures that SDN controllers can allocate bandwidth in real time if the network demands and resource utilization can be optimized, but critical applications are ensured that critical applications have access to resources **(Samiullah and Rajesh, 2024).**

Traffic measurement entails gathering, measuring, and monitoring network status data. Traffic measurement is difficult in the hybrid SDN network because only a small percentage of devices are SDN-enabled. Traffic management is the study of controlling and arranging network traffic based on network status data provided by traffic measurement. Recently in the SDN networks, Traffic management has become a prominent issue. With SDN network development, we can now manage network flows flexibly and modify their routing in a real-time network. Google and Microsoft have previously built their small-scale SDN-enabled Inter Data Centers network and are capable of nearly 100% network utilization **(Samiullah and Rajesh, 2024).**

The factors influencing the management of Software-Defined Networks are scalability; SDN is highly scalable with dynamic, real-time adjustments, flexibility; High flexibility with dynamic traffic management in SDN, Network Management; centralized, this feature simplifies network management and troubleshooting, also SDN has full control over traffic flows, optimized traffic management, Cost Efficiency; Lower operational costs due to automation and programmability, Security; Dynamic, policy-based, and flow-level security.

Data centers, cloud environments, and large-scale networks are examples of SDN used **(Mahajan et al., 2022; Hodaei and Babaie, 2021). Fig. 2** shows the key factors of TM-SDN.

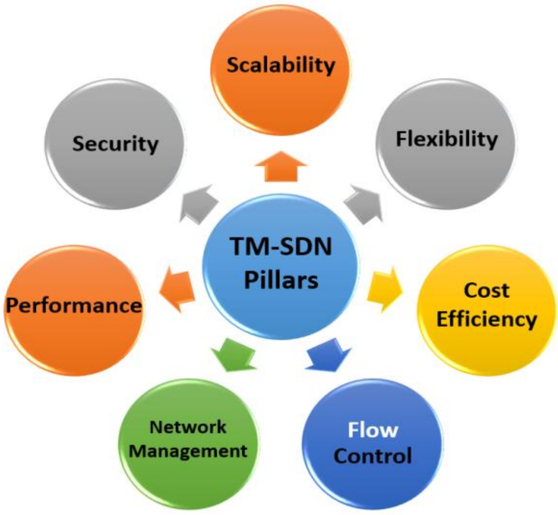

Figure 2. Key factors of TM-SDN.

3. INTELLIGENT TRAFFIC MANAGEMENT BASED SDN (ITM-SDN)

Artificial intelligence can significantly enhance traffic management in SDN by introducing intelligent, adaptive mechanisms that go beyond traditional rule-based approaches. Artificial Intelligence and Machine Learning, Deep Learning, Reinforcement Learning and more are revolutionizing SDN networks, making networks smarter, more efficient, and more flexible. These technologies enable automated optimization, advanced analytics, and predictive maintenance, thus taking SDN to advanced heights. It predicts traffic and detects anomalies. In addition, artificial intelligence enhances SDN capabilities in all fields. Self-healing networks and reinforcement learning advance network management and control. AI can perform these operations for traffic management in SDN:

- Traffic Prediction and Anomaly Detection**:** Machine learning (ML) models can analyze historical traffic data and predict future traffic patterns which helps in proactively allocating resources and avoiding congestion **(Gunavathie, 2021).** On the other hand, AI algorithms can detect anomalies in traffic patterns to indicate potential issues like network congestion or detect unusual patterns. Early detection allows for reducing the latency and increases accuracy **(Khairi et al., 2021).**
- Optimal Path Selection and Load Balancing: Reinforcement learning (RL) algorithms can learn from the network environment and dynamically improve path selection. As a result, RL models improve their performance due to their continuous interaction with the network, finding paths that reduce response time, which increases throughput, and also meet other specific criteria **(Dennis et al., 2024).** AI-based traffic load prediction algorithm for predicting traffic load at the next time interval and distributing traffic across multiple paths and links to prevent congestion in SDN and ensure efficient use of resources **(Alhilali and Montazerolghaem, 2023).**
- Automated Policy: AI-enabled SDN systems can dynamically update and improve policies through continuous data-driven learning, to maintain service quality and quality. They are adaptive policies that optimize resource utilization, focus on reducing overheads, and empower SDN controllers to respond proactively in anticipation of emerging network

conditions **(Pathak et al., 2023)**. The definition of deep reinforcement learning (DRL) is a combination of deep learning and reinforcement learning. DRL can learn policies from experience through continuous self-learning. This technology is concerned with creating a business policy quickly and is based on the state of the current environment and improves the policy over time in order to improve network performance adaptively and in real time. Using AI helps prioritize critical applications automatically **(Huang et al., 2021).**

- Resource allocation: refers to improving the allocation of resources in SDN networks to meet traffic requirements and focus on reducing costs and increasing performance to a minimum, and this is a strong challenge. The process of integrating AI models is possible leads to improved network resource allocation. Traffic pattern analysis gives these models a dynamic allocation of resources, such as bandwidth, thus making effective use, reducing latency and improving performance **(Masood et al., 2023).**

Any AI-based approach gives important advantages, whether its use in SDN is based on its need for automation or it can be real-time adaptation or network performance optimization. **Fig. 3** illustrates the main methods of intelligent traffic management (ITM). AI technologies such as machine learning, deep learning, reinforcement learning, and evolutionary algorithms play an important role in automating and optimizing SDN. These technologies give SDN controllers the authority to automate complex tasks such as traffic management, load balancing and resource allocation, making the network more efficient, scalable and responsive.

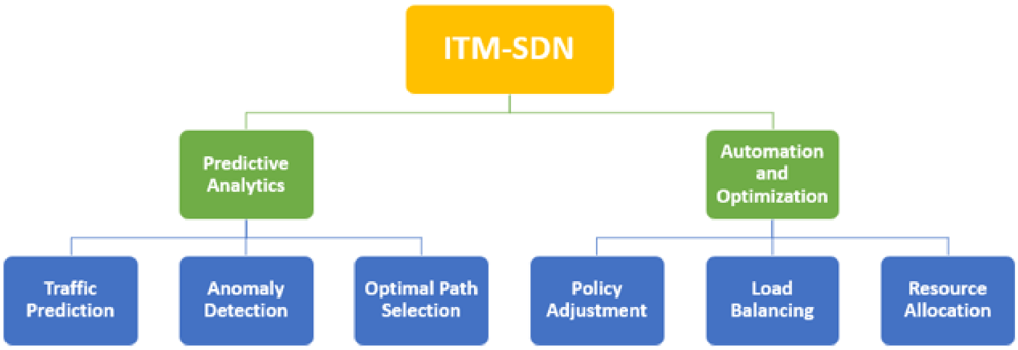

Figure 3. Main methods of intelligent traffic management.

Table 1 shows an analysis of several studies that have applied AI techniques, these techniques are:

- Deep Reinforcement Learning (DRL): The idea of DRL is to combine deep learning and reinforcement learning so as to facilitate handling complex traffic management tasks. DRL agents can learn the skill of making decisions and how to analyze the data, as these decisions obtained are for the purpose of improving network performance fundamentally and significantly **(Belgaum et al., 2021; Masood et al., 2023; Antonio et al., 2022).**
- Neural networks: The process of using convolutional neural networks (CNNs) and repetitive neural networks (RNNs) whose purpose is to identify patterns and predict time series in traffic forecasting and accompanying traffic anomalies **(Al-Jamali and Al-Raweshidy, 2021).**
- Optimization algorithms: Several algorithms aimed at solving complex network optimization problems of multipurpose traffic management, from these algorithms are

the ant colony algorithm, genetic algorithms, and other optimization techniques **(Guo and Yuan, 2021).**

- Open source platforms: Important tools in the application of algorithms on the network such as TensorFlow, PyTorch and Keras can be integrated with SDN controllers (e.g., ONOS, OpenDaylight) whose purpose is to develop intelligent solutions used in AI-based traffic management **(Chandroth et al., 2022).**

When talking about the emerging technologies represented by cloud computing, the Internet of Things and SDN, it can be said that they will bring about a significant and sophisticated transformation in the delivery of services to end users **(Belgaum et al., 2021).** There are several ideas that have been addressed in this topic, and among the most important of these ideas that have been addressed is the integration of artificial intelligence with these modern technologies to explore and change the mysteries of the world of networks and what can be obtained. For example, SDN is a technology that has the potential to improve the flexibility of IoT devices through the cloud, another example is related to 5G technology where the frequencies of this technology carry many connectivity challenges. On the other hand, IoT devices produce huge amounts of data that in turn mainly need to be processed and processed in the cloud and must be accessed through vendor-neutral networks. For network conditions such as network congestion or lag, IoT devices here can still connect to SDN networks and cloud resources **(Huang et al., 2020**). AI further boosts efficiency and performance in this ecosystem.

Table 1. Many analysis studies of ITM-SDN technologies.

Ref.	AI Methods	Optimization Algorithms	Neural Networks	Open Source Platforms	Metrics
(Masood et al., 2023)	√	√	√	√	Scalability, latency
(Bhavani et al., 2023)	√	χ	χ	√	Scalability, accuracy, latency
(Jameel et al., 2023)	√	√	√	√	Latency, packet loss
(Badotra et al., 2023)	√	√	√	√	Latency, reiliability
(Dayang et al., 2022)	√	√	χ	√	Latency, QoS
(Huang et al., 2022)	√	χ	√	√	Routing efficiency, convergence time
(Ye et al., 2024)	√	χ	χ	√	Accuracy, latency
(Byakodi et al., 2023)	√	χ	χ	√	Latency, efficiency
(Jia et al., 2021)	√	χ	√	√	Accuracy, error rate
(Al-Jawad et al., 2021)	√	√	χ	√	Latency, accuracy
(Al-Jawad et al., 2021)	√	χ	√	√	QoS, packet loss
(Jaafari et al., 2022)	√	√	χ	√	Latency, efficiency

(Boussaoud et al., 2022)	√	χ	χ	√	Accuracy, detection rate
(Zabeehullah et al., 2022)	√	χ	√	√	Scalability
(Xiong and Hongyu, 2021)	√	χ	√	√	convergence time, energy effeciency
(Faezi and Shirmarz, 2023)	√	√	√	√	--
(Rischke et al., 2020)	√	χ	√	√	Latency
(Wu et al., 2021)	√	χ	√	√	Throughput, traffic accuracy
(Sun et al., 2021)	√	χ	√	√	Scalability, latency
(Kamboj et al., 2023)	√	√	χ	√	QoS, latency
(Agca et al., 2022)	√	√	√	√	--
(Nyaramneni et al., 2023)	√	√	√	√	Prediction accuracy
(Praveen et al., 2022)	√	√	χ	√	Latency
(Magadum et al., 2021)	√	χ	χ	χ	Latency, QoS
(Mubashar et al., 2024)	√	√	χ	√	Accuracy, privacy
(Guo and Yuan, 2021)	√	√	χ	χ	Accuracy
(Singh et al., 2024)	χ	√	χ	χ	Latency

4. CURRENT THOUGHTS ON ITM-SDN

This section highlights recent research related to the use of AI and intelligent learning techniques in traffic management for SDN environments. Researchers have explored various methods such as reinforcement learning and deep learning for traffic routing and optimization, as well as machine learning for traffic distribution and congestion management. Additionally, traffic prediction, proactive routing using neural networks, load balancing, and prioritization of critical applications through AI were discussed. The presented research focuses on utilizing AI and intelligent learning techniques to improve Quality of Service (QoS), manage diverse traffic, and enhance network efficiency and overall performance.

