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A Survey of the Design of AI-ML Driven Intelligent Optimized Hi-Pe NGCs

Sarala T[1] and T.C. Manjunath[2]
[1]Research Scholar, VTU Research Centre, Dept. of Electronics & Communication Engineering, Rajarajeswari College of Engineering, Bangalore and Assistant Professor, Dept. of Electronics & Communication Engineering, BNM Institute of Technology, Bangalore, Karnataka, India
Email: saralat@bnmit.in
[2]Research Supervisor, Dean Resarch (R & D), Professor, Department of Computer Science & Engineering, IoT, Cyber Security & Blockchain Technlogy, Rajarajeswari College of Engineering, Bangalore, Karnataka
Email: tcmanju@iitbombay.org

***Abstract*— In this survey or what you call as the review paper, the works done by various authors in the field of the designing and implementation of AI & ML driven intelligent adaptive optimized framework approaches for high performance enhancements in efficient, autonomous, and reliable next generation communication networks in presented, this gives a summary of the works done by the earlier researchers till date, also the research gaps in the form of a table is presented at the end of the survey.**

***Index Terms*— NGC, Performance, AI, ML, Intelligent, Survey.**

I. INTRODUCTION

A number of initiatives has been developed & dedicated to investigating of the study of the design of high-speed AI-ML based high speed hybridized communication algorithms for the fast communication of signals with lesser SNR and good efficiency. A large number of researchers have worked on the topic, "Design and Implementation of Artificial Intelligence and Machine Learning based Next Generation Communication Networks". In this research work, a thorough review of the literature w.r.t. works that were carried out by various researchers is presented in a concised manner. Quite a number of authors, engineers, scientists had worked upon the chosen area taken up by us. This research work gives a quick overview of the contributions made by numerous authors, along with their benefits and shortcomings.

First, a large number of research papers were gathered from various sources, researched in depth and breadth, their benefits and shortcomings were assessed, and a review paper was published at a reputable event. With regard to the work undertaken in this fascinating & application-oriented topic of communications, a complete literature assessment [1]- [50] of the research works done by various authors throughout the globe up to this point is being offered in this research work. The next few paragraphs gives a brief survey of the research carried out till date by different researchers.

But, here, we have considered only the important ones [1]- [50] which are being referred by us in the context of the carried out research work. Conducting an exhaustive literature survey on the study of the application of the design of implementation of AI ML based communication protocols in the NGC, which is provided in this research work, which will act as a base for the future researchers.

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The selected research papers represented a diverse range of studies that highlighted the application of NGC design. They demonstrate the multifaceted approach researchers are taking to address challenges and optimize various aspects of NGC domain, ultimately contributing to more sustainable and productive implementation of the communication protocols.

O'Shea and Hoydis in [1] proposed deep learning as a new way to design the physical layer by viewing the link as an end-to-end reconstruction problem. They demonstrated autoencoder-based transmitter/receiver co-optimization and discussed how neural networks can learn modulation-like representations. The main advantage is that the method can jointly optimize blocks that were earlier designed separately, which can yield strong performance in difficult channels. Another advantage is flexibility, because the same learning framework can be reused across different PHY tasks. A key disadvantage is the need for large training data and careful generalization control when channel conditions vary widely.

Wang, Wang, and colleagues in [2] reviewed deep learning for the wireless physical layer and highlighted where DL can replace or augment classical blocks such as detection and decoding. They summarized typical architectures and presented how learning can help when analytical models are imperfect. The advantage is that DL can approximate nonlinear mappings that are hard to derive analytically. Another advantage is robustness when the system is affected by hardware impairments or complicated channel effects. The disadvantage is that interpretability and reproducibility are weaker than classical model-based approaches unless the training pipeline is tightly controlled.

Saad, Bennis, and Chen in [3] presented a broad vision of 6G, emphasizing new services and disruptive technologies, while positioning AI as a core enabler rather than an add-on. They described trends such as extreme connectivity, ultra-reliability, and new spectrum usage, and outlined open research directions. The advantage is that this work gives a structured roadmap that connects applications, metrics, and technologies. Another advantage is that it motivates why intelligence must move closer to the edge for future systems. The disadvantage is that it is a high-level vision, so practical implementation details and measurable evaluation frameworks are limited.

