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# COMPLEX COMMUNICATION NETWORKS MANAGEMENT WITH DISTRIBUTED AI: CHALLENGES AND OPEN ISSUES

## **ABSTRACT**

*The rapid evolution of communication networks, particularly with the introduction of 5G and the anticipated arrival of 6G, has introduced new complexities in managing traffic, routing, and resource allocation. Distributed Artificial Intelligence (DAI) is emerging as a promising solution to address challenges related to scalability, adaptability, and performance in these dynamic environments. With the unpredictable nature of network traffic patterns and the dynamic infrastructure of modern networks, effective network management is crucial for ensuring optimal resource utilization and preventing congestion. This is essential to maintain high performance, reliability, and scalability in today's communication systems.*

*This paper explores the application of AI techniques in network management, with a focus on key areas such as congestion control, routing management, and traffic prediction. By examining both centralized and distributed AI approaches—such as Multi-Agent Reinforcement Learning (MARL)—it highlights their potential to enhance network efficiency, improve latency, increase throughput, and reduce packet loss. The paper also addresses the limitations of current methods, while discussing potential future directions for AI-driven solutions in large-scale, real-time network operations.*

## **KEYWORDS**

*Network management, complex communication networks, congestion control, traffic prediction, routing management, machine learning, distributed artificial intelligence*

## **1. INTRODUCTION**

The rapid growth of IoT devices and applications, combined with the evolving needs of network operators and end-users, presents significant challenges in managing modern communication networks. These networks must now accommodate increasing demands, including handling substantial data loads, providing greater bandwidth, achieving ultra-low latency, and maintaining energy efficiency.

In complex communication environments, high processing demands, unpredictable traffic patterns, and evolving network topologies strain resources, making efficient network management critical for preventing congestion and maintaining performance. Dynamic

adaptation is essential to ensure optimal Quality of Service (QoS) metrics—such as latency, bandwidth, and energy efficiency—while handling massive traffic loads and ensuring real-time responsiveness. These factors are particularly crucial for delivering seamless, time-sensitive services in emerging technologies like 5G, 6G, IoT, and mobile edge computing. Traditional network management solutions often rely on static rules, which are inadequate for the dynamic and evolving nature of modern networks. This has created a need for more adaptive, intelligent approaches capable of managing the increasing complexity of communication networks. The

demand for ultra-low latency, high bandwidth, and consistent QoS requires innovative, flexible strategies that can dynamically adapt to changing conditions in real time.

Current techniques also struggle with scalability and responsiveness, underscoring the need for decentralized, real-time solutions to meet the challenges of today's communication networks. While there has been significant research on AI-driven network management, much of the focus has been on centralized approaches. In contrast, less attention has been paid to recent advancements in Distributed AI for network management. This paper seeks to address this gap by exploring the latest developments in Distributed AI techniques, such as Multi-Agent Reinforcement Learning (MARL), specifically in the context of managing complex communication networks.

This study examines various approaches to network management in complex environments, categorizing different strategies from the literature and evaluating their potential. We provide an in-depth analysis of current and emerging ML applications in communication networks, focusing on key areas such as congestion control, traffic prediction, and routing management. Section 2 introduces key concepts, including complex communication networks, network management, and the role of machine learning (ML) and distributed AI (DAI) in these contexts. Section 3 identifies the core challenges faced in network management, particularly as networks grow in scale and complexity. In Section 5, we analyze centralized ML solutions for network management, assessing their strengths and limitations. In Section 6, we transition to distributed AI approaches, exploring how these models address the limitations of centralized systems by enhancing scalability, adaptability, and real-time decision-making in dynamic networks. Throughout the paper, we highlight both the potential and the challenges of implementing these solutions, providing an evaluation of current trends and open issues in AI-driven network management.

## **2. CONCEPTS**

### **2.1. Complex Communication Networks**

Complex communication networks refer to modern and advanced networks, such as 5G, 6G, and large-scale IoT systems, characterized by their dynamic topologies, diverse applications, and varying traffic patterns. These networks must accommodate a vast number of connected devices, provide high data throughput, and meet stringent Quality of Service (QoS) requirements, such as ultra-low latency and high reliability. The complexity arises from factors like the integration of heterogeneous technologies, the need for real-time data processing, and the management of fluctuating traffic loads caused by event-driven applications and services like VR/AR. These characteristics make managing and optimizing such networks a challenging task, requiring advanced and adaptive solutions.

These networks have been defined in various ways in the literature, emphasizing their irregular structure, dynamic behavior, and representation of real-world systems. Table 1 summarizes several definitions, highlighting the diversity in how these networks are understood.

### **2.2. Title Network Management**

Building on the concept of complex communication networks, network management aims to ensure efficient, secure, and reliable operation within these dynamic environments. Network management entails a range of different activities and concepts, including congestion control, routing management, traffic prediction, and performance optimization.

In these complex networks, nodes can become overloaded due to intensive processing tasks such as traffic routing, data analysis, video encoding/decoding, and data encryption/decryption.

Moreover, network bandwidth often exhibits unpredictable or chaotic patterns driven by high-bandwidth-consuming applications like virtual reality (VR), augmented reality (AR), and mixed reality (XR). Consequently, the application of automated reasoning algorithms is increasingly necessary to allow dynamic adaptation to changes in user experience and Quality of Service (QoS).

Congestion control (CC) is vital for preventing network overload. It manages data flow to minimize packet loss and latency, ensuring high throughput and maintaining network stability even under heavy traffic conditions.

Routing management also plays a significant role in network management by determining optimal paths for data transmission. Traditionally, this involves predefined algorithms and protocols that can be proactive, reactive, or hybrid, each offering different strategies for effectively directing traffic through the network.

Traffic prediction complements these efforts by forecasting future network traffic patterns based on historical data and current conditions. By anticipating changes in traffic behavior, the network can adapt proactively, optimizing its performance and resource allocation. Together, these aspects form the foundation of managing complex communication networks.

Table 1. Definitions of Complex Networks in Literature.

Reference	Definition
[1]	Networks whose structure is irregular, complex and dynamically evolving in time.
[2]	By definition, complex networks are networks with more complex architectures than classical random graphs with their “simple” Poissonian distributions of connections.
[3]	Complex weblike structures describe a wide variety of systems of high technological and intellectual importance.
[4]	For instance, there may be more than one different type of vertex in a network, or more than one different type of edge. And vertices or edges may have a variety of properties, numerical or otherwise, associated with them.

### 2.3. Machine Learning and Distributed AI

Conventional automated reasoning solutions fall short of meeting these rigorous demands because they rely heavily on predefined rules and static knowledge bases, which are inadequate for capturing the dynamic and evolving nature of modern complex networks. This necessitates the development of new, more adaptable approaches.

To address this, the automated network management paradigm is shifting towards the integration of Artificial Intelligence (AI) techniques, including Machine Learning (ML). This shift aims to optimize network management operations while dynamically adapting to changing network conditions and user requirements. Particularly in the realm of future mobile communication networks like 6G, the stringent QoS demands necessitate a comprehensive approach to an increasingly intricate communication environment. This environment is marked by exponential growth in network traffic due to applications, video streaming, VR/AR/XR; the extensive deployment of IoT devices; the proliferation of mobile edge computing; and the emergence of highly dynamic network topologies.

While numerous ML techniques have been proposed for network management, most rely on a centralized controller for network-wide monitoring and decision-making. Despite simplifying network operations, these centralized ML methods face significant limitations, such as lack of scalability, a single point of failure, limited fault tolerance, high latency, and restricted service coverage. Distributed ML approaches present a promising alternative to overcome these limitations.

A promising approach in Distributed AI is MARL, where multiple AI agents can either collaborate or operate independently to optimize network management. In MARL, agents gather data from their environment, learn over time through feedback (rewards) for actions that enhance network performance, and can adjust parameters such as bandwidth allocation or traffic routing in response to local conditions. Whether collaborating or acting independently, these agents collectively improve network efficiency without depending on a centralized controller, which enhances scalability and resilience to failures.

Figure 1 illustrates the structure of MARL within a 5G core network. Each agent, such as Agent 2, processes local state information, observes rewards, and takes action based on these inputs. These agents can communicate with each other and share learned knowledge to enhance overall network performance. By distributing decision-making across the network, MARL allows for dynamic adaptation to traffic conditions in large-scale, complex networks like 5G and 6G.

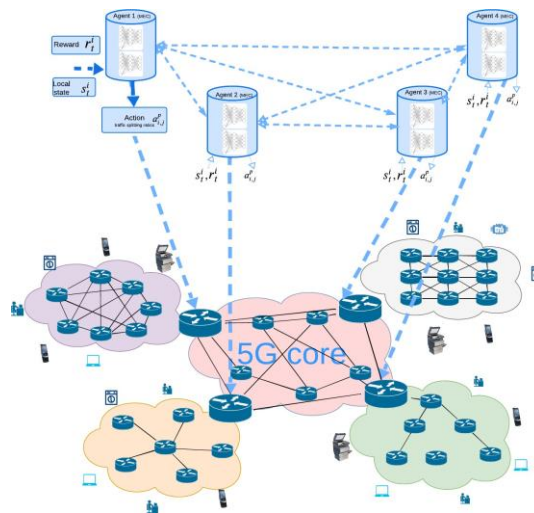


Figure 1: Multi-Agent Reinforcement Learning (MARL) in a 5G Core Network.

### 3. NETWORK MANAGEMENT CHALLENGES

Managing complex communication networks for optimal performance and security presents numerous challenges that require strategic planning and meticulous oversight. These challenges are outlined below:

- Multi-layer interactions among interconnected nodes: The interactions between multiple layers in a network complicate management by making it harder to track and optimize performance across different layers. These interactions introduce dependencies and potential vulnerabilities that can affect the network’s reliability and efficiency.
- Diversity of communication protocols: The wide range of communication protocols in use creates challenges for ensuring interoperability and optimal performance across the network.

Managing this diversity requires sophisticated configuration strategies to enable seamless communication between devices with varying capabilities and protocol requirements.

- Unpredictable traffic patterns: Sudden fluctuations in traffic, caused by high-demand applications or event-driven services, make it challenging to predict and manage network resources efficiently. The ability to anticipate and react to these unpredictable patterns is critical for maintaining optimal performance and avoiding congestion.

- Accommodating technological advancements: Integrating new technologies with legacy systems poses challenges in maintaining network functionality and performance. Balancing innovation with backward compatibility demands careful planning to ensure that new advancements enhance the network without disrupting existing services.

- Network congestion and control strategies: Network administrators must manage congestion and latency while balancing centralized and decentralized control. The challenge is to develop strategies that mitigate congestion and reduce latency without compromising the benefits of either management approach, ensuring efficient and responsive network operations.

These challenges drive the need for new approaches, particularly those leveraging AI and machine learning.

## **4. TRADITIONAL SOLUTIONS**

Traditional network management solutions have long relied on established techniques. Conventional adaptive congestion control (CC) protocols for Transmission Control Protocol (TCP) [5], ECN [6], and AQM [7] and its improvements such as BIC and CUBIC [8], are not well adapted to accommodate ever-evolving characteristics and requirements of communication networks, especially when it comes to considering unpredictable traffic patterns. This is particularly the case with event-driven applications (such as IoT notifications and alarms) and immersive scenarios like VR/AR/XR-based applications.

In routing management, traditional techniques have predominantly been rule-based, following predefined algorithms. Proactive protocols like Distance Vector Routing Protocol (DVRP) [10] and Open Shortest Path First (OSPF) [11] maintain constantly updated routing tables for immediate route availability but are less scalable due to the high overhead involved. Reactive protocols, such as Ad hoc On-Demand Distance Vector (AODV) [12] and Dynamic Source Routing (DSR) [13], create routes on demand, which reduces overhead but can increase latency in large networks. While these methods provide basic routing solutions, they often lack the adaptability needed for complex and rapidly changing network environments.

In traffic prediction, traditional techniques such as statistical models and time series analysis methods (e.g., Autoregressive (AR), Moving Average (MA), ARMA, and ARIMA, [9]) have been widely used. These models are effective for basic predictions in relatively stable environments but struggle to capture the complexities of modern, dynamic networks. The non-linear and chaotic traffic patterns in contemporary networks render these methods less effective.

The primary drawback of these traditional methods is their inability to handle the non-linear, chaotic, and highly variable nature of traffic in modern networks, driven by event-based applications and real-time services.

## **5. CENTRALIZED ML SOLUTIONS**

In response to these challenges, AI techniques, such as ML, are gaining popularity in network management. ML techniques can capture non-linear relationships and dynamically adjust to variations. In this section, we review recent ML-based solutions for congestion control, routing management, and traffic prediction.

## 5.1. Congestion Control

Several researchers have explored Machine Learning (ML) approaches for optimizing congestion control, with a strong focus on reinforcement learning (RL) techniques. One notable trend is the integration of RL with traditional networking protocols. For example, Abbasloo et al. [14] proposed a hybrid model combining the traditional TCP (BBR) protocol with an RL agent to dynamically adjust the congestion window. While this approach demonstrates potential for enhancing network responsiveness, it operates within a centralized framework, which raises concerns about scalability as network sizes increase.

Similar challenges arise in the work of S. et al. [15], where an RL-based method for wireless networks was developed to improve throughput. Although the results indicate performance improvements, the need for real-world validation highlights the gap between experimental outcomes and practical deployment. This underscores a common limitation across many RL-based approaches, where theoretical gains need to be tested in more varied and complex network environments.

Beyond RL, other approaches have sought to leverage alternative ML techniques in specific contexts. For instance, Goteti et al. [16] and Andrade-Zambrano et al. [17] explored the use of Q-learning and Deep Q-Networks (DQN) in Wireless Sensor Networks (WSNs) and smart grids. These methods offer dynamic path selection and congestion control, showing potential to enhance network efficiency. However, as with RL, the lack of large-scale testing raises questions about their scalability and robustness in real-world conditions, particularly in more heterogeneous network architectures.

Meanwhile, Elbery et al. [24] introduced Machine Learning Aided Congestion Control (MLACC), a hybrid approach that blends heuristic-based adjustments with ML to predict bandwidth availability. This technique successfully reduces latency, but its reliance on predefined heuristic parameters limits its flexibility. Such parameters may struggle to adapt to the varied and unpredictable conditions characteristic of modern networks, a recurring challenge in ML-based congestion control.

In a different approach, Ahamed et al. [25] employed Genetic Algorithms (GA) to manage congestion in Vehicular Ad Hoc Networks (VANETs) by adjusting transmission power and data rates. Although the algorithm proved effective in simulations, scalability concerns remain, particularly in mitigating channel congestion in larger, more dense networks. Table 2 provides a summary of the advantages and limitations of these approaches.

In conclusion, while RL, DRL, and other heuristic-driven ML approaches have led to significant advancements in congestion control, a consistent set of challenges emerges across these methods: ensuring scalability, achieving real-world validation, and maintaining adaptability in the face of dynamic and diverse network conditions. These techniques, while innovative and promising, still require further refinement and empirical testing before they can be fully realized in large-scale, operational environments.

Table 2: Centralized ML Solutions for Congestion Control

Reference	Network Environment	ML model	Advantage	Limitation
[14]	General TCP	RL + traditional TCP (BBR)	Adaptive congestion window adjustment in varied scenarios	Centralized learning limits scalability in unseen environments
[25]	VANETs	Genetic algorithms	Reduces latency, optimizes transmission power and data rates	Faces channel congestion challenges in large networks
[16]	WSNs	Q-learning	Dynamically avoids congestion based on residual energy	Requires large-scale testing to confirm effectiveness
[17]	Smart Grids	DQN	Effective real-time state information for congestion control	Needs different neural network architectures for optimization
[24]	Inter-datacenter Networks	Heuristic + ML	Reduces latency by predicting bandwidth availability	Relies on predefined heuristic parameters, limiting adaptability
[26]	SDNs, Data Centers	Soft Actor Critic (SAC)	Real-time adaptation of congestion window	Requires further training in heterogeneous environments
[27]	Data Center Power Networks	DPG + POMDP	Outperforms traditional algorithms in fairness and utilization	Only tested in simulations, needs real hardware integration

## 5.2. Routing Management

Machine learning (ML) has become a powerful tool for routing tasks in communication networks, with diverse approaches designed to tackle dynamic traffic patterns, scalability, and real-time adaptability. Despite varying methodologies, they share a goal of enhancing routing efficiency, network performance, and quality of service (QoS).

In path management, Chung et al. [36] introduced MPTCP-ML, a random forest-based scheme that dynamically optimizes Wi-Fi path quality. While it shows clear improvements in signal strength and throughput, its scalability and robustness in real-world environments remain to be tested. This underscores the challenge of translating promising models from controlled experiments to large-scale deployments.

In Software-Defined Networking (SDN), Graph Neural Networks (GNN) have emerged as a sophisticated approach to improving routing decisions. Zhu et al. [34] proposed GCLR, which uses GNNs to optimize Multipath TCP (MPTCP) routing by predicting throughput based on network topology. However, prediction accuracy remains a limitation. Similarly, Ipek et al. [22] used various ML models, with Logistic Regression outperforming others for dynamic route selection. While these works demonstrate ML's role in SDN, challenges like prediction accuracy and real-world validation persist.

Reinforcement Learning (RL) and Deep RL (DRL) have also advanced routing optimization. Yajadda et al. [39] combined shortest path principles with RL to adjust routes based on real-time traffic intensity. While effective, its handling of multicast traffic and congestion control requires improvement. DRL has also been applied to SDN, as seen in Yu et al.'s [43]



DROM model, which continuously updates routing decisions. However, maintaining QoS in large-scale deployments remains challenging. In wireless mesh networks (WMNs), RL models like Sun et al.'s [45] optimize Packet Delivery Probability (PDP), but frequent updates and complexity may impact scalability.

RL's flexibility is evident in specialized networks like the Internet of Medical Things (IoMT), where Nazari et al. [48] developed an RL-based routing mechanism for medical applications, though real-world testing is still required.

Hybrid models, like Almasan et al.'s [18] integration of GNN with DRL agents, show improvements in routing efficiency, though adding more network state features could enhance performance. Similarly, their extension to IP networks [20] balances computational cost and optimization gains. In quantum communication networks, Roik et al. [23] used Proximal Policy Optimization (PPO) to outperform classical algorithms, though its performance against other ML techniques remains uncertain.

Table 3 summarizes the key advantages and limitations of these approaches.