These studies illustrate the application of machine learning (ML) and artificial intelligence (AI) techniques to optimize traffic distribution, reduce latency, and enhance user experience in SDN environments. Authors of **(Badotra et al., 2023)** The integration of machine learning techniques with SDN environments ensures improvement and adaptation to changing network conditions and provides a promising approach to improving network performance and user satisfaction in modern networks. Similarly, authors of **(Kumar et al., 2020)** applied machine learning ML algorithms using the Ryu controller to propose a congestion-aware traffic routing model for selecting the least congested route for routing traffic in an

SDN that optimized routing, and enhanced throughput. This model provides the possible routes according to the network statistics information provided by the SDN controller dynamically. Additionally, authors of **(Wu et al., 2020)** presented an artificial intelligence-enabled routing (AIER) mechanism with congestion avoidance in SDN, providing learning ability and routing decisions using AI demonstrated with metrics of throughput, packet loss ratio, and packet delay. Together, these studies underscore the potential of AI and ML integration in SDN for intelligent traffic management and continuous adaptation to network demands.

Other studies highlight the effectiveness of deep learning and ensemble machine learning techniques in predicting traffic patterns and optimizing routing within SDN environments. Authors of **(Guo and Yuan, 2021)** designed a network control mechanism for network intelligent control focused on traffic optimization based on SDN and artificial intelligence, consisting of a network status collection/perception module, an AI intelligent analysis module, and an SDN controller module. Routing calculation algorithms and routing optimization algorithms (particle swarm optimization, simulated annealing, and genetic algorithms) are analyzed in this work. Additionally, authors of **(Jia et al., 2021)** proposed an intelligent routing control strategy based on deep learning Deep Q-Learning (DQN) in SDN, selecting different routing paths according to the different QoS levels of the flow, generating the specific routing for forwarders and mitigating congestion, reducing delay, and improving throughput to outperforms traditional routing algorithms in high-traffic network. This approach by proposing a routing control strategy based on convolutional neural networks (CNNs) provides an intelligent solution for traffic management in SDN. Also, the Authors of **(Nyaramneni et al., 2023)** predicted the SDN traffic using machine learning models for congestion avoidance and outperformed the other models.

These studies examine AI-based optimization techniques to enhance load balancing, reliability, and resource utilization in SDN-managed networks. Authors of **(Ali et al., 2020)** proposed SDN with an optimization algorithm to manage more operative configurations, efficient enhancements, and further elasticity to handle massive network schemes and test the performance of the load balance LB. With increased throughput, data transfer, bandwidth, and decreased average delay. Complementing this, authors of **(Dayang et al., 2022)** proposed an intelligent scheduling system for traffic in the power communication network and applied SDN with an intelligent scheduling system into the power network by three practical scenarios, including establishing businesses, adjusting network bandwidth, and QoS-based network service management. Similarly, authors of **(Wu et al., 2021)** proposed a multi-agent deep reinforcement learning (DRL) approach for managing traffic and channel reassignment in SDN-based IoT networks, developed a Multi-Agent Deep Deterministic Policy Gradient (MADDPG)-based traffic control and multi-channel reassignment (TCCA-MADDPG) algorithm to optimize the objection function to achieve traffic control and channel reassignment to maximize the throughput and to minimize packet loss rate and the time delay. A long- and short-term neural networks (LSTM) layer was added to the neural network in the experiment to capture the timing information of the channel. Future work could focus on extending this approach to more heterogeneous network environments and integrating additional AI techniques for further optimization.

Key contributions include RL-based solutions that dynamically explore and identify optimal routing paths, distributed multi-agent deep reinforcement learning models for cross-domain traffic routing, and CNN-based routing computations for real-time traffic adaptation. The integration of AI techniques allows these systems to predict traffic states, minimize latency, improve throughput, and enhance user experience. Simulation and experimental results demonstrate the superiority of these approaches over traditional techniques, showing improvements in metrics such as packet loss, delay, throughput, and quality of service. The research highlights the effectiveness of AI-driven strategies for intelligent automation and optimization in SDN environments, offering promising solutions for next-generation network management. This body of work not only focuses on novel methodologies for traffic management but also examines the real-time applicability of AI models for improving network performance and scalability in SDN environments. **Fig. 4** shows the publication years studied.

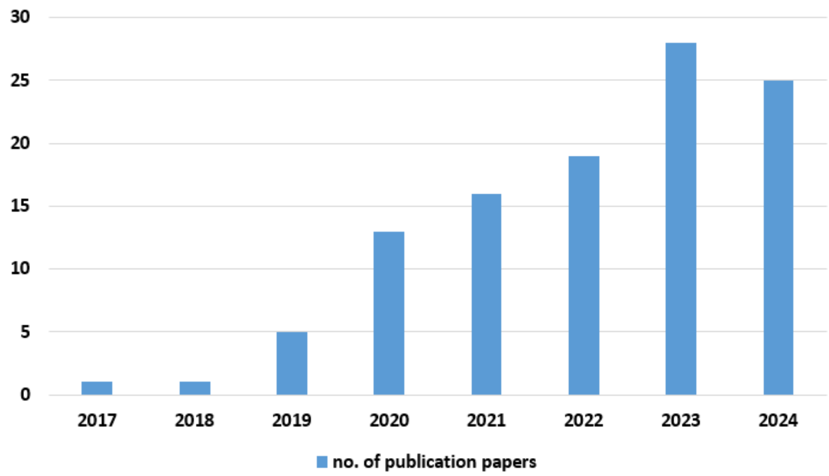

Figure 4. Publication years studied.

5. CURRENT GAPS OF ITM-SDN

Currently, SDN is witnessing a remarkable development in terms of flexibility and control, which has caused breakthroughs in network management. SDN controllers are open source and are of high importance in dynamic traffic management such as RYU, ONOS, Floodlight etc. This development has been added to the integration of intelligent algorithms with SDN to become a key axis in terms of traffic management in networks. This article presented recent research contributions to intelligent traffic management using the SDN console and discussed expected future solutions and their potential impacts as shown in **Fig. 5**. The research overview focused and abstracted the introduction and created significant advances in intelligent traffic management, particularly with the integration of machine learning (ML) and artificial intelligence (AI) into SDN frameworks.

A distinctive contribution to the integration of machine learning models with the SDN controller (Kumar et al., 2020). The researchers looked at machine learning algorithms that include decision trees and support vector machines (SVM) **(Vaishali et al., 2023)** as they predict traffic patterns and improve routing. Taking advantage of real-time data that the controller is responsible for collecting, these models dynamically adjust traffic flows, to achieve load balancing and reduce congestion. The approach has proven effective in improving network performance indicators, most importantly productivity and uptime. Another important contribution is the application of RL to dynamic traffic management **(Karunakaran and Geetha, 2022).**

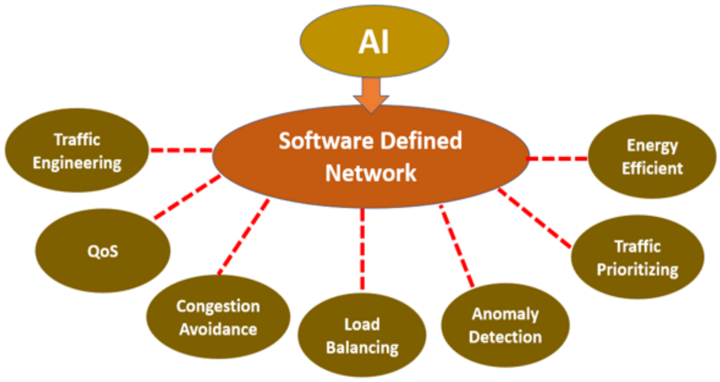

Figure 5. Contributions of recent research in intelligent traffic management.

Reinforcement learning models when integrated with the SDN console give networks the ability to automatically adapt to changing circumstances. This is known as following a continuous learning mechanism for network situations, which results in improved traffic distribution, reducing delays and packet loss. Many hands-on experiments in simulation environments such as Mininet have shown the potential of this approach to significantly improve network efficiency. There is also research that focuses on traffic management related to the quality of service, and this is added to what has been previously addressed in the management and classification of various traffic based on the quality of service and the priorities of applications by network, represented by the adoption of machine learning and reinforcement learning. Systems based on SDN controllers ensure that critical services receive the necessary bandwidth and low latency. One of the algorithms used for this purpose is the weighted queue (WFQ) or priority queue (PQ), as it was adopted at the transformers to prioritize critical traffic. As for artificial intelligence, it has the ability to dynamically adjust queue weights and priorities depending on the traffic load and application type. Among the important areas that exist is energy-efficient traffic management. The researchers have developed several algorithms whose function is to reduce energy consumption by combining traffic through fewer active links and dynamically reconfiguring the network on demand. As a result of what has been addressed, these solutions provide sustainability as well as ensure effective network performance, mainly concerned with green grids. In the end, this research focused on modern methods that have been widely adopted for predictive control, that contributes centrally and fundamentally to congestion management. Among these methods discussed are machine learning models, represented by Long and Short Term Memory (LSTM) and Integrated Moving Average (ARIMA) to predict traffic congestion, and researchers have found that the SDN controller can proactively direct traffic to prevent bottlenecks. The function of this proactive approach is to improve network reliability and reduce congestion-related issues.

In conclusion, it can be said that the different smart learning approaches represented by machine learning (ML), deep learning (DL), reinforcement learning (RL), deep reinforcement learning (DRL), and unified learning (FL) - have a significant and very important role in improving traffic management in SDN environments. Speaking of DLR, it is an important tool dedicated to complex scenarios such as cross-domain routing and computer control networks, and is a flexible, scalable and adaptable tool for managing expression traffic at work. FL is less commonly used as it is a newly introduced tool, and it is intended for distributed SDN networks that preserve privacy. DRL is used for long-term optimization in large and dynamic SDN environments and is very ideal for these networks.