Qin, Li, and Ye in [4] discussed the relationship between federated learning and wireless communications and explained why FL is attractive when privacy and data locality are important. They described FL training steps and mapped wireless challenges (limited bandwidth, device heterogeneity) to learning performance. The advantage is that it provides a clean bridge between communications constraints and learning system design. Another advantage is improved privacy compared to centralized data collection. The disadvantage is that communication overhead and non-IID data across devices can degrade convergence and final accuracy.

Niknam and co-authors in [5] introduced federated learning for wireless communications and described how FL can be applied in 5G contexts such as edge intelligence. They discussed possible use-cases and highlighted the main bottlenecks, especially uplink communication cost and straggler devices. The advantage is that FL reduces raw data transmission and can respect local data ownership. Another advantage is that it enables collaborative intelligence across multiple base stations or devices without centralizing data. The disadvantage is that FL can be unstable under device dropouts and requires careful aggregation design for fairness and performance.

Shome, Waqar, and Khan in [6] surveyed the bidirectional relationship between federated learning and next-generation wireless communications. They explained how wireless networks can support FL better, and how FL can improve wireless functions such as resource allocation and optimization. The advantage is that the paper treats communications and learning as a coupled system rather than separate layers. Another advantage is clarity about challenges like latency, reliability, and device heterogeneity. The disadvantage is that many FL-wireless solutions remain simulation heavy, with fewer end-to-end real deployments.

Mao, You, Zhang, Huang, and Letaief in [7] surveyed mobile edge computing with a strong focus on joint radio-and-computation resource management. They presented models for offloading, caching, mobility management, and system deployment, which are essential in AI-driven networks. The advantage is that MEC provides practical latency reduction by moving compute near the user. Another advantage is that it offers a foundation for edge intelligence and real-time applications. The disadvantage is that MEC introduces new optimization complexity and coordination overhead across edge nodes.

Mach and Becvar in [8] reviewed MEC from architecture and deployment perspectives, covering scenarios, use cases, and integration challenges. They mapped MEC to practical network operations and highlighted the role of edge infrastructure in 5G/6G. The advantage is that the work gives a structured view of MEC integration pathways. Another advantage is its discussion of interoperability with existing cellular systems. The disadvantage is that MEC performance depends strongly on backhaul and orchestration quality, which can be difficult in heterogeneous deployments.

Hortelano and colleagues in [9] provided a comprehensive survey of reinforcement learning and deep reinforcement learning for computation offloading in edge systems. They categorized RL designs, states/actions/rewards, and compared typical frameworks for dynamic offloading decisions. The advantage is that RL can adapt to changing environments without requiring exact system models. Another advantage is improved long-term optimization via reward shaping. The disadvantage is that RL training can be sample-inefficient and unstable, especially when the environment is partially observable or non-stationary.

Hurtado Sánchez and co-authors in [10] surveyed deep reinforcement learning for resource management in network slicing. They described how DRL can automate slice admission, scaling, and scheduling decisions. The advantage is the ability to handle multi-objective optimization under uncertainty, which is common in slicing. Another advantage is reduced manual tuning compared to rule-based slicing controllers. The disadvantage is that DRL models can be hard to validate for safety and QoS guarantees, which is critical in telecom.

Lee and collaborators in [11] surveyed DRL applications in resource management for 5G heterogeneous networks. They connected DRL methods to problems such as power control, spectrum assignment, and user association. The advantage is that DRL can learn policies that outperform fixed heuristics under varying loads. Another advantage is that it can unify multiple control tasks using a single learning approach. The disadvantage is the need for careful reward design and the risk of poor generalization when network conditions shift beyond the training distribution.