Table 3: Centralized ML solutions for Routing

Reference	Network Environment	ML model	Advantage	Limitation
[36]	MPTCP, Wi-Fi	Random Forest-Based Path Management	Improves signal strength, data rate, and throughput	Requires real-world validation
[34]	SDN, MPTCP	GNN for Routing Optimization	Predicts throughput, adapts to varying topologies	Faces challenges in prediction accuracy
[22]	SDN	AI for Dynamic Route Selection	Logistic Regression improves dynamic route selection	Needs broader real-world validation
[39]	General Networks	RL + Shortest Path Routing	Dynamically adjusts routes based on traffic intensity	Limited exploration of multicast and uniform traffic patterns
[43]	SDN	DDPG-based Routing Optimization	Optimizes routing through continuous state analysis	Requires strategies for maintaining QoS
[45]	WMNs	RL for Packet Delivery Optimization	Improves PDP while adhering to end-to-end delay constraints	Frequent updates may limit scalability
[48]	Internet of Medical Things (IoMT)	RL-based QoS Routing	Adapts routing mechanism to meet QoS demands	Scalability and resource efficiency need further testing
[18]	General Networks	GNN + DRL for Routing optimization	Enhances routing with GNN models and DRL agents	Lacks additional network state features for better accuracy
[23]	Quantum Communication Networks	PPO	Optimizes routing in quantum error-prone networks	Lacks comparison with other ML techniques

These studies highlight the growing sophistication of ML-driven routing solutions, though challenges like scalability, prediction accuracy, and balancing computational overhead persist.

### 5.3. Traffic Prediction

Machine learning (ML) has greatly enhanced network management by enabling accurate traffic prediction, allowing for proactive decisions that improve network efficiency and performance.

In cellular networks, the AML-CTP framework [28] clusters traffic using density-based algorithms like KDC and DBSCAN. Models such as Linear Regression, SVR, Decision Tree, and LightGBM are applied to these clusters, reducing computational time and improving model selection. LTE-A data shows that this framework maintains accuracy during peak hours, making it highly scalable. Future work will focus on traffic steering techniques to further improve Quality of Service (QoS).

In optical fiber communication systems, [29] introduces an RNN and LSTM-based traffic prediction algorithm. This approach differentiates between actual traffic fluctuations and random variability, providing real-time data that helps prevent congestion and optimize resource allocation. The model significantly reduces mean absolute error compared to existing methods.

For 6G networks, [65] proposes a parallel CNN architecture for traffic prediction. Using the Matrix Format Method (MFM) to convert traffic data into image representations, this model enhances resource allocation and energy management. While promising, further research is needed to adapt it to the evolving 6G environment.

In fog-IoT architectures, [32] integrates edge caching and load balancing with ML-based traffic prediction and resource management. RNNs and LSTMs are used for forecasting, while Random Forests handle real-time load balancing. Future enhancements could involve hybrid methods, such as combining LSTMs with SVMs or incorporating reinforcement learning.

For 5G networks, [60] presents a hybrid traffic prediction model that combines Holt smoothing and time series transformers to manage network traffic in dynamic slices. By using digital twins for real-time traffic prediction, this model improves resource management, though further testing is needed for scalability in IIoT environments.

Table 4: Centralized ML solutions for Traffic Prediction

Reference	Network Environment	ML model	Advantage	Limitation
[28]	Cellular Networks	AML-CTP with clustering and ML models	Reduces training time, scalable for peak hour predictions	Further exploration of traffic steering for QoS is needed
[29]	Optical Fiber Networks	RNNs, LSTMs for traffic prediction	Differentiates traffic patterns, lowers mean absolute error	Requires validation in real-time congestion prevention
[65]	6G Networks	CNN with Matrix Format Method (MFM)	Tailored to 6G traffic, improves resource allocation	Needs adaptation for evolving 6G environments
[32]	Fog-IoT Architectures	RNNs, LSTMs for traffic prediction, Random Forest for load balancing	Reduces latency, efficient resource distribution	Potential for hybrid methods with SVMs and RL for further optimization
[60]	5G Networks	Holt Smoothing and Time Series Transformer	Improves resource allocation, dynamic 5G slice management	Effectiveness varies by traffic distribution, requires real-world testing

Table 4 summarizes the advantages and limitations of these distributed AI approaches for network management. These works highlight the diversity of ML-based traffic prediction across cellular, optical fiber, 6G, and fog-IoT networks. Each solution addresses specific challenges in its network environment, though real-world validation is needed to ensure efficiency and adaptability.

## 6. DISTRIBUTED AI SOLUTIONS

While centralized ML solutions have shown promise in improving network performance, their reliance on centralized models limits scalability and adaptability, particularly in large and dynamic environments. To address these challenges, distributed AI approaches have emerged as powerful alternatives, leveraging decentralized intelligence to optimize traffic flow and enhance network performance in real time.

### 6.1. Congestion Control

Distributed AI approaches for congestion control have made significant strides, especially with the application of MARL and distributed ML models. In [68], MARL is used for network congestion management, where agents collaborate across network layers to adjust parameters such as queue lengths and sending rates. This approach demonstrates the potential of MARL in enhancing network performance under dynamic conditions, though its validation has been limited to simplified simulated environments, necessitating further research into its real-world applicability and scalability.

A similar application of MARL is seen in [61], where the authors propose a framework for managing congestion in software-defined networks (SDNs), focusing on both host- to-host and switch-controller congestion. In this setup, two agents independently optimize paths and load balancing based on local observations like bandwidth and jitter. The approach uses a cooperative Q-learning algorithm to adapt to changing network conditions. However, the authors acknowledge that performance comparisons with existing algorithms are still needed.

Another study, [70], presents a scalable DRL-based online routing algorithm (DRL- OR-S) within an SDN framework. Each node optimizes routing decisions independently based on factors like latency, throughput, and packet loss. Despite its scalability, the reliance on hop-by-hop routing may not be as resource-efficient as multi-path solutions. Likewise, [71] extends the DDPG algorithm to MA-DDPG for decentralized congestion control in network switches, where each switch makes independent decisions to optimize traffic flow. This approach addresses millisecond-level traffic fluctuations but faces similar challenges as [72], which applies MARL to MPTCP networks for congestion control in IoT and 5G environments. Both methods introduce significant computational complexity and rely on a global state, limiting their effectiveness when network conditions or node behavior are not fully observable.

For green energy harvesting in massive machine-type communications (mMTC), [69] introduces DDRQN for congestion control by optimizing uplink power control. Devices adjust policies based on historical data to mitigate traffic congestion, while sharing a centrally learned Q-network. This decentralized approach reduces communication and computation costs, though the initial training overhead presents a challenge in resource constrained environments.

In high-speed data center networks (DCNs), the PET approach [66] leverages the Independent Proximal Policy Optimization (IPPO) algorithm to dynamically adjust ECN thresholds based on factors like queue length, data rate, and traffic composition. Operating within a decentralized training and execution framework, PET improves flow completion time and reduces queue length variance. However, further research is needed to evaluate PET's scalability in real-world deployments.

Table 5 summarizes the key advantages and limitations of these distributed AI approaches for congestion control.

Table 5: Distributed AI Solutions for Congestion Control

Reference	Network Environment	ML Model	Advantage	Limitation
[68]	General network	MARL	Collaborates across network layers to dynamically manage traffic and optimize network performance	Tested only in simplified simulations; needs real-world validation for scalability
[61]	SDNs	Cooperative Q-learning	Optimizes paths and load balancing, adapts to changing network conditions	Lacks comparison with existing Q-learning algorithms, limiting evaluation
[70]	SDNs	DRL based on hop-by-hop routing	Scalable DRL-based routing algorithm, improves routing efficiency based on latency, throughput, and packet loss	Hop-by-hop routing is less efficient compared to multi-path routing
[71]	Network switches	MA-DDPG	Each switch makes independent decisions to optimize traffic flow in real-time	High computational complexity and reliance on a global state
[72]	IoT	MARL	Manages subflows based on parameters like RTT and throughput, improving congestion control in dynamic environments	Significant computational complexity; reliance on a global state reduces effectiveness
[69]	Green energy harvesting mMTC	Deep DDQ-Learning	Optimizes uplink power control, reduces communication and computation costs	High initial training overhead in resource-constrained environments
[66]	High-speed (DCNs)	Independent PPO	Dynamically adjusts ECN thresholds, improving flow completion time and queue length variance	Requires further research to assess scalability in real-world deployments

Across these works, the use of distributed AI, particularly MARL, demonstrates significant potential for enhancing congestion control in diverse network environments. However, common challenges such as reliance on a global state, computational complexity, and the need for real world validation persist. These methods highlight the growing sophistication of AI-driven congestion control solutions while emphasizing the need for further exploration to ensure scalability, efficiency, and adaptability in practical applications.

## 6.2. Routing Management

The exploration of distributed AI approaches for network management has led to significant advancements, especially with the integration of RL and federated learning (FL) models. These methods are not only improving network efficiency and resource allocation but also reshaping real-time decision-making in complex network environments.

In WSNs, a standout method involves decentralized Q-learning, as proposed in [73]. Here, sensor nodes operate autonomously, optimizing energy efficiency and data aggregation through local interactions. This distributed decision-making model is particularly promising for scaling WSNs, as it reduces the need for central control. The potential for extending this model into larger, more complex environments is clear, but real-world testing is crucial to validate its effectiveness in large-scale deployments.

Federated learning (FL) also plays a transformative role, especially in UAV networks. In [74], the B.A.T.M.A.N. protocol integrates FL, enabling UAVs to collaboratively learn from localized data. This method reduces bandwidth consumption and ensures data privacy while making routing decisions more adaptable to dynamic topologies. The promise of this decentralized approach lies in its ability to optimize routing decisions without overwhelming

network resources, though its efficacy in more complex, real-world UAV networks remains to be proven. A similar approach is seen in [75], where FL is used to enhance resource allocation in UAV-based edge computing for 5G networks. The role of FL in managing next-generation networks is further highlighted by the QoSPR protocol in [80], which applies federated RL to 5G-IIoT networks. By decentralizing the task of routing and resource management to regional centers, this method preserves privacy and improves network performance. Challenges such as balancing latency and load across a larger scale still require further investigation, particularly as these systems scale to larger deployments in industrial applications. While these FL-based approaches demonstrate great potential, the models need further refinement to handle the complexities of real-world environments.

Another key component of distributed AI, reinforcement learning, is playing an increasingly pivotal role in advancing network management strategies. For instance, in [76], the distributed RL model (DCRL-R) allows WSN nodes to make autonomous routing decisions based on local data, thus minimizing reliance on a global network view. This is especially valuable in infrastructureless environments, though the model’s scalability in larger networks needs validation. Similarly, in maritime networks, [77] applies multi-agent deep Q-learning to improve routing efficiency. The collaborative learning between agents provides a more informed decision-making process, but further testing in variable environments is needed to ensure robustness. Federated learning continues to show its versatility in network management. In [78], CNN-based agents are employed to monitor and predict congestion in WMNs. These agents analyze the network state, allowing for proactive rerouting and congestion avoidance. While this approach has demonstrated its potential in simulations, its effectiveness in real-world scenarios with more diverse network conditions requires further exploration. In [81], multi-agent deep RL is utilized for packet routing in computer networks, where each router acts independently based on local and neighbouring data. This decentralized method optimizes packet delivery efficiency, yet the simulations fail to capture the full complexity of real-world traffic, indicating a need for more comprehensive testing to ensure practical applicability.

Lastly, in the context of IoT networks, [79] tackles energy efficiency using MARL. IoT devices autonomously make routing decisions, focusing on sustainable network operations. While this approach shows great promise for optimizing energy use in IoT systems, the computational overhead of deploying MARL at scale remains a considerable challenge.

Table 6 summarizes the key advantages and limitations of these distributed AI approaches for routing.

As distributed AI techniques continue to mature, they offer the potential to transform traditional network management strategies. These innovative approaches promise to enhance the scalability, adaptability, and efficiency of communication networks, but further real-world testing and optimization are essential to unlock their full capabilities. The journey towards smarter, more autonomous networks is just beginning, and these advancements lay the foundation for a more intelligent and efficient future in network management.

Table 6: Distributed AI Solutions for Routing

Reference	Network Environment	ML Model	Advantage	Limitation
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[73]	WSNs	Decentralized Q-Learning	Autonomously optimizes energy efficiency and data aggregation	Requires empirical validation for large-scale networks
[74]	UAV Networks	FL with B.A.T.M.A.N protocol	Maintains data privacy, reduces bandwidth, and adapts to changing topologies	Needs real-world validation in complex UAV scenarios
[75]	5G UAV-based Edge Computing	FL, RL	Efficient data routing and resource allocation	Simplified models, needs further testing under realistic conditions
[76]	Wireless Sensor Networks (WSNs)	Distributed	Decentralized decision-making, ideal for infrastructureless environments	Scalability in large networks unproven
[77]	Maritime Networks	Multi-Agent Deep Q-Learning	Improves routing efficiency via agent collaboration	Needs further testing in highly variable environments
[78]	Wireless Mesh Networks	CNN	Predicts congestion and dynamically reroutes traffic	Requires broader real-world testing
[80]	5G-IIoT Networks	FL	Preserves data privacy, optimizes performance for regional challenges	Needs real-world validation in large-scale applications
[81]	Computer Networks	MA-DRL	Independent routing decisions based on local data	Simulations do not fully capture real-world network complexities
[79]	IoT Energy-Harvesting Networks	MARL	Promotes energy-efficient routing and sustainable IoT development	High computational overhead in large-scale IoT networks

### 6.3. Traffic Prediction

Shifting focus to traffic prediction, distributed AI techniques are becoming instrumental in forecasting network traffic patterns and optimizing resource management, ensuring more efficient and proactive network operations.

[62] tackles the challenge through an innovative use of transfer learning. Instead of relying on traditional centralized models that require extensive data collection, this distributed approach trains models at the Network Operations Center (NOC) before fine-tuning them locally at each VSAT. This method effectively reduces bandwidth consumption while maintaining high accuracy, demonstrating how distributed AI can efficiently balance resource constraints and prediction precision in bandwidth-limited environments.

Table 7: Distributed AI Solutions for Traffic Prediction

Reference	Network Environment	ML model	Advantage	Limitation
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[62]	Satellite Communication Networks	Transfer Learning	Reduces bandwidth usage while maintaining high prediction accuracy	Limited exploration of real-world scalability and generalization across diverse satellite conditions
[63]	Internet Traffic Networks	Distributed Multi-Agent Learning (LSTM/GRU)	Enhances prediction performance through decentralized, cooperative agent interaction	Fixed weight matrices limit adaptability in more complex scenarios (e.g., grid or graph-format predictions)
[64]	Cellular Networks	Federated Learning (FL) with Sustainability Indicator	Balances energy consumption with prediction accuracy, minimizing environmental impact	Further research needed on model convergence speed and scaling FL across more diverse datasets and clients
[65]	at Network Edges	Federated Learning (LSTM)	Improves privacy, reduces processing time and bandwidth usage in decentralized setups	Handling non-IID data across clients remains a challenge, requiring utility optimization for fairness
[67]	Multi-Agent Network Automation System (MANA- NMS)	LSTM for Traffic Prediction, Decision Trees for Classification	Autonomous agents improve prediction and classification accuracy, aiding resource management	Needs further integration of additional network services such as routing and QoS monitoring for a complete system

A fully decentralized framework is explored by [63], which introduces a multi-agent learning system for Internet traffic prediction. Each agent operates autonomously, training its own LSTM or GRU models, with predictions synchronized through a collaborative Markov chain process. This decentralized structure not only enhances prediction performance but also ensures scalability across agents. However, the reliance on fixed weight matrices limits flexibility when handling complex, dynamic network topologies, highlighting a potential area for future enhancements in distributed AI traffic prediction systems.

[64] takes a different approach with federated learning (FL) in cellular traffic prediction, addressing concerns around privacy and data transfer limitations. The introduction of a sustainability indicator highlights the growing need to balance the environmental cost of training AI models with accuracy, especially in large-scale distributed systems. While FL allows for distributed training without sharing raw data, its environmental footprint, particularly for larger models, poses a significant challenge, prompting future research into optimizing the balance between energy efficiency and model performance.

For 5G networks, [65] further leverages the advantages of FL for LSTM-based traffic prediction at the network edge. This decentralized setup reduces processing time and enhances privacy compared to traditional centralized methods. However, the challenge of managing non-IID data across clients remains, impacting prediction fairness and consistency. Future efforts focused on utility optimization functions could address this limitation, ensuring a more equitable distribution of resources across clients while preserving accuracy in distributed AI systems.

Lastly, [67] proposes a multi-agent network automation architecture (MANA-NMS) that combines LSTM for traffic prediction with Decision Trees for traffic classification. These autonomous agents improve resource allocation and load balancing in network management. However, the system's full potential has yet to be realized, with further work needed to integrate

additional network services, such as routing and QoS monitoring, into the framework, thus leveraging the power of distributed AI for more comprehensive network management.

The table 7 summarizes the advantages and limitations of distributed AI solutions for traffic prediction, highlighting each approach's contribution to network management as well as areas that require further development.

In conclusion, distributed AI approaches for traffic prediction show great promise in enabling smarter and more adaptive network management across a variety of communication environments. These techniques not only improve efficiency and accuracy but also offer solutions to privacy, scalability, and environmental challenges. As the field continues to evolve, refining these systems and testing them in real-world conditions will be key to fully realizing their potential in optimizing network performance.

## CONCLUSIONS

In this paper, we have explored the evolving landscape of AI-driven solutions for complex communication networks, covering both centralized and distributed approaches in congestion control, routing management, and traffic prediction. While centralized solutions perform well in controlled environments, distributed AI techniques stand out for their scalability, adaptability, and potential to operate effectively in dynamic, large-scale network environments. However, despite their promise, distributed AI approaches also face challenges; more work is needed to refine these techniques and address these limitations.

Future research will continue to optimize these AI-driven approaches to meet the growing demands of modern communication networks. To tackle these ongoing challenges, our current research focuses on developing and evaluating a Multi-Agent Deep Reinforcement Learning (MA-DRL) traffic management solution. This approach is designed to dynamically adapt to network conditions, prevent congestion, and improve key metrics such as throughput, latency, and packet loss, providing a more robust and adaptive alternative to existing traffic management methods while addressing some of the current limitations of distributed AI.

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