On the other hand, the importance of ML and DL cannot be underestimated as a tool of specific importance for specific tasks. **Fig. 6** and **Table 2** show an analysis of AI learning methods for ITM-based SDN in recent years.

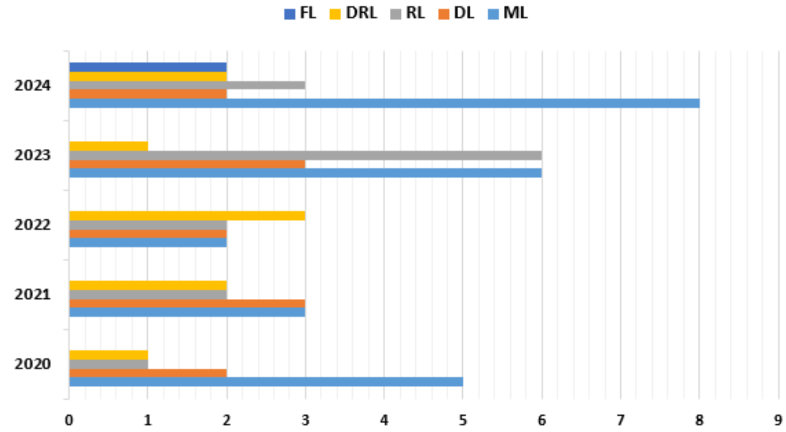

Figure 6. Analysis of AI techniques for ITM.

Table 2. AI learning methods for Intelligent Traffic Management.

Ref.	ML	DL	RL	DRL	FL
(Khairi et al., 2021)	√				
(Max et al., 2024)			√		
(Eldhai et al., 2024)	√				
(Huang et al., 2020)		√			
(Sable et al., 2023)			√		
(Vaishali et al., 2023)	√				
(Antonio et al., 2022)				√	
(Xu et al., 2023)		√			
(Mahajan et al., 2022)		√			
(Gunavathie et al., 2021)	√				
(Al-Jamali and Al-Raweshidy, 2021)		√			
(Chaganti et al., 2023)		√			
(Saleh and Fathy, 2023)		√			
(Bhavani et al., 2023)				√	
(Jia et al., 2021)			√		
(Rischke et al., 2020)			√		
(Wu et al., 2021)				√	
(Sun et al., 2021)				√	
(Agca et al., 2022)	√				
(Nyaramneni et al., 2023)	√				
(Mubashar et al., 2024)	√				
(Jameel et al., 2023)	√				
(Badotra et al., 2023)			√		
(Dayang et al., 2022)	√				
(Huang et al., 2022)				√	
(Ye et al., 2024)			√		
(Byakodi et al., 2023)			√		
(Al-Jawad et al., 2021)	√				
(Mao et al., 2021)		√			
(Al-Jawad et al., 2021)		√			

(Jaafari et al., 2022)			√		
(Kumar et al., 2020)	√				
(Casas-Velasco et al., 2021)			√		
(Boussaoud et al., 2022)	√				
(Guo and Yuan, 2021)	√				
(Zabeehullah Arif and Abbas, 2022)		√			
(Xiong and Hongyu, 2021)				√	
(Faezi and Shirmarz, 2023)	√				
(Guzman et al., 2023)			√		
(Magadum et al., 2021)				√	
(Malik et al., 2020)		√			
(Pei et al., 2024)				√	
(Mohammed and Nadia, 2023)	√				
(Zhang et al., 2022)			√		
(Chen et al., 2023)				√	
(Shafique and Alhassoun, 2024)	√				
(Houda et al., 2023)					√
(Ossongo et al., 2024)					√
(Naibaho et al., 2023)	√				
(Amin et al., 2021)	√				
(Chen et al., 2020)				√	
(Karunakaran and Geetha, 2022)			√		
(Chen et al., 2021)		√			
(Tiwana and Singh, 2023)	√				
(Prabhavat et al., 2022)		√			
(Kwak et al., 2020)	√				
(Soud and Al-Jamali, 2023)	√				
(Marwa and Muna, 2024)			√		
(Nain et al., 2024)	√				
(Zhang et al., 2023)				√	
(Aouedi et al., 2022)	√				
(Manso et al., 2020)		√			
(Janjua et al., 2023)	√				

6. KEY CHALLENGES OF ITM-BASED SDN

The research on intelligent traffic management in SDN controllers faces several key challenges, as shown in **Fig. 7**. These challenges span various aspects of implementation, scalability, and security. Here are the main challenges identified by the researchers according to many studies and experimental works These studies' challenges are described below:

6.1 Scalability

The increasing complexity of network traffic, particularly in IoT applications, requires greater flexibility and scalability in management. In SDN, scalability is a critical issue due to the centralized nature of the control plane, which can lead to high communication costs between the control and data planes, limiting the SDN controller's expansion capacity **(Hodaei and Babaie, 2021).** As traffic volume, systems, and users grow, scalability and extensibility become essential for effective traffic management. Network size and traffic affect performance in routing, congestion control, and load balancing due to its dependence on it, and this of course affects key metrics such as mass delay, throughput, and packet delivery ratio (PDR). AI can be considered as the main tool facing challenges in cloud computing, IoT and SDN **(Belgaum et al., 2021).**

Figure 7. Key challenges of ITM-based SDN.

Networks are growing in size and becoming more complex, so it is important to focus more on finding smart solutions to manage traffic. Technologies that work well in small networks cannot be adopted in large and complex environments because they will not be able to manage their resources efficiently. Managing resources efficiently over a large network requires maintaining performance and reliability and cannot be easily achieved. Therefore, solutions must be provided that suit the changing network conditions as well as with different needs in addition to cost savings **(Masood et al., 2023).**

6.2 Real-Time Adaptation

Some applications require real-time decisions in traffic management and this is considered a critical factor in real-time. Through continuous learning, the system can adapt to changes in real time, so it is robust and responsive to dynamic traffic conditions **(Vaishali et al., 2023).** The primary function of an intelligent traffic management system is to predict traffic patterns and optimize signal timing in controllers. In previous years, some researchers have used AI algorithms in network routing algorithms. Notably, current algorithms take into account one or more quality of service (QoS) parameters, ignoring the consumption of network resources **(Guo and Yuan, 2021).** Traffic patterns and loads change frequently with dynamic networks. That's why it's hard to ensure that traffic management solutions can adapt in real time to these changes without negatively impacting performance. Because slow convergence results in suboptimal performance during the learning phase.

6.3 Complexity of AI Models

Developing and implementing complex AI models, which include deep reinforcement learning and others, requires extensive computational resources that are extensive and advanced expertise. This complexity slows down or prevents the deployment and maintenance of these solutions. It is important to adjust the parameters of AI models because this leads to optimal performance and meets network requirements, and is an easy process that takes time. Incorrect settings may be the cause of network instability and, therefore, unwanted performance and unintegrated management.

6.4 Privacy and Security

A major challenge in AI and federal or decentralized AI is ensuring data privacy and the ability to train effective models. A remarkable balance between privacy and performance must be achieved; this may need to be studied in depth, and the orientation to the use of powerful technologies **(Bhavani et al., 2023).** An important focus in addressing AI-based traffic management solutions is security threats, represented by breaches and attacks on the network. This leads to the development and finding of ways to detect these threats, and it is possible to mitigate them while maintaining the performance of the network **(Masood et al., 2023).** Addressing these challenges requires a collaborative effort from the research community, as shown in **Table 3.** An important point for future research is to find and develop adaptable development solutions in real-time, provided that they ensure privacy and security, and do not conflict with the existing network infrastructure, where their integration is flexible.
Authors **(Mubashar et al., 2024)** addressed the topic of federal learning integrated with SDNs to detect and enhance intrusion while ensuring user privacy by maintaining data that is decentralized. This model focuses on the idea of collaborative training across distributed data sources, in this case there is no need to centralize sensitive data, because this model maintains privacy. The results obtained have found that standardized learning has the ability to maintain and enhance intrusion detection accuracy without compromising network security and user privacy. This study highlighted the essential role of unified learning in addressing security challenges and its importance in SDN environments, with the need for continuous research and future extensive study to assess its scalability and effectiveness in more comprehensive and complex network infrastructures.

Table 3. Common Issues of Related Works.

Ref.	Issues of Related Works						
	Overhead	Congestion	Scalability	QoS	Accuracy and reliability	Real-time decision making	Routing optimization
(Rischke et al., 2020)		√				√	
(Wu et al., 2021)		√			√		
(Sun et al., 2021)		√	√				
(Agca et al., 2022)		√				√	
(Nyaramneni et al., 2023)					√		
(Mubashar et al., 2024)		√					
(Jameel et al., 2023)				√			√
(Badotra et al., 2023)		√					
(Dayang et al., 2022)					√		
(Huang et al., 2022)		√					√

(Ye et al., 2024)							√
(Byakodi et al., 2023)		√					√
(Al-Jawad et al., 2021)						√	√
(Mao et al., 2021)	√	√					√
(Al-Jawad et al., 2021)				√			
(Jaafari et al., 2022)		√		√			√
(Kumar et al., 2020)	√		√				
(Casas-Velasco et al., 2021)		√				√	√
(Boussaoud et al., 2022)			√		√		
(Guo and Yuan, 2021)		√	√			√	
(Zabeehullah et al., 2022)							√
(Xiong and Hongyu, 2021)		√					√
(Faezi and Shirmarz, 2023)			√				
(Guzman et al., 2023)		√					√
(Huang et al., 2021)							√
(Saleh and Fathy, 2023)						√	

6.5 Performance Metrics

SDN's key performance measures are throughput, delay, resource utilization, control level convergence time, and packet loss **(Max et al., 2024; Sharma et al., 2024; Shaw et al., 2023).** Productivity is defined as a successful data transfer rate, as its work reflects the efficiency of the network. Current applications face real-time delays because they measure network response speed, and their focus is on the lowest levels of delay. This is very important to note. Resource utilization is to evaluate the optimal use of CPU, memory and bandwidth as well as focus on the high level of performance and the importance of maintaining it. Control plane convergence time is the network recovery time after changes or crashes occur, thus it will affect the controller response. Packet loss, which is the proportion of undelivered data, is directly related to and affects the reliability and quality of the service, so it is important to reduce it so that the data flow is smooth. Generally, these metrics are necessary to assess the effectiveness and flexibility of SDN deployment.