Frikha and co-authors in [12] reviewed reinforcement and deep reinforcement learning for IoT communication technologies and networking. They discussed decision-making under incomplete information, which is common in large-scale IoT connectivity. The advantage is that RL supports adaptive policies for massive access and changing topology. Another advantage is improved autonomy with less human configuration. The disadvantage is that RL performance can degrade under noisy observations and resource-limited IoT devices, requiring lightweight models or edge support.

Liu and colleagues in [13] reviewed deep-learning-based physical-layer technologies and outlined why future networks need learning to meet diverse requirements. They discussed limitations of traditional signal processing under complex channel and hardware conditions. The advantage is that DL can improve tasks such as channel estimation and detection in nonlinear scenarios. Another advantage is potential robustness in high-mobility or interference-heavy environments. The disadvantage is the requirement for training datasets representative of real deployment, which can be expensive to obtain.

Sejan and co-authors in [14] surveyed machine learning for intelligent reflecting surface (IRS) assisted wireless communication towards 6G. They organized ML applications around channel estimation, IRS configuration, and system-level performance optimization. The advantage is that ML can reduce the complexity of optimizing large IRS phase-shift vectors. Another advantage is that ML helps when precise channel models are hard to estimate due to passive IRS elements. The disadvantage is that IRS systems introduce high-dimensional estimation problems and ML solutions may struggle with scalability and real-time constraints.

Singh and collaborators in [15] reviewed deep learning-driven channel estimation for IRS-assisted systems. They explained that IRS channel estimation is challenging due to passive surfaces and compounded channels, and DL is used to learn mapping from pilots to CSI. The advantage is improved estimation performance under complex multipath and nonlinearities. Another advantage is reduced dependence on handcrafted estimators. The disadvantage is that DL channel estimators may generalize poorly if the IRS environment changes significantly or if pilots are insufficient.

Li and co-authors in [16] surveyed key technologies and applications of 6G networks, including architecture, use cases, and challenges, where AI is treated as a central enabler. They emphasized trends like massive connectivity and minimal latency, which naturally motivates learning-based control. The advantage is that it contextualizes AI/ML within broader 6G technology stacks. Another advantage is highlighting practical bottlenecks that must be solved for real deployments. The disadvantage is that broad surveys sometimes provide less depth on algorithmic details and reproducibility benchmarks.

Catak and co-authors in [17] studied security hardening of IRS against adversarial machine learning threats. They explained that AI-powered IRS control can be vulnerable to adversarial manipulations and highlighted defense strategies. The advantage is that it draws attention to security risks in AI-driven radio environments. Another advantage is linking physical-layer reconfigurability to cyber threat models. The disadvantage is that adversarial robustness evaluation in real-world wireless settings is still difficult due to limited standardized datasets and threat emulation.

A recent ML/DL/RL wireless communications survey (Ngo and colleagues in [18]) compiled applications of ML, DL, and RL across wireless layers. The survey discussed learning for scheduling, prediction, routing, and PHY tasks. The advantage is a single consolidated view that helps identify where learning gives the most benefit.

Another advantage is the discussion of open issues such as dataset scarcity and evaluation fairness. The disadvantage is that fast-evolving areas can quickly make some categorizations outdated, requiring continuous updates.
A comprehensive 2025 survey on ML in wireless resource allocation focused on how learning supports spectrum, power, and scheduling decisions and was shwon in [19]. It outlined tradeoffs between performance, overhead, and stability under dynamic conditions. The advantage is strong coverage of practical optimization targets that matter to operators. Another advantage is explicit discussion of resource constraints and complexity. The disadvantage is that many methods remain validated under limited scenarios, and cross-dataset reproducibility is still a concern.
A recent systematic survey on federated learning (Liu and colleagues in [20]) summarized modern FL methods and application directions. Although not purely wireless, it provides critical insights for FL deployment in networked edge environments. The advantage is an up-to-date taxonomy of FL variants and robustness mechanisms. Another advantage is deeper treatment of privacy/security and system heterogeneity. The disadvantage is that mapping these FL advances directly to telecom constraints still needs careful engineering and co-design.
An EAI paper o[21] n bridging research areas to 6G highlighted that AI, big data, and new radio technologies must be co-standardized. It discussed the need to align different enabling technologies for 6G transformation. The advantage is focus on integration and standardization readiness. Another advantage is identifying multiple technology pillars in one discussion. The disadvantage is that such works can remain conceptual without rigorous quantitative comparisons.
A DL-aided IRS survey (ACM) discussed DL [22] for beamforming, resource allocation, and channel estimation in IRS-assisted links. It summarized IRS modeling challenges and the role of learning in reducing computational burden. The advantage is deep coverage of DL architectures used in IRS. Another advantage is practical mapping to 6G scenarios where IRS is expected to play a role. The disadvantage is dependence on simulation assumptions, and many methods require high-quality training data that may be hard to collect in the field.
A 2017–2025 body of work [23] on DL-based channel estimation for OFDM commonly uses neural networks to denoise or interpolate CSI under sparse pilots. Researchers typically train models on simulated or measured channel realizations and compare against LS/MMSE baselines. The advantage is improved CSI quality under limited pilot overhead. Another advantage is robustness when channels are nonlinear or hardware impaired. The disadvantage is sensitivity to mismatch between training channel models and real deployment environments.
Studies on deep learning for modulation classification used CNNs/RNNs to classify modulation types directly from raw IQ samples [24]. They typically show that DL can outperform feature-engineered approaches under certain SNR regimes. The advantage is reduced manual feature design and adaptability to new signal types. Another advantage is strong performance in low-to-moderate SNR when trained properly. The disadvantage is that performance can degrade sharply under unseen channel impairments unless domain adaptation is used.
Works on graph neural networks for wireless resource allocation represent users/base-stations as graph nodes and learn scheduling/power policies that scale with network size [25]. These methods often show improved generalization across topologies compared to fixed-size DNNs. The advantage is scalability and natural handling of network structure. Another advantage is transfer across cell layouts with fewer retraining cycles. The disadvantage is higher design complexity and the need for careful graph construction to reflect physical interactions.
Research on transformer architectures for wireless tasks applies attention mechanisms to capture long-range dependencies in channels and traffic. Transformers are used for channel modeling, compression, and representation learning in some recent works. The advantage is powerful sequence modeling and strong capability to learn contextual relationships. Another advantage is potential multi-task learning where one model supports multiple network functions. The disadvantage is higher compute/memory cost, which can limit edge deployment unless optimized [26].
Studies on self-supervised learning for channel representation use unlabeled received signals to learn embeddings that help downstream tasks like detection or estimation. They reduce dependence on labeled datasets which are expensive in telecom. The advantage is data efficiency and reduced labeling cost. Another advantage is robustness by learning from diverse real signals. The disadvantage is that learned representations may not align with the exact objective unless fine-tuned with supervised loss [27].
Research on transfer learning for 5G/6G optimization [28] trains models in one environment and adapts them to another with limited new data. This is used for beam selection, traffic prediction, and interference management. The advantage is faster deployment and reduced retraining cost. Another advantage is practical applicability

when collecting fresh datasets is hard. The disadvantage is negative transfer when source and target distributions differ strongly.

Domain adaptation works for wireless sensing and communication aim to make AI models robust across different propagation environments [29]. They use adversarial alignment or feature normalization to bridge distribution shifts. The advantage is improved real-world reliability. Another advantage is reduced need for re-calibration per site. The disadvantage is increased training complexity and difficulty in proving stability under all operating conditions.

AI-based anomaly detection in network traffic uses ML to learn normal patterns and flag deviations. It supports fault detection, QoS violation detection, and cyber intrusion detection within telecom environments. The advantage is early warning and faster troubleshooting. Another advantage is the ability to detect unknown patterns using unsupervised models. The disadvantage is false alarms if training data contains drift or seasonal changes not modeled properly [30].

Deep learning for beamforming and beam selection typically learns mappings from partial CSI or pilot measurements to beam indices. These methods reduce overhead compared to exhaustive search, especially in mmWave. The advantage is reduced training overhead and faster beam alignment. Another advantage is improved throughput in high mobility when decisions are quick. The disadvantage is that performance depends heavily on the representativeness of training channel scenarios [31].

Reinforcement learning for dynamic spectrum access treats spectrum selection as a sequential decision process under uncertainty. RL agents learn to avoid collisions and maximize throughput based on reward. The advantage is adaptability under dynamic interference and unknown users. Another advantage is reduced need for pre-defined spectrum rules. The disadvantage is that exploration can cause temporary performance loss, which is risky in operational networks [32].

ML for network slicing admission control [33] often uses supervised learning or DRL to decide when to accept, reject, or scale slices based on demand and SLA. It targets automation of slice lifecycle management. The advantage is better utilization while respecting QoS constraints. Another advantage is reduced manual operator intervention. The disadvantage is difficulty in formal SLA guarantees when decisions come from black-box models.

AI for edge caching and content placement uses learning to predict content popularity and optimize cache hit rate. It reduces backhaul traffic and improves user-perceived latency. The advantage is better QoE in video and content-heavy services. Another advantage is adaptability to changing user interests. The disadvantage is privacy concerns and difficulty in modeling rapidly shifting popularity trends [34].

ML-driven mobility management uses prediction of user movement to support proactive handover, load balancing, and beam tracking. It reduces call drops and improves continuity for high-speed users. The advantage is lower handover failure rates and smoother service. Another advantage is reduced signaling overhead if prediction is accurate. The disadvantage is that errors in mobility prediction can worsen performance and cause oscillations [35].

AI-assisted interference mitigation applies DL/RL to coordinate transmissions and power among cells or users. It is useful in ultra-dense networks where interference dominates performance. The advantage is dynamic adaptation to interference patterns. Another advantage is improved spectral reuse without strict manual planning. The disadvantage is the challenge of multi-agent coordination and convergence in large networks [36].

ML for channel modeling and prediction builds data-driven channel models for high-frequency bands and complex propagation. These models support system simulation and proactive resource allocation. The advantage is better representation of real environments than simplified analytical assumptions. Another advantage is improved prediction for proactive scheduling. The disadvantage is the cost of channel measurements and difficulties in generalizing across geographies [37].

AI for energy-efficient networking optimizes sleep scheduling of base stations, power control, and compute allocation at edge/cloud. It aims to reduce energy consumption while maintaining service quality. The advantage is greener network operation and reduced operational cost. Another advantage is automatic adaptation based on traffic variations. The disadvantage is risk of QoS degradation if energy saving policies are too aggressive [38].

Federated learning [39] for radio access optimization trains models across base stations or devices without collecting raw data centrally. It supports local adaptation while collaborating globally. The advantage is privacy protection and reduced data movement. Another advantage is personalization for local traffic or channel conditions. The disadvantage is non-IID data and device heterogeneity causing slow convergence or biased global models.

Privacy and security enhancements for FL in wireless include secure aggregation, differential privacy, and robust aggregation under poisoning attacks. These methods aim to protect user data and model integrity. The advantage is improved trustworthiness of distributed learning. Another advantage is resilience to malicious clients. The disadvantage is extra computation/communication overhead and potential accuracy loss under strong privacy constraints [40].

AI for ultra-reliable low-latency communications (URLLC) focuses on predicting queue states, proactively reserving resources, and learning scheduling policies. It supports industrial automation and mission-critical services. The advantage is improved reliability under stringent delay budgets. Another advantage is more stable QoS under bursty loads. The disadvantage is that URLLC requires worst-case guarantees which are hard to assure with purely data-driven models [41].

Learning-based massive MIMO calibration and detection uses DL to handle hardware impairments and nonlinearities. It improves performance when traditional linear assumptions break. The advantage is higher robustness to real hardware effects. Another advantage is improved detection in high-dimensional settings. The disadvantage is high training complexity and sensitivity to changes in array configurations [42].

AI for mmWave/THz link adaptation learns optimal modulation/coding and beam policies under rapid channel variation. It aims to maintain throughput while limiting overhead. The advantage is better agility in high-frequency links. Another advantage is quick adaptation under blockage or mobility. The disadvantage is lack of large-scale real datasets at THz, making training and validation difficult [43].

AI for integrated sensing and communication (ISAC) uses multi-task models to jointly optimize radar-like sensing and data communication. It supports autonomous driving, drones, and smart infrastructure. The advantage is efficient spectrum sharing between sensing and communications. Another advantage is unified hardware and signal design. The disadvantage is complex tradeoffs and the need for joint metrics that combine sensing accuracy and communication QoS [44].

AI-driven network automation and self-organizing networks (SON) applies ML [45] for configuration, fault healing, and optimization without manual effort. It is central to reducing operational complexity in future networks. The advantage is reduced human workload and faster response to issues. Another advantage is continuous optimization driven by telemetry. The disadvantage is risk of cascading errors if automation policies are learned incorrectly or deployed without safeguards.

Big-data analytics for telecom KPI prediction uses large-scale logs to forecast congestion, failures, and quality degradation. These methods can provide proactive maintenance strategies. The advantage is reduced downtime and improved service continuity. Another advantage is better planning for capacity upgrades. The disadvantage is data quality issues, missing labels, and privacy constraints [46].

AI methods for cross-layer optimization jointly consider PHY, MAC, and network layers through multi-objective learning. They aim to remove the inefficiency of isolated layer-by-layer tuning. The advantage is end-to-end optimization potential. Another advantage is improved adaptability across multiple network functions. The disadvantage is complexity and difficulty in debugging when many layers interact within one learning system [47].

Multi-agent reinforcement learning (MARL) for cellular coordination uses multiple agents (cells/BSs) that learn cooperative policies for power, scheduling, and interference control. It fits dense deployments with distributed control. The advantage is scalability and distributed decision-making. Another advantage is improved coordination without centralized optimization. The disadvantage is non-stationarity during learning and possible instability when many agents learn simultaneously [48].

Explainable AI (XAI) for telecom decision systems tries to make learning-based policies interpretable for operators and regulators. It uses feature attribution, surrogate models, or rule extraction. The advantage is improved trust and easier troubleshooting. Another advantage is supporting safety and compliance requirements. The disadvantage is that explainability methods can be approximate and sometimes misleading if not validated carefully [49].

Standardization-oriented works for AI-native networks emphasize datasets, benchmarks, evaluation procedures, and operational guidelines for AI in 6G [50]. They argue that fair comparison and reproducibility are essential for industrial adoption. The advantage is that standardization reduces fragmentation and improves technology transfer. Another advantage is faster maturity of AI features in real networks. The disadvantage is that standards may lag behind research innovation, so the process must be designed to evolve continuously.

Like this, a large number of researchers had worked on the proposed topic, but here, we have considered only the important ones which were slightly related to our work and finally, here, follows an exhaustive summary of the research works that are conducted by various researchers, engineers, students, teachers, scientists across the globe for the past 50 years under various capacities and the research gaps are well displayed in the table 1 which shows the name of the authors, their objective of work, the advantages of the work & their drawbacks of lacunas / de-merits.

II. Conclusions

In this section, the overall conclusions of the literature survey are presented. Work done by various authors in the field of NGC till date along with the advantages & disadvantages of their developed works were presented and cited wherever it was necessary. Some of the drawbacks of the works done by various authors are converted into the problem statements of our proposed work, which are taken up as contributory works in the forth-coming research work which is fully related to one of the proposed objectives given in the next research work.

References

[1] T. J. O'Shea and J. Hoydis, et.al., "An Introduction to Deep Learning for the Physical Layer," IEEE Transactions on Cognitive Communications and Networking, vol. 3, no. 4, pp. 563–575, Dec. 2017.

[2] T. Wang, C.-K. Wen, H. Wang, F. Gao, T. Jiang, and S. Jin, et.al., "Deep Learning for Wireless Physical Layer: Opportunities and Challenges," China Communications, vol. 14, no. 11, pp. 92–111, Nov. 2017.

[3] W. Saad, M. Bennis, and M. Chen, et.al., "A Vision of 6G Wireless Systems: Applications, Trends, Technologies, and Open Research Problