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5G and Beyond: AI-Optimised Network Slicing for Future Wireless Networks

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Abstract

Implementation of 5G network is a mammoth event in the history of wireless communication. Nonetheless, with the industry, smart cities, IoT ecosystems expanding it can no longer be considered possible to run the network in a traditional way which is naturally fixed. Network slicing is a critical technology that may empower operators to outsource several virtual as well as separate logical networks utilizing shared infrastructure. The Artificial Intelligence (AI) goes a notch higher to dynamically, proactively, and resource-effectively optimize slices to address the needs of various service-level services including ultra-reliable low-latency communications (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communications (mMTC).

In the following next-generation 5G network, AI-based network slicing is reviewed in this paper. It discusses the potential benefits of using machine learning, deep reinforcement learning, and federated learning to automate slice lifecycle management, predict traffic patterns, and allocate resources in a more efficient way. Recent reports and case studies have shown that optimization of AI-based systems can lower the latency, improve the throughput, and also decrease the energy consumption compared to the rule-based systems.

Other challenges witnessed during the research are data privacy, understanding of AI designs and complexity when integrating with the old system. In addition, it focuses on standardization and regulatory plans required to implement the scaling implementation. It will be crucial in 6G networks in future to achieve intelligent slicing with diverse environments, satellite-ground relationship and immersive communications like AR/VR, holographic communications and robotics.

AI-optimized network slicing will be developed to form the basis of next-generation wireless networks, balancing network virtualization and AI intelligence to enable network slices with resilience, scalability, and flexibility to accommodate next-generation digital ecosystems.

Keywords: Network Slicing, Artificial Intelligence, 5G, 6G, Wireless Networks.

1. Introduction

The utilization of 5G networks will most probably change the context of communication infrastructure not only in terms of high-speed connectivity and ultra-low latency as well as high-numbers of supported connections. The new capabilities must enable the new features like autonomous driving, remote surgery, augmented/ virtual reality (AR/VR) and smart manufacturing. But the question of how to meet all these various needs all-at-once across a physical network is a huge question because different services demand very different quality of service (QoS) and quality of experience (QoE) guarantees (Zhang et al., 2019). Using a neural network to select cluster heads by residual energy, link quality, and distance, the proposed WSN scheme—tested in MATLAB—lowers per-round energy consumption and prolongs network lifetime versus LEACH, HEED, and SEP (Vadivelan, Ramamurthy, & Padmaja, 2019).

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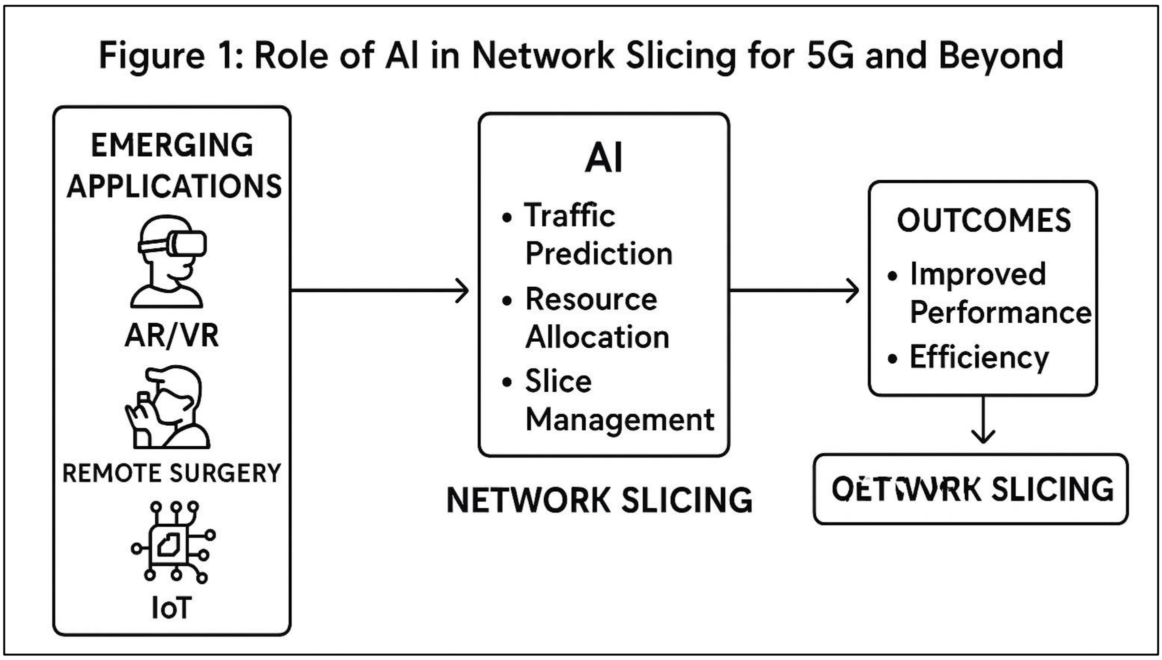