6.6 Controller Model

One of the challenges is choosing the optimal SDN controller; each controller has many supporting features associated with key aspects. Scalability is the assessment of a controller's ability to adapt to different network sizes and complexities and to maintain performance across different loads. Evaluate productivity performance and calculate latency and response time under traffic conditions and diverse workloads. Reliability measures a controller's resilience in adverse scenarios, such as network or controller failures, along with its recovery capabilities. Functionality considers the controller's features, protocol support, API compatibility, and integration with third-party systems for advanced networking. Flexibility measures customization options, extension support, and compatibility with other SDN components. Finally, ease of use evaluates the simplicity of deployment, configuration, and management, including user interfaces, documentation, and available community resources. **Table 4** compares these factors across Open Daylight, ONOS, and RYU SDN controller models **(Chandroth et al., 2022).**

Table 4. Differences between OpenDaylight, ONOS, and RYU controllers.

Feature	Open Daylight	ONOS	Ryu
Supported Protocols	OpenFlow, NETCONF, SNMP, BGP, PCEP, etc.	OpenFlow, NETCONF, BGP, SNMP, etc.	OpenFlow, OF-config, NETCONF, SNMP, etc.
APIs	RESTful API, Java API, YANG-based APIs	RESTful API, Java API	Python API
Integration Capabilities	Integration with cloud platforms (OpenStack, Kubernetes), virtualization technologies (VMware, KVM), and other SDN solutions through standard protocols and APIs.	Integration with cloud platforms, virtualization technologies, and other SDN solutions through standard protocols and APIs.	Integration with Python-based applications, libraries, and frameworks for data processing, analytics, and automation.

To evaluate the performance of SDN controllers, several key steps are followed. First, a network topology is designed to reflect real-world scenarios, including switches, routers, hosts, and links with varying capacities and latencies. Next, the selected SDN controllers (such as OpenDaylight, ONOS, or Ryu) are deployed in the testing environment and configured with appropriate settings and parameters. Physical or virtual network devices, compatible with the SDN controllers and supporting relevant protocols like OpenFlow, NETCONF, and SNMP, are used. Traffic generation tools, such as perf or Ostinato, are then utilized to simulate traffic patterns and workloads for various use cases. Finally, monitoring tools are implemented to collect performance data from the network devices, SDN controllers, and testing environment, capturing important metrics like throughput, latency, packet loss, and CPU/memory utilization. **Table 5** summarizes the software used and topologies for different controller models with different metrics.

Table 5. Software and Topologies for Different Controller Models.

Ref.	Software Used	Controller Model	Topology	Metrics
(Rischke et al., 2020)	Mininet	Ryu	Fat-tree	Packet loss, latency, throughput
(Wu et al., 2021)	NS-3	Floodlight	Custom SDN-IoT topology	Packet delivery ratio, latency, energy efficiency
(Sun et al., 2021)	Mininet, TensorFlow	OpenDaylight	Fat-tree, linear, mesh	Network utilization, delay, convergence time
(Nyaramneni et al., 2023)	Python (Sci-Kit Learn, TensorFlow)	Floodlight, Ryu	Tree and linear topologies	Accuracy, precision, F1 score, throughput

(Mubashar et al., 2024)	TensorFlow	ONOS	Custom topology	Training time, accuracy, data privacy
(Jameel et al., 2023)	Mininet, TensorFlow	Ryu	Tree	Latency, jitter, throughput, QoS
(Badotra et al., 2023)	Mininet	Ryu, Floodlight	Custom multi-controller topology	Load balancing efficiency, packet loss, delay
(Dayang et al., 2022)	OMNeT++	Floodlight	Power communication network	Throughput, delay, packet delivery ratio
(Huang et al., 2022)	Mininet, TensorFlow	Ryu	Fat-tree, custom graph topology	Routing efficiency, packet loss, delay
(Ye et al., 2024)	Mininet	Ryu, OpenDaylight	Multi-domain network	Routing efficiency, packet delivery, latency
(Guzman et al., 2023)	Mininet, TensorFlow	OpenDaylight	Tree, mesh	Packet loss, throughput, routing efficiency
(Al-Jawad et al., 2021)	Mininet	Floodlight	Tree, fat-tree	Routing accuracy, latency, throughput
(Mao et al., 2021)	TensorFlow, Mininet	ONOS	Fat-tree, mesh, linear	Latency, packet loss, routing accuracy
(Al-Jawad et al., 2021)	Mininet	Floodlight, ONOS	Multimedia topology	QoS metrics (latency, jitter, bandwidth), packet loss
(Jaafari et al., 2022)	Mininet, Matlab	Floodlight	Custom topology	Latency, jitter, fuzzy inference-based decision metrics
(Kumar et al., 2020)	Python	Ryu, OpenDaylight	Custom topology	Traffic provisioning efficiency, latency, bandwidth
(Casas-Velasco et al., 2021)	Mininet	ONOS	Fat-tree	Routing efficiency, delay, throughput
(Boussaoud et al., 2022)	Python (Sci-Kit Learn)	Ryu	Fat-tree	Detection accuracy, recall, precision
(Guo and Yuan, 2021)	Mininet, TensorFlow	ONOS	Custom SDN topology	Network control efficiency, traffic optimization
(Zabeehullah et al., 2022)	TensorFlow, Mininet	Ryu	IoT-based SDN topology	Routing accuracy, packet delivery ratio, latency
(Xiong and Hongyu, 2021)	Mininet, TensorFlow	Ryu	Fat-tree, custom topology	Routing efficiency, packet loss, delay
(Guzman et al., 2023)	NS-3	OpenDaylight	Intersection traffic network	Traffic congestion, waiting time, packet delay
(Aouedi et al., 2022)	Mininet	OpenDaylight	Custom next-gen network topology	Traffic management efficiency, latency, throughput
(Chen et al., 2020)	Mininet	Floodlight	Fat-tree	Routing efficiency, packet loss, latency
(Karunakaran and Geetha, 2022)	NS-3	Ryu	Custom topology	Packet retransmission rate, latency, throughput
(Ram et al., 2024)	Mininet	Ryu	Fat-tree	Flow setup time, throughput, latency

(Da Cruz De Lima and Rodrigues, 2021)	Mininet	OpenDaylight	5G network topology	QoS metrics (latency, jitter, bandwidth)
(Lee et al., 2022)	Mininet	ONOS	Multi-domain SDN topology	Effective delay, packet loss, throughput
(Chen et al., 2021)	TensorFlow, Mininet	Ryu	Tree topology	Energy efficiency, traffic prediction accuracy
(Bhardwaj and Panda, 2022)	Mininet	Ryu	Custom topology	Flow setup time, throughput, delay
(Prabhavat et al., 2022)	Mininet, TensorFlow	OpenDaylight	Custom congestion-aware topology	Congestion detection time, packet delivery ratio
(Selvi and Thamilselvan, 2022)	Mininet, TensorFlow	ONOS	5G network topology	Traffic prediction accuracy, throughput, delay

7. INSIGHT THOUGHTS OF ITM-SDN

Traffic management in SDN faces numerous challenges, as highlighted in the previous section, due to the ongoing advancements in modern networks, particularly the increase in network size and the growing demands to meet modern networking requirements. Based on the study and review of researchers' ideas and recent works in the field of network traffic management and control within SDN and other environments, along with the various methods and mechanisms employed in their research, we can derive modern insights, presenting them as forward-thinking concepts regarding the future of traffic management to enhance network efficiency and capabilities in intelligent, modern management. Some methods and mechanisms used in SDN have been developed for solutions not directly related to traffic management. However, through analysis and study, it can be said that these methods can be beneficial for modern management given their effectiveness in other networks. Such methods include Multi-Agent Systems, Pinning Control Systems, and Federated Learning, which have proven efficient and adaptable in complex and dynamic network environments. Some of these approaches exhibit high capabilities that align with the characteristics of modern network management, enabling their application and allowing for an exploration of their effects on SDN behavior.
Additionally, some ideas serve as alternatives to traditional methods, providing flexibility to adapt to the evolving conditions of networks. Artificial intelligence techniques, widely used in various fields, can be leveraged for traffic analysis and selecting the optimal path, instead of relying on traditional approaches. AI-based methods can potentially deliver higher quality, faster processing, improved efficiency, and reduced congestion. The impact of using advanced models, such as deep learning models, can be examined to assess their effectiveness in enhancing intelligent network traffic management. In addition, machine learning mechanisms can be leveraged, as they are among the most commonly used ideas across various fields, particularly for network classification and extracting relevant metrics and information from data arriving at the SDN controller. In this study, it can be stated that machine learning mechanisms can be beneficial for improving traffic flow and reducing congestion, as well as for network security, detecting and managing attacks, and automating network resource management in areas like routing and traffic optimization. These concepts are illustrated in **Fig. 8** and include:

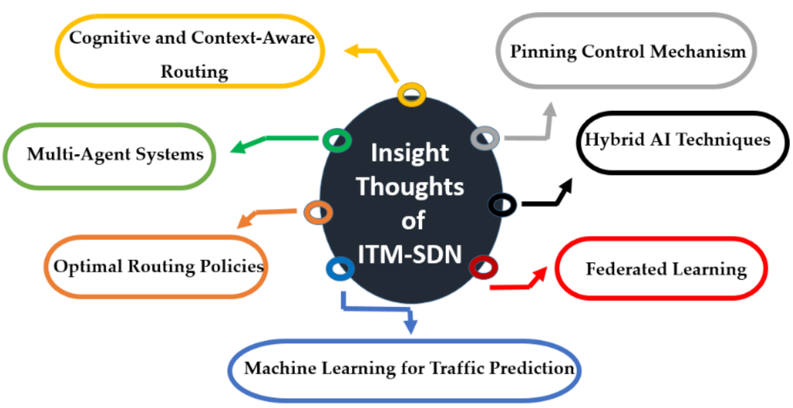

Figure 8. Insight thoughts of ITM-SDN.

7.1 Optimal Routing Policies

DRL combines deep learning and reinforcement learning to enable agents to make decisions based on high-dimensional input data. It allows the SDN controller to learn optimal routing policies through interactions with the network environment. DRL models such as Deep Q-Networks (DQN), Policy Gradient methods, and Actor-Critic models dynamically adjust routing paths and optimize network performance to adapt to network changes and improve traffic management by learning from network states, actions, and rewards.

7.2 Multi-Agent Systems

Multi-agent systems involve multiple autonomous agents that cooperate or compete to achieve individual or collective goals. Each agent operates independently but communicates with others to optimize overall network performance. Multiple agents learn and optimize their policies simultaneously, considering the actions of other agents to manage traffic and channel reassignment in IoT networks.

7.3 Machine Learning for Traffic Prediction

This talk here deals with machine learning algorithms that are responsible for analyzing historical network traffic data to be used to predict future traffic patterns, which leads to proactive traffic management. There are many techniques used,such as supervised learning (e.g., regression, decision trees) and unsupervised learning (e.g., aggregation, anomaly detection) and the purpose of all of them is to predict traffic trends as well as detect anomalies in network traffic.

7.4 Federated Learning

Unified learning is the function of training machine learning models using decentralized devices with a large number or servers that contain local data samples, without exchanging them. This model maintains data privacy and at the same time has the potential to enable group learning. It is possible to use unified learning as this helps in training traffic management models on distributed network data, so sensitive data will be translated and thus the contribution to a global model has been achieved, but on the condition that user privacy is maintained and traffic management is ensured.

7.5 Hybrid AI Techniques

Hybrid AI techniques represent their working techniques is the use of different artificial intelligence methods as they combine several methods, they can combine reinforcement learning and supervised learning or they can integrate optimization algorithms with machine learning models. These hybrid models must be developed and increased in efficiency to take advantage of the strengths of different artificial intelligence technologies, and the durability and performance of traffic management solutions can be significantly improved.

7.6 Cognitive and Context-Aware Routing

Cognitive routing uses artificial intelligence to make intelligent routing decisions based on real-time network conditions and historical data. For contextual routing, the specific context of traffic flows may depend, such as application requirements and user behavior. Machine learning and AI models, when implemented intelligently and thoughtfully, will focus on context and dynamically adapt routing policies based on the current network situation.

7.7 Pinning Control Mechanism

Pinning control involves stabilizing the dynamic behavior of a network by selectively applying control inputs to a subset of nodes. Pinning control can be used in combination with DRL to stabilize the learning process ensure consistent performance in large-scale networks and manage traffic in scalable networks.
These mechanisms and methods collectively contribute to the development of intelligent traffic management solutions in SDN, addressing challenges related to scalability, real-time adaptation, complexity, privacy, security, and integration. In the reviewed works on intelligent traffic management in SDN controllers, researchers have employed various metrics to evaluate the performance and effectiveness of their proposed methods. Here are the main metrics commonly used latency, throughput, packet loss, and network utilization.

8. RECOMMENDATIONS FOR FUTURE RESEARCH OF ITM-SDN

These areas represent significant opportunities for advancing network management and leveraging AI to address current and future challenges, as shown in **Fig. 9**. Research and development in these areas are key to achieving more efficient, secure and adaptable networks.

8.1 Improved Scalability and Efficiency

The focus of future research is on the possibility of developing the scalability of AI and machine learning models where they can solve and deal with the problem of the increasing size and complexity of modern networks **(Hodaei and Babaie, 2021)**. When dealing with modern networks, it can be said that they are complex and have many devices as well as high data volumes, so it has become necessary to design and develop artificial intelligence and machine learning models in order to have the ability and ability to deal with this expansion effectively.
This also includes optimizing algorithms to increase performance and efficiency, reducing congestion, and focusing on the use of distributed computing technologies. Highly efficient AI models that manage and analyze data on a large-scale network.

Figure 9. Recommendation for Future Research of ITM-SDN.

(Pei et al., 2024; Posti and Segal, 2021) directed the attention to improving machine learning algorithms in order to be able to deal with the complexity and data volumes faced by large-scale SDN environments, as well as work was done to test the potential of distributed artificial intelligence technologies and their impact on traffic management in SDN networks, and the possibility of enhancing efficiency without compromising performance, and coordination was done using artificial intelligence models to meet the increasing complexity and traffic of SDN environments and manage it intelligently, and this leads to increased scalability, as well as the adoption of A deep reinforcement learning approach to scale traffic management effectively in increasingly complex SDN networks.

8.2 Real-time Adaptation

It is clear that there is a need to enhance the real-time adaptation capabilities of AI models as this will help in responding instantly to the required dynamic network conditions. To achieve this it is important to achieve advances in typical training techniques, faster data processing capabilities, and real-time analytics tool integration. Effective adaptation provides the required assistance in real time in order to maintain the best performance of the network represented by alleviating the problems you face such as congestion or interruptions when they arise. Authors **(Zhang et al., 2022; Chen et al., 2023; Lee et al., 2024; Jadav et al., 2022)** introduced several methods centered on artificial intelligence as these methods have been adopted to monitor traffic as well as modify them as needed in real time in SDN, as a result, there will be a significant improvement in network performance when congestion occurs, due to the use of adaptive artificial intelligence models, the purpose of which is mainly to quickly react to changing network situations, and make decisions in real time in order to balance loads and thus One of the most prominent technologies that have been used for this purpose will be the reinforcement learning technology applied to adaptive traffic real-time management in SDN and was intended to ensure the efficient use of network resources during dynamic traffic situations.

8.3 Integration with Emerging Technologies

The process of integration with emerging technologies such as 5G, IoT, and edge computing is essential to improve network performance across diverse applications **(Luo et al., 2018).** For integrating AI with technologies such as 5G, IoT, and edge computing effectively affects the improvement of network performance. One of the most important advantages of artificial intelligence is that it can contribute to the management of massive data traffic generated from IoT devices and can increase the chances of improving the efficiency of advanced computing resources. Talking about the 5G network and the impact of artificial intelligence on it, it can be said that artificial intelligence plays an effective role in managing dynamic spectrum and optimizes network segmentation to ensure efficient use of resources. **(Walia et al., 2024; Jaber et al., 2022; Sukaina and Mustafa, 2019; Kumar and Tiwari, 2023; Wang et al., 2023)** addressed the methods that are based on the adoption of artificial intelligence to be able to manage the massive data traffic generated by IoT devices in SDN networks that support 5G, and discussed how to improve network performance using these methods, and focus on the integration of advanced computing and artificial intelligence because this leads to improving IoT traffic in SDN environments, the main goal is to manage the data flow with high efficiency between IoT devices and network infrastructure, and models have been explored Artificial intelligence that has been used and applied to obtain network segmentation in 5G environments and sophisticated computing thus improve the use of resources in networks controlled by SDN, and it is worth noting the role and potential of artificial intelligence in improving the huge amounts of IoT traffic in 5G SDN networks, providing better quality of service and better resource management.

8.4 Enhanced Privacy and Security

Developing advanced privacy-preserving techniques to protect user data while optimizing network traffic. Privacy and security are paramount in network management. Future advancements should focus on developing techniques like federated learning and differential privacy, which allow AI models to learn and optimize without exposing sensitive user data. Improved encryption methods and secure data-sharing protocols will also be crucial for safeguarding user information while maintaining network performance. **(Mubashar et al., 2024; Ossongo et al., 2024; Gheisari et al., 2024)** explores federated learning techniques to enhance privacy while detecting intrusions in SDN, introduces differential privacy techniques for traffic management in SDN, aiming to balance network optimization with user data protection, combines blockchain technology with federated learning to enable secure and private data sharing in SDN environments, and proposes federated learning as a means to maintain privacy while leveraging AI for real-time network management in SDN.

8.5 Cross-layer Optimization

Incorporating cross-layer optimization strategies that consider multiple layers of the network stack for more comprehensive traffic management solutions. Optimization across layers demonstrates strategies that can span multiple layers of the network stack (such as application, transport, network, and data link layers) for optimal overall performance. This approach addresses the subject of traffic management decision making and examines the interactions between different classes, to find better solutions and achieve more effective and comprehensive network management. **(Marwa and Muna, 2024; Nain et al., 2024; Zhang et al., 2023)** presented strategies that were adopted and it integrates cross-layer design into SDN-based wireless networks aimed at improving resource allocation in addition to traffic handling, and addressed the challenges of resource allocation across application, network and transport layers in SDN-enabled advanced computing environments, focused significantly on cross-layer optimization techniques designed to manage IoT traffic in SDN environments, noting the importance of reducing latency and improving data flow efficiently, as it touched on To discuss layered traffic management methods for SDN-based mobile networks, which in turn are responsible for optimizing network usage and reducing congestion across different protocol layers.

9. CONCLUSIONS

The idea of using AI in SDN leads to improved key performance metrics represented by productivity, latency, packet loss, resource utilization, and control level convergence time, which is important for the dynamic optimization of network flows. AI algorithms give networks the ability to independently adapt to changing traffic loads, as well as enable them to detect and mitigate congestion, and can efficiently allocate resources in real-time. Reinforcement learning may be used, for example, to improve routing decisions and traffic flows, while deep learning can be used in the process of predicting traffic patterns to ensure proactive management. There are optimization technologies that are AI-based, including multi-factor systems, installation control, and unified learning, which help improve SDN as they improve scalability, security, and privacy.

Future contributions to intelligent network traffic management will focus on several key areas:

- Scalability and efficiency will also be investigated and studied by developing artificial intelligence and machine learning models to deal with the complexity that exists and can be increased for modern networks while maintaining performance.
- Real-time adaptation capabilities have the potential to give AI models the ability to respond instantly to dynamic network conditions, to ensure the best performance and avoid congestion or interruptions.
- Integration with emerging technologies such as 5G, the Internet of Things and cutting-edge computing will lead to improved network performance across diverse applications, while advanced privacy technologies, such as federal learning and differential privacy, will protect user data without compromising traffic management.
- Finally, cross-layer optimization strategies will improve traffic management as this mechanism enables interactions between different layers of the network stack, leading to more efficient and comprehensive network management. These advancements will be the future of AI-based SDN, ensuring scalable, adaptable, and more secure network environments.

Acknowledgements

This work was supported by the University of Baghdad, College of Engineering, Electrical Engineering Department, PhD work.

Credit Authorship Contribution Statement

Sara Sadiq Jawad: Writing original draft, Editing, Validation and Methodology. Dheyaa Jasim Kadhim: Writing – review & editing, Methodology and Supervising this work. Yusmadi Yah Bt Jusoh: Review & Discuss the Research Methodology of this work.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

Abbasi, M., Rezaei, H., Menon, V., Qi, L., and Khosravi, M., 2021. Enhancing the performance of flow classification in SDN-based intelligent vehicular networks. *IEEE Transactions on Intelligent Transportation Systems*, 22(7), pp. 4141-4150. https://doi.org/10.1109/TITS.2020.3014044.

Agca, M., Faye, S., and Khadraoui, D., 2022. A survey on trusted distributed artificial intelligence. *IEEE Access,*10, pp. 55308-55337. https://doi.org/10.1109/ACCESS.2022.3176385.

Ahmad, S., Jamil, F., Ali, A., Khan, E., Ibrahim, M., and Whangbo, T., 2021. Effectively handling network congestion and load balancing in software-defined networking. *Computers, Materials and Continua*, https://doi.org/10.32604/cmc.2022.017715.

Ahmed Abdulsaheb, J., Jasim Kadhim, D., 2023. Real-time SLAM mobile robot and navigation based on cloud-based implementation. *Journal of Robotics*. https://doi.org/10.1155/2023/9967236.

Alhilali A., and Montazerolghaem, A., 2023. Artificial intelligence based load balancing in SDN: A comprehensive survey. *Internet of Things (Netherlands). Elsevier B.V.*, 22. https://doi.org/10.1016/j.iot.2023.100814.

Ali, T., Morad, A., and Abdala, M., 2020. Traffic management inside software-defined data center networking. *Bulletin of Electrical Engineering and Informatics*, 9(5).

Al-Jamali, N., and Al-Raweshidy, H., 2021. Intelligent traffic management and load balance based on spike ISDN-IoT. *IEEE Systems Journal,* 15(2), pp. 1640-1651. https://doi.org/10.1109/JSYST.2020.2996185.

Al-Jawad, A., Comsa, I., and Shah, P., 2021. REDO: A reinforcement learning-based dynamic routing algorithm selection method for SDN. In *2021 IEEE Conference on Network Function Virtualization and Software Defined Networks, NFV-SDN*. https://doi.org/10.1109/NFV-SDN53031.2021.9665140.

Al-Jawad, A., Comşa, I., Shah, P., Gemikonakli, O., and Trestian, R., 2021. An innovative reinforcement learning-based framework for quality of service provisioning over multimedia-based SDN environments. *IEEE Transactions on Broadcasting*, 67(4), pp. 851-867. https://doi.org/10.1109/TBC.2021.3099728.

Amin, R., Rojas, E., Aqdus, A., Ramazan, S., Casillas-Perez, D., and Arco, J., 2021. A survey on machine learning techniques for routing optimization in SDN. *IEEE Access*, 9, pp. 104582-104611. https://doi.org/10.1109/ACCESS.2021.3099092

Antonio, G., Maria-Dolores, C., 2022. Multi-agent deep reinforcement learning to manage connected autonomous vehicles at tomorrow's intersections. *IEEE Transactions on Vehicular Technology*, 71(7), pp. 7033-7043. https://doi.org/10.1109/TVT.2022.3169907.

Aouedi, O., Piamrat, K., and Parrein, B., 2022. Intelligent traffic management in next-generation networks. *Future Internet*, 14(2). https://doi.org/ 10.3390/fi14020044.

Badotra, S., Sundas, A., Ganguli, I., Verma, A., and Singh, G., 2023. Intelligent network load balancing system with geographic routing and SDN multi-controller architecture. In *2023 2nd International Conference on Smart Technologies for Smart Nation, SmartTechCon*. https://doi.org/10.1109/SmartTechCon57526.2023.10391811.

Belgaum, M., Alansari, Z., Musa, S., Alam, M., and Mazliham, M., 2021. Role of artificial intelligence in cloud computing, IoT and SDN: Reliability and scalability issues. *International Journal of Electrical and Computer Engineering*, 11(5), pp. 4458-4470. https://doi.org/10.11591/ijece.v11i5.pp4458-4470.

Bhardwaj, S., Panda, S., 2022. Performance evaluation using RYU SDN controller in software-defined networking environment. *Wireless Personal Communications*, 122, pp. 701-723. https://doi.org/10.1007/s11277-021-08920-3.

Bhavani, A., Ekshitha, Y., Mounika, A., and Prabu, U., 2023. Reinforcement learning-based traffic engineering in SDN: Problem Formulation, Parameters, and Topology. In *Lecture Notes in Networks and Systems*. (Vol. 383, pp. 311-328). https://doi.org/10.1007/978-981-19-4960-9_25. Springer.

Boussaoud, K., Ayache, M., and En-Nouaary, A., 2022. Performance evaluation of supervised ML algorithms for elephant flow detection in SDN. In *8th International Conference on Optimization and Applications, ICOA 2022*. https://doi.org/10.1109/ICOA55659.2022.9934652.

Byakodi, A., Hungund, M., Athani, A., Afghan, K.; Patlil, S., and Narayan, D., 2023. Maximising efficiency of network resources in SDN through optimal packet routing using reinforcement learning. In *2023 International Conference on Computer Communication and Informatics, ICCCI.* https://doi.org/10.1109/ICCCI56745.2023.10128241

Casas-Velasco, D., Rendon, O., and Da Fonseca, N., 2021. Intelligent routing based on reinforcement learning for software-defined networking. *IEEE Transactions on Network and Service Management*, 8(1), pp. 870-881. https://doi.org/10.1109/ICOIN48656.2020.9016529.

Chaganti, R., Suliman, W., Ravi, V., and Dua, A., 2023. Deep learning approach for SDN-enabled intrusion detection system in IoT networks. *Information (Switzerland),* 14(1). https://doi.org/10.3390/info14010041.

Chandroth, J., Roh, B., and Ali, J., 2022. Performance analysis of python based SDN controllers over real internet topology. In *International Conference on Ubiquitous and Future Networks, ICUFN*. https://doi.org/10.1109/ICUFN55119.2022.9829591.

Chen, J., Liao, C., Wang, Y., Jin, L., Lu, X., Xie, X., and Yao, R., 2023. AQMDRL: Automatic quality of service architecture based on multistep deep reinforcement learning in software-defined networking. *Sensors*, 23(1). https://doi.org/ 10.3390/s23010429.

Chen, X., Wang, X., Yi, B., He, Q., and Huang, M., 2021. Deep learning-based traffic prediction for energy efficiency optimization in software-defined networking. *IEEE Systems Journal*, 15(4), pp. 5583-5594. https://doi.org/10.1109/JSYST.2020.3009315.

Chen, Y., Rezapour, A., Tzeng, W., Tsai, S., 2020. RL-routing: An SDN routing algorithm based on deep reinforcement learning. *IEEE Transactions on Network Science and Engineering*, 7(4), pp. 3185- 3199. https://doi.org/10.1109/TNSE.2020.3017751.

Da Cruz De Lima, J., and Rodrigues, E., 2021. Quality of service control in software-defined 5G networks. In *2021 IEEE International Conference on Automation/24th Congress of the Chilean Association of Automatic Control, ICA-ACCA.* https://doi.org/10.1109/ICAACCA51523.2021.9465305.

Dayang, W., Hao, C., Yi, S.; Song, J., Chunxia, J., and Xilao, W., 2022. Intelligent scheduling of business and traffic in power communication network based on SDN. In *2022 IEEE 4th International Conference on Power, Intelligent Computing and Systems, ICPICS.* https://doi.org/10.1109/ICPICS55264.2022.9873536.

Dennis, A., Alvaro, D., and Janise, M., 2024. Enhanced network metric prediction for machine learning-based cyber security of a software-defined UAV relay network. *IEEE*, 12, pp. 54202-54219. https://doi.org/10.1109/ACCESS.2024.3387728.

Eldhai, A., Hamdan, M., Abdelaziz, A., Hashem, I., Babiker, S., Marsono, M., Hamzah, M., and Jhanjhi, N., 2024. Improved feature selection and stream traffic classification based on machine learning in Software-Defined Networks. *IEEE Access*, 12, pp. 34141-34159. https://doi.org/10.1109/ACCESS.2024.3370435.

Faezi, S., and Shirmarz, A., 2023. A comprehensive survey on machine learning using in software defined networks (SDN). *Human-Centric Intelligent Systems*, 3, pp. 312-343. https://doi.org/10.1007/s44230-023-00025-3.

Gheisari, M., Khan, W., Najafabadi, H., mcArdle, G, Rabiei-Dastjerdi, H, Liu, Y, Fernandez-Campusano, C, and Abdalla, H, 2024. CAPPAD: a privacy-preservation solution for autonomous vehicles using SDN, differential privacy and data aggregation. *Applied Intelligence*, 54, pp. 3417-3428. https://doi.org/ 10.1007/s10489-023-04991-w.

Gunavathie, M., 2020. A survey on traffic prediction and classification in SDN. *IOS Press*. https://doi.org/10.3233/APC200168.

Guo, A., and Yuan, C., 2021. Network intelligent control and traffic optimization based on SDN and artificial intelligence. *Electronics (Switzerland),* 10(6). https://doi.org/10.3390/electronics10060700.

Guzman, J., Pizarro, G., and Nunez, F., 2023. A reinforcement learning-based distributed control scheme for cooperative intersection traffic control. *IEEE Access*, 11, pp. 57037-57045. https://doi.org/10.1109/ACCESS.2023.3283218.

Hasan, M., and Kadhim, D., 2022. A new smart approach of an efficient energy consumption management by using a machine-learning technique. *Indonesian Journal of Electrical Engineering and Computer Science*, 25(1), pp. 68-78. https://doi.org/10.11591/ijeecs.v25.i1.pp68-78.

Hodaei, A., and Babaie, S., 2021. A Survey on traffic management in software-defined networks: challenges, effective approaches, and potential measures. *Wireless Personal Communications*, 118, pp. 1507-1534. https://doi.org/ 10.1007/s11277-021-08100-3.

Houda, Z., Hafid, A., and Khoukhi, L., 2023. MiTFed: A privacy preserving collaborative network attack mitigation framework based on federated learning using SDN and blockchain. *IEEE Transactions on Network Science and Engineering*, 10(4), pp. 1985-2001. https://doi.org/ 10.1109/TNSE.2023.3237367.

Huang, V., Chen, G., and Zhang, P., 2020. A scalable approach to SDN control plane management: High utilization comes with low latency. *IEEE Transactions on Network and Service Management*, 17, pp 682-965. https://doi.org/ 10.1109/TNSM.2020.2973222.

Huang, W., Yuan, B., Wang, S., Zhang, J., Li, J. and Zhang, X., 2022. A generic intelligent routing method using deep reinforcement learning with graph neural networks. *IET Communications*, 16(19), pp. 2343-2351. https://doi.org/10.1049/cmu2.12487.

Huang, X., Zeng, M., and Xie, K., 2021. Intelligent traffic control for QoS optimization in hybrid SDNs. *Computer Networks*, 189. https://doi.org/10.1016/j.comnet.2021.107877.

Isong, B., Samuel Molose, R., Abu-Mahfouz, A., and Dladlu, N., 2020. Comprehensive review of SDN controller placement strategies. *IEEE Access, (8), pp. 170070-170092*. https://doi.org/10.1109/ACCESS.2020.3023974.

Jaafari, S., Nassiri, M., and Mohammadi, R., 2022. Traffic-aware routing with softwaredefined networks using reinforcement learning and fuzzy logic. *International Journal of Computing*. https://doi.org/10.47839/ijc.21.3.2687.

Jabbar, S., Kadhim, D., and Li, Y., 2018. Proposed an adaptive bitrate algorithm based on measuring bandwidth and video buffer occupancy for providing smoothly video streaming. *International*

Journal of Advanced Computer Science and Applications, 9(2). https://doi.org/10.1109/ACCESS.2022.3140646.

Jaber, Z.H.K., Al-Araji, D.J., and Sabah, A., 2022. Medium access control protocol design for wireless communications and networks review. *International Journal of Electrical and Computer Engineering,* 12(2). https://doi.org/ 10.11591/ijece.v12i2.pp1711-1723.

Jadav, N., Nair, A., Gupta, R., Tanwar, S., Lakys, Y., and Sharma, R., 2022. AI-driven network softwarization scheme for efficient message exchange in IoT environment beyond 5G. International *Journal of Communication Systems*. https://doi.org/ 10.1002/dac.5336.

Jameel, M., Kanakis, T., Turner, S., Al-Sherbaz, A., Bhaya, W., and Al-Khafajiy, M., 2023. An intelligent routing approach for multimedia traffic transmission over SDN. In *2023 15th International Conference on Developments in eSystems Engineering, DeSE*. https://doi.org/10.1109/DeSE58274.2023.10100250.

Janjua, H., de Miguel, I., Durán Barroso, R., Masoumi, M., Hosseini, S., Aguado, J., Merayo,N., and Abril, E., 2023. A framework for next generation cloud-native SDN cognitive resource orchestrator for IoTs (NG2CRO). *Lecture Notes in Networks and Systems,* pp. 399-407. https://doi.org/10.1007/978-3-031-38318-2_39

Jia, J., Fu, Y., Zhang, G., Liang, X., and Xu, P., 2021. The intelligent routing control strategy based on deep learning. In *Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST*. https://doi.org/10.1007/978-3-030-67514-1_46.

Kaczmarek, S., and Litka, J., 2024. Impact of SDN controller's performance on quality of service. *IEEE Access*, 12. https://doi.org/10.1109/ACCESS.2024.3352433.

Kamboj, P., Pal, S., Bera, S., and Misra, S., 2023. QoS-Aware multipath routing in software-defined networks. *IEEE Transactions on Network Science and Engineering*, 10(2), pp. 723-732. https://doi.org/10.1109/TNSE.2022.3219417.

Karunakaran, V., and Geetha, A., 2022. Applying reinforcement learning in SDN: A packet re-transmission policy. *Lecture Notes in Networks and Systems*, pp. 279-289. https://doi.org/10.1007/978-981-16-7952-0_26.

Kaur, H., 2021. Cross-layer design in Software Defined Networks (SDNs): Issues and possible solutions. *Researchgate. Net.*

Khairi, M., Ariffin, S., Latiff, N., Yusof, K., Hassan, M., Al-Dhief, F, Hamadan, M, Khan, S, and Hamzah, M, 2021. Detection and classification of conflict flows in SDN using machine learning algorithms. *IEEE Access*, 9, pp. 76024 - 76037. https://doi.org/10.31026/j.eng.2022.05.05.

Kumar, R.U.V., and Tiwari, V., 2023. Optimized traffic engineering in Software Defined Wireless Network based IoT (SDWN-IoT): State-of-the-art, research opportunities and challenges. *Computer Science Review*, 49. https://doi.org/ 10.1016/j.cosrev.2023.100572.

Kumar, S., Bansal, G., and Shekhawat, V., 2020. A machine learning approach for traffic flow provisioning in software defined networks. In *2020 International Conference on Information Networking (ICOIN)*. IEEE. https://doi.org/10.1109/ICOIN48656.2020.9016529.

Kwak, J., Cho, C., Shin, Y., and Yang, S., 2020. IntelliTC: Intelligent inter-DC traffic controller for the Internet of everything service based on fog computing. *IET Communications*. https://doi.org/ 10.1049/iet-com.2018.6184.

Lee, G., Lee, C., and Roh, B., 2022. QoS support path selection for inter-domain flows using effective delay and directed acyclic graph in multi-domain SDN. *Electronics (Switzerland),* 11(14). https://doi.org/10.3390/electronics11142245.

Lee, J., Solat, F., Kim, T., Poor, H., 2024. Federated learning-empowered mobile network management for 5G and beyond networks: From access to core. *IEEE Communications Surveys and Tutorials*, 26(3), pp. 2176-2212. https://doi.org/ 10.1109/COMST.2024.3352910.

Luo, W., Deng, X., and Zhang, F., 2018. Positioning and guiding educational robots by using fingerprints of WiFi and RFID array. *Eurasip Journal on Wireless Communications and Networking*, https://doi.org/10.1186/s13638-018-1183-5.

Magadum, A., Ranjan, A., and Narayan, D., 2021. DeepQoSR: A deep reinforcement learning based QoS-aware routing for software defined data center networks. In *2021 12th International Conference on Computing Communication and Networking Technologies, ICCCNT 2021*. https://doi.org/10.1109/ICCCNT51525.2021.9579514. IEEE.

Mahajan, S., Harikrishnan, R., and Kotecha, K., 2022. Prediction of network traffic in wireless mesh networks using hybrid deep learning model. *IEEE Access,* 10, pp. 7003-7015. https://doi.org/10.1109/ACCESS.2022.3140646.

Malik, A., De Frein, R., Al-Zeyadi, M., and Andreu-Perez, J., 2020. Intelligent SDN traffic classification using deep learning: Deep-SDN. In *2020 2nd International Conference on Computer Communication and the Internet, ICCCI*. https://doi.org/10.1109/ICCCI49374.2020.9145971.

Manso, C., Vilalta, R., Casellas, R., Martinez, R., and Munoz, R., 2020. Cloud-native SDN controller based on micro-services for transport networks. In *2020 IEEE Conference on Network Softwarization: Bridging the Gap Between AI and Network Softwarization, NetSoft*. https://doi.org/10.1109/NetSoft48620.2020.9165377.

Mao, B., Tang, F., Fadlullah, Z., and Kato, N., 2021. An intelligent route computation approach based on real-time deep learning strategy for software defined communication systems. *IEEE Transactions on Emerging Topics in Computing*, 9(3), pp. 1554-1565. https://doi.org/10.1109/TETC.2019.2899407.

Marwa, M., and Muna, H., 2024. Efficient intrusion detection through the fusion of AI algorithms and feature selection methods. *Journal of Engineering*, 30(7), pp. 184-201. https://doi.org/10.31026/j.eng.2024.07.11.

Masood, F., Khan, W., Jan, S., and Ahmad, J., 2023. AI-enabled traffic control prioritization in software-defined IoT networks for smart agriculture. *Sensors*,23(19). https://doi.org/10.3390/s23198218.

Max, B., Lateef, A., Stephen, O., Muhammad, F., and Agbotiname, L., 2024. Scalable hybrid switching-driven software defined networking issue: from the perspective of reinforcement learning standpoint. *IEEE*, 12, pp. 63334-63350. https://doi.org/10.1109/ACCESS.2024.3387273.

Mohammed M., and Nadia A., 2023. Automatic spike neural technique for slicing bandwidth estimated virtual buffer-size in network environment. *Journal of Engineering*, 29(6), pp. 87-97. https://doi.org/ 10.31026/j.eng.2023.06.07.

Mubashar, R., Muhammad, J., Muhammad, B., Muhammad, A., 2024. Federated learning for privacy-preserving intrusion detection in software-defined networks. *IEEE Access*, 12, pp. 69551-69567. https://doi.org/ 10.1109/TII.2020.3023430.

Naibaho, L., Saxena, P., Sharma, K., Alfurhood, B., Pallavi, L., and Pant B., 2023. Integration of artificial intelligence in software defined networking technology through developing machine learning algorithms. In *2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE*. https://doi.org/10.1109/ICACITE57410.2023.10182618.

Nain, A., Sheikh, S., Shahid, M., and Rohit, M., 2024. Resource optimization in edge and SDN-based edge computing: a comprehensive study. *Cluster Computing*, 27, pp. 5517-5545. https://doi.org/10.1007/s10586-023-04256-8.

Soud, N.S. and Al-Jamali, N.A.S., 2023. Intelligent congestion control of 5G traffic in SDN using dual-spike neural network. *Journal of Engineering*, 29(01), pp.110-127. https://doi.org/10.31026/j.eng.2023.01.07.

Nyaramneni, S., Potluri, T., and Somavarapu, J., 2023. Advanced ensemble machine learning models to predict SDN traffic. *Procedia Computer Science*, 230, pp. 417-426. https://doi.org/10.1016/j.procs.2023.12.097.

Ossongo, E., Esseghir, M., and Merghem-Boulahia, L., 2024. A multi-agent federated reinforcement learning-based optimization of quality of service in various LoRa network slices. *Computer Communications*. https://doi.org/10.1016/j.comcom.2023.11.015.

Pathak, Y., Prashanth, P., and Tiwari, A., 2023. *6G enabled fog computing in IoT: Applications and opportunities.* Springer Cham. ISBN: 978-3-031-30101-8.

Pei, X., Sun, P., Hu, Y., Li, D., Chen, B., and Tian, L., 2024. Enabling efficient routing for traffic engineering in SDN with Deep Reinforcement Learning. *Computer Networks,* 241. https://doi.org/10.1016/j.comnet.2024.110220.

Posti, R., and Segal, M., 2021. Improved routing in networks through load prediction strategy. In *2021 17th International Conference on the Design of Reliable Communication Networks, DRCN*. https://doi.org/ 10.1109/DRCN51631.2021.9477322.

Prabhavat, S., Thongthavorn, T., and Pasupa, K., 2022. Deep learning-based early detection and avoidance of traffic congestion in software-defined networks. In *the 14th International Conference on Information Technology and Electrical Engineering ICITEE*, https://doi.org/10.1109/ICITEE56407.2022.9954107

Praveen, S., Sarala, P., Kumar, T., Manuri, S., Srinivas, V, and Swapna, D, 2022. An adaptive load balancing technique for multi SDN controllers. In *International Conference on Augmented Intelligence and Sustainable Systems, ICAISS 2022*. https://doi.org/10.1109/ICAISS55157.2022.10010881

Ram, A., Dutta, M., and Chakraborty, S., 2024. A flow-based performance evaluation on RYU SDN controller. *Journal of The Institution of Engineers (India): Series B,* 105, pp. 203-215. https://doi.org/10.1007/s40031-023-00982-0.

Rischke, J., Sossalla, P., Salah, H., Fitzek, F., and Reisslein, M., 2020. QR-SDN: towards reinforcement learning states, actions, and rewards for direct flow routing in software-defined networks. *IEEE Access,* 8, pp. 174773-174791. https://doi.org/10.1109/ACCESS.2020.3025432.

Sable, N., Rathod, V., Salunke, M., Jadhav, H., Tambe, R., and Kothavle, S., 2023. Enhancing routing performance in software-defined wireless sensor networks through reinforcement learning. *International Journal of Intelligent Systems and Applications in Engineering*, 11(10).

Sahran, F., Altarturi, H., and Anuar, N., 2024. Exploring the landscape of AI-SDN: A comprehensive bibliometric analysis and future perspectives. *Electronics (Switzerland),* 13(1). https://doi.org/10.3390/electronics13010026.

Saleh, S., and Fathy, C., 2023. A novel deep-learning model for remote driver monitoring in SDN-based internet of autonomous vehicles using 5G technologies. *Applied Sciences (Switzerland),* 13(2). https://doi.org/10.3390/app13020875.

Samiullah, M., and Rajesh, K., 2024. Traffic engineering and quality of service in hybrid software defined networks. *IEEE,* 21(2), pp. 96-121. https://doi.org/10.23919/jcc.fa.2022-0860.202402.

Sarabia-Jácome, D., Giménez-Antón, S., Liatifis, A., Grasa, E., Catalan, M., and Pliatsios, D., 2024. Progressive adoption of RINA in IoT networks: Enhancing scalability and network management via SDN integration. *Applied Sciences (Switzerland)*, 14(6). https://doi.org/10.3390/app14062300.

Selvi, K., and Thamilselvan, R., 2022. An intelligent traffic prediction framework for 5G network using SDN and fusion learning. *Peer-to-Peer Networking and Applications*, 15, pp. 751-767. https://doi.org/10.1007/s12083-021-01280-6.

Shafique, K., and Alhassoun, M., 2024. Going beyond a simple RIS: Trends and techniques paving the path of future RIS. *IEEE Open Journal of Antennas and Propagation*, 5(2), pp. 265-276. https://doi.org/ 10.1109/OJAP.2024.3360900.

Sharma, A., Balasubramanian, V., and Kamruzzaman, J., 2024. A Temporal deep Q learning for optimal load balancing in software-defined networks. *Sensors*, 24(4). https://doi.org/10.3390/s24041216.

Singh, G., Tripathi, V., Dumka, A., Rathore, R., Bajaj, M., Escorcia-Gutierrez, J., 2024. A novel framework for capacitated SDN controller placement: Balancing latency and reliability with PSO algorithm. *Alexandria Engineering Journal*, 87, pp. 77-92. https://doi.org/10.1016/j.aej.2023.12.018

Sridharan, A., Othman, B., and Tongkachok, K., 2022. The emerging role of integrating artificial intelligence (AI) in the software defined network for effective traffic prediction using correlation analysis. In *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering ICACITE*. https://doi.org/10.1109/ICACITE53722.2022.9823926. IEEE.

Sukaina, R., and Mustafa, I., 2019. Link failure recovery for a large-scale video surveillance system using a software-defined network. *Journal of Engineering*,26(1), pp. 104-120. https://doi.org/10.31026/j.eng.2020.01.09.

Sun, P., Guo, Z., Lan, J., Li, J., Hu, Y., and Baker, T., 2021. ScaleDRL: A scalable deep reinforcement learning approach for traffic engineering in SDN with pinning control. *Computer Networks*, 190. https://doi.org/10.1016/j.comnet.2021.107891.

Tiwana, P., and Singh, J., 2023. Software-defined networking's adaptive load ptimisation technique for multimedia applications with multi-controller utilisation. In *2023 9th International Conference on Signal Processing and Communication, ICSC*. https://doi.org/10.1109/ICSC60394.2023.10441149.

Vaishali, S., Vikas, K., Sampath, K., and Bhushankumar, N., 2023. Intelligent traffic management for vehicular networks using machine learning. *ICTACT JOURNAL*, 14(3), pp. 2998-3004. https://doi.org/ 10.21917/ijct.2023.0446.

Walia, G., Kumar, M., and Gill, S., 2024. AI-empowered Fog/Edge resource management for IoT applications: A comprehensive review, research challenges, and future perspectives. *IEEE Communications Surveys and Tutorials*, 26(1), pp. 619-669. https://doi.org/10.1109/COMST.2023.3338015.

Wang, J., Liu, .J, Li, J., and Kato, N., 2023. Artificial intelligence-assisted network slicing: Network assurance and service provisioning in 6G. *IEEE Vehicular Technology Magazine*, 18(1), pp. 49-58. https://doi.org/10.1109/MVT.2022.3228399.

Wu, T., Zhou, P., Wang, B., Li, A., Tang, X., Xu, Z., Chen, K., and Ding, X., 2021. Joint traffic control and multi-channel reassignment for core backbone network in SDN-IoT: A multi-agent deep reinforcement learning approach. *IEEE Transactions on Network Science and Engineering*, 8(1), pp. 231-245. https://doi.org/10.1109/TNSE.2020.3036456.

Wu, Y., Hwang, P., Hwang, W., and Cheng, M., 2020. Artificial intelligence enabled routing in software defined networking. *Applied Sciences (Switzerland)*, 10(18). https://doi.org/10.3390/APP10186564.

Xiong, Z., and Hongyu, G., 2021. An intelligent routing optimization strategy based on deep reinforcement learning. *Journal of Physics: Conference Series*. https://doi.org/10.1088/1742-6596/2010/1/012046.

Xu, C., Xu, C., and Li, B., 2023. Multi-agent deep Q-network based dynamic controller placement for node variable software-defined mobile edge-cloud computing networks. *Mathematics*, 11(5). https://doi.org/10.3390/math11051247.

Yankam, Y., Tchendji, V., Myoupo, J., 2024. WoS-CoMS: Work stealing-based congestion management scheme for SDN programmable network. *Journal of Network and Systems Management*, 32(23). https://doi.org/10.1007/s10922-023-09798-1.

Ye, M., Huang, L., Wang, X., Wang, Y., Jiang, Q., and Qiu, H., 2024. A new intelligent cross-domain routing method in SDN based on a proposed multiagent reinforcement learning algorithm. *International Journal of Intelligent Computing and Cybernetics*. https://doi.org/10.1108/IJICC-09-2023-0269.

Zabeehullah Arif, F., and Abbas, Y., 2022. DLIRS: Deep learning based intelligent routing in software defined IoT. In *2022 19th International Bhurban Conference on Applied Sciences and Technology, IBCAST*. https://doi.org/10.1109/IBCAST54850.2022.9990473. IEEE.

Zhang, J., Wang, K., Li, R., 2023. MaCro: Mega-constellations routing systems with multi-edge cross-domain features. *IEEE Wireless Communications*, 30(6), pp. 69-76. https://doi.org/10.1109/MWC.006.2300216.

Zhang, L., Lu, Y., Zhang, D., Cheng, H., and Dong, P., 2022. DSOQR: Deep reinforcement learning for online QoS routing in SDN-based networks. *Security and Communication Networks*. https://doi.org/10.1155/2022/4457645.

Zhang, Q., Wang, X., Lv, J., and Huang, M., 2020. Intelligent content-aware traffic engineering for SDN: an AI-driven approach. *IEEE Network,* 34(3), pp. 186-193. https://doi.org/10.1109/MNET.001.1900340.

Żotkiewicz, M., Szałyga, W., and Domaszewicz, J., 2021. Artificial intelligence control logic in next-generation programmable networks. *Applied Sciences (Switzerland)*, 11(19), 9163. https://doi.org/10.3390/app11199163.

افكار ثاقبة في ادارة المرور الذكية للشبكات المعرفة برمجياً

ساره صادق جواد[1]*، ضياء جاسم كاظم[1] ، ياوسمدي ياهبات جووسه[2]

[1]جامعة بغداد، كلية الهندسة، قسم الهندسة الكهربائية، بغداد، العراق
[2]كلية علوم الحاسوب وتكنولوجيا المعلومات، جامعة بوترا، ماليزيا

الخلاصة

تزايد الحاجة على نطاق واسع لدراسة أدارة المرور في الشبكات المعرفة بالبرمجيات (SDN) نظرًا لأهميتها الكبيرة في تعزيز كفاءة الشبكات وقدرتها على التكيف مع الطلبات المتزايدة على البيانات والتطبيقات الحديثة. وما يزيد من أهمية هذه الدراسات هو دمج تقنيات الذكاء الاصطناعي (AI)، والتي بدورها توفر قدرات تحليل واستجابة ذكية تساهم في تحسين جودة الخدمة (QoS) وتجنب الازدحام وتحقيق توزيع متوازن للحمل عبر الشبكة. تتضمن أدارة المرور الذكية في وحدة التحكم SDN استخدام خوارزميات وتقنيات حديثة تم استخدامها سابقًا وأعطت نتائج مرغوبة في هذا المجال لتحسين التحكم في موارد الشبكة وتكوينها وأتمتتها بشكل متقدم. أما بالنسبة لوحدات التحكم SDN، فلها دور رئيسي في هياكل بناء شبكات SDN، حيث أنها مسؤولة عن إدارة تدفق البيانات إلى أجهزة الشبكة في طبقة مستوى البيانات مثل المحولات والموجهات. تقدم هذه الورقة دمج خوارزميات الذكاء الاصطناعي في وحدة التحكم SDN حتى تتمكن من اتخاذ قرارات ذكية باستخدام التحليلات التنبؤية لحركة المرور المستقبلية وما تتطلبه ومتطلبات سعة الشبكة. بالإضافة إلى تقديم مقارنة قيمة في هذه الورقة البحثية والتي تضمنت نهج الآخرين المتبع في إدارة المرور الذكية لشبكات SDN، فإن عملية دمج الذكاء الاصطناعي و SDN تفتح آفاقًا نحو تطوير شبكات متقدمة تدعم متطلبات الشبكات الحديثة مثل إنترنت الأشياء والاتصالات وغيرها، وينصب التركيز الرئيسي على التكامل الشامل حتى يكون البحث مساهمة فعالة ومواكبة للتطور المستمر لاستراتيجيات إدارة الشبكة الذكية.

الكلمات المفتاحية: الشبكات المعرفة بالبرمجيات (SDN)، وإدارة حركة المرور، والذكاء الاصطناعي (AI)، والتعلم الآلي (ML)، والتعلم الفيدرالي (FL)، والتعلم المعزز العميق (DRL).