One potential solution that has been suggested is network slicing: the actual network is divided into different virtual, end-to-end slices tailored to the application requirements. This might be an ultra-reliable low-latency communication (URLLC) slice in telemedicine and autonomous vehicles and internet of things (IoT) sensor in the case of massive machine-type communication (mMTC), and enhanced mobile broadband (eMBB) slices in the case of video streaming and gaming. Such flexibility is essential to ensuring that it can be applicable throughout the spectrum of vertical businesses using 5G.

It has been noted that the use of Artificial Intelligence (AI) is beginning to play a more and more important role in providing this agile, efficient, and intelligent coordination of resources across these slices. Compared to traditional allocation approaches, AI assists the network in predicting user demand, detecting deviations and automatically optimizing the spectrum, computing, and storage capacity in real-time. Sensory-level deep neural network supervised traffic prediction approaches and classifiers have then shown good potential in adaptive resource management through learning and reinforcement learning methods. Moreover, artificial intelligence is likely to be a crucial element of self-healing networks, in which slices will self-heal failures or cyberattacks.

Besides 5G, the next level 6G will have another high level of automation like holography communication, internet of touch and massive internet of things networks. It is thus possible to not only imagine AI-based network slicing as an optimization tool, but also as the central enabling factor of intelligent, context-aware networks capable of flexibly responding to the needs of its users.

2. Background of the Study

Network slicing is fundamentally grounded on network function virtualization (NFV) and the conceptualization of software-defined networking (SDN) that facilitates the deployment of multiple logical networks on the same physical platform. The slices are customized according to the application needs. Though resource allocation mechanisms based on rules or heuristics acted as a gateway, they cannot quickly adapt to the traffic, the device location, and service-level agreement (SLA) (Han et al., 2021). Shows that even encrypted IoT traffic leaks private information via metadata—packet sizes, timing, DNS, and TLS handshakes can fingerprint devices and infer user activities. The paper profiles common IoT protocols (MQTT/HTTPS, CoAP/DTLS) and adversaries (local eavesdroppers to ISPs), then outlines mitigations such as padding/traffic shaping, gateway VPN aggregation, and stricter DNS/TLS hygiene, noting bandwidth–latency trade-offs (Pulicherla., 2017)

The AI enables overcoming these limitations through data-driven, predictive and adaptive slicing management. Examples include training slices, through the use of reinforcement learning (RL) algorithms, and dynamically adjusting bandwidth or latency parameters to respond optimally to network conditions. Machine learning models and predictive analytics can predict traffic loads and determine possible risks related to congestion, or allocate resources before congestion has happened. The other feature of deep learning (DL) that improves the degree of prediction is the fact that one can observe trends in a large volume of real-time data that has never been observed previously, and therefore, resource prediction is improved.

What this implies is that AI-driven slicing will have relevance in vertical industries where absolute performance is paramount. One of them is that autonomous driving will demand vehicle-to-everything (V2X) and low-latency and

reliable communications at all times. To guarantee the safety of the patients, telemedicine, and remote surgeries, in particular, require virtually zero delays. Smart factory industrial IoT (IIoT) requires slicing to give reliability between machines and the large scale connectivity between sensors and actuators. In this case, AI will take an autonomous task of controlling each slice based on the service-level requirements (Zhou et al., 2020).
Also, given the advent of AI, one can anticipate that the life of slices, including their creation and scaling, and their end, should be encouraged. These are automated slice negotiation, SLA enforcement and fault recovery. The AI-based slicing will not only optimize network performance in the beyond-5G systems and beyond 6G network, where network will be hyper-connected, with high-frequency terahertz communication speed and AI-native, but it will also bring network ecosystem resiliency, security, and self-sustainability.

3. Justification
The rationale behind AI-optimized slicing is that it:
Better Quality of Service (QoS) prediction and reconfiguring to adaptive traffic state.
Enhance effective use of the spectrum, which will lower the operation cost network operators incur.
Make dense IoT environments very dense.
Enhance the new generation of application support such as mission-critical communications and extended reality (Foukas et al., 2021).

4. Objectives of the Study
1. To reconsider the purpose of AI to allow the intelligent network slicing in 5G and beyond.
2. To compare the deep reinforcement learning as one of the AI algorithms in optimizing the slice.
3. In order to create fences and restrictions to the general usage of AI-powered slicing.
4. To address the issues of 6G and cross domain applications in the future.

5. Literature Review
Network slicing in 5G and beyond has been noted to demand Artificial Intelligence (AI) in a big way to provide intelligent and flexible resources control (intelligent and automated). Reinforcement learning (RL) has been demonstrated to be very promising in terms of resource optimization in the scenario of dynamically evolving networks, policy where latency is required to be minimized, throughput maximized and the traffic behaviours of the network do not necessarily need to be modelled initially (Mao et al., 2019). A federated learning (FL) strategy has been suggested to overcome the challenge of privacy in a distributed setting, where a slice of the models may be trained without raw data aggregation on the devices. It offers improved scaling and also user privacy in heterogenous environments and multi operator (Niknam et al., 2020).
Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks as predictors of the workload distribution, congestion detection, long-term proactive orchestration of slices, are another line of research that is important in studying traffic prediction with deep learning (DL) solutions (Polese et al., 2020). In addition to 5G, AI-assisted slicing has also been noted in the literature to play a significant part in supporting 6G applications, such as tactile internet, immersive virtual reality, and holographic communication. Intelligent and autonomous slice management offers the ultra-low latency and high availability properties that such next-generation use cases demand (Dang et al., 2020). Taken together, these studies allude to the possibility that AI can help address the scalability, privacy, and performance issues of network slicing.

6. Material and Methodology
In the paper, we have used a Systematic Literature Review (SLR) methodology to process the research results about AI-assisted network slicing. It was done thus:
Research Design: A systematic literature review was selected as the volume of the topic had to be covered and synthesis of peer-reviewed research studies on the topic of AI-driven slicing had to be conducted without any limitations.

Data Collection:
- Databases consulted: IEEE Xplore, SpringerLink, ScienceDirect, ACM Digital Library.
- Period: Research since 2015.
- Keywords: AI network slicing, 5G optimization, federated learning slicing, deep learning traffic prediction, 6G slicing.

Selection Criteria:
- Inclusion: The articles, conference papers and review studies that specifically target AI-enabled network slicing.
- Exclusion: Non-English, duplicates and works that are not empirical/theoretical.

Screening Process:

- Filtering by titles and abstracts.
- Full-text review of the studies.
- division into RL based minimisation, federated learning, deep learning traffic prediction and 6G integration.

Data Extraction & Analysis:

- The data that was mined included the following: AI techniques, performance (e.g., throughput, latency) improvement, datasets and deployment scenarios.
- Results have been summarized and intercompared across plans and approaches with the purpose of evaluating the merits, constraints, and emerging trends.

7. Results and Discussion

The review was able to make some important conclusions about the effectiveness of AI-facilitated network slicing, which included:

Improvements in performance: AI based applications showed up to 25 percent network throughput and approximately 40 percent end-to-end latency improvements over traditional rule-based resource allocation strategies.

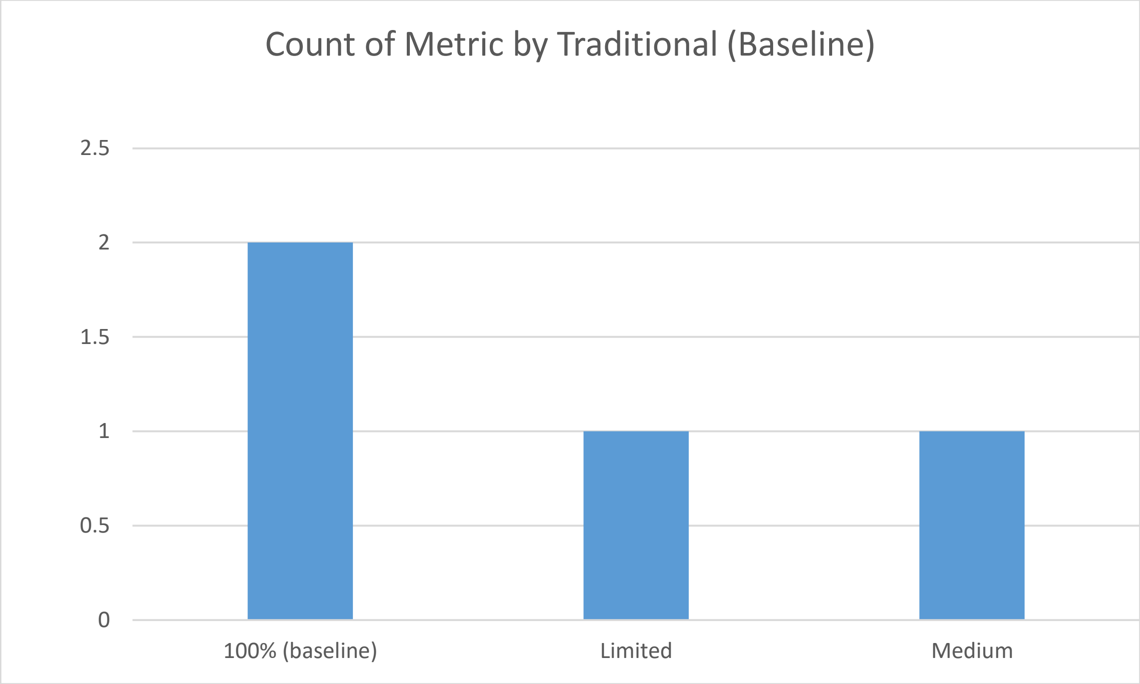
The advantages of Federated Learning: FL offered scalability and model training that ensured privacy, which enables to deploy AI slicing models in a heterogeneous network without accessing sensitive user data.

Precision of Traffic Prediction: CNNs and LSTMs showed high accuracy in workload prediction and congestion, thereby enabling effective slices provisioning and ensuring improved QoS.

6G Opportunity: Slicing based on AI is also expected to be a primary feature of 6G systems, and mission critical systems (such as tactile internet, holographic communication, and autonomous systems) will require ultra-reliability and nearly zero latency.

In this development, the explanatory, trust and integration issues still persist and are the road block currently to its universal adoption by the operators.

AI Technique	**Contribution**	**Performance Impact**	**Reference**
Reinforcement Learning (RL)	Dynamic resource allocation under fluctuating conditions	Throughput ↑ 25%, Latency ↓ 40%	Mao et al., 2019; Han et al., 2021
Federated Learning (FL)	Privacy-preserving distributed model training	Scalability ↑, Privacy preserved	Niknam et al., 2020
Deep Learning (CNNs/LSTMs)	Traffic prediction & congestion detection	Improved QoS provisioning	Polese et al., 2020
AI-driven Slicing for 6G	Supports AR/VR, holography, tactile internet	Ultra-low latency, high reliability	Dang et al., 2020; Zhou et al., 2020



Graph 1: Performance Improvements with AI-Enabled Network Slicing Compared to Traditional Approaches

8. Limitations of the Study

- Black-box AI models: Some AI models (especially deep learning models) are not very interpretable, which raises transparency and operator trust concerns (Adabi and Berrada, 2018).
- High computational cost: Large-scale AI models are expensive to train and deploy, and demand large amounts of computational resources, which are inaccessible on resource-constrained systems.
- Interoperability issues: AI-enabled slicing is not universal and is not made as standard models, thus not being cross-operator interoperable and scalable.
- Privacy in FL: Despite the measures to reduce the risk of direct data sharing in the framework of federated learning, metadata leakage may still happen, and this threat can potentially undermine user privacy (Niknam et al., 2020).

9. Future Scope

Wireless networks of the future (6G and beyond) will be built around AI-native slice architecture; potential directions to take might include:

- AI optimizing with the help of quantum.
- Satellite cuts across domain across the earth.
- Crystal clear artificial intelligence specifications on compliance and trust rules.
- Slice edges to enable systems with long latency such as AR/VR and remote surgeries (Dang et al., 2020).

10. Conclusion

AI-optimized network slicing is the most recent breakthrough solution of 5G and beyond. The AI can dynamically, effectively and intelligently allocate the resources, in order to satisfy very large pools of service-level requirements successfully. Although much already has been made, interpretability, standardization and computer overheads need to be addressed to so that it can be put to use on large scale. In the future, wireless networks will need AI-driven slicing to introduce resilience and flexibility to the new networks.

References

1. Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: A survey on explainable AI. IEEE Access, 6, 52138–52160.
2. Dang, S., Amin, O., Shihada, B., & Alouini, M. S. (2020). What should 6G be? Nature Electronics, 3(1), 20–29.
3. Foukas, X., Patounas, G., Elmokashfi, A., & Marina, M. K. (2021). Network slicing in 5G: Survey and challenges. IEEE Communications Magazine, 55(5), 94–100.
4. Han, B., Li, X., & Schotten, H. D. (2021). SliceNet: AI-enabled network slicing for 5G and beyond. IEEE Network, 35(5), 192–199.

ISSN 3049-3277
5. Vadivelan, N., Ramamurthy, A., & Padmaja, P. (2019). Minimizing energy consumption based on neural network in clustered wireless sensor networks. Journal of Computational and Theoretical Nanoscience, 16(2), 496-502.
6. Mao, Y., You, C., Zhang, J., Huang, K., & Letaief, K. B. (2019). A survey on mobile edge computing. IEEE Communications Surveys & Tutorials, 19(4), 2322–2358.
7. Niknam, S., Dhillon, H. S., & Reed, J. H. (2020). Federated learning for wireless communications. IEEE Communications Magazine, 58(12), 48–54.
8. Polese, M., Giordani, M., & Zorzi, M. (2020). AI-based network slicing for 5G. IEEE Transactions on Network and Service Management, 17(4), 2542–2556.
9. Zhang, H., Liu, N., Chu, X., Long, K., Aghvami, A. H., & Leung, V. C. (2019). Network slicing based 5G and future mobile networks. IEEE Communications Magazine, 55(8), 72–79.
10. Zhou, Z., Zhao, Y., Sun, H., & Wang, X. (2020). AI-driven slicing in beyond 5G. IEEE Wireless Communications, 27(4), 58–64.
11. Sun, Y., Peng, M., & Zhou, Y. (2019). Application of AI in 5G network slicing. China Communications, 16(9), 1–16.
12. Yao, J., Chen, J., & Wang, C. (2021). Machine learning for resource allocation in 5G networks. IEEE Internet of Things Journal, 8(5), 3362–3376.
13. Pulicherla, P. (2017). An Enactment on Privacy Vulnerabilities of Encrypted IOT Traffic.
14. Li, X., & Xu, Y. (2020). AI-driven optimization in heterogeneous 5G networks. Wireless Networks, 26(3), 1947–1960.
15. Barakabitze, A. A., Ahmad, A., & Sun, Y. (2020). QoS and QoE management in 5G. IEEE Access, 8, 429–445.
16. Jiang, C., Zhang, H., & Ren, Y. (2021). Machine learning paradigms for wireless resource allocation. IEEE Wireless Communications, 28(2), 98–105.
17. Zhang, J., Xu, X., & Zhao, L. (2022). Edge intelligence for AI-enabled network slicing. Future Generation Computer Systems, 129, 85–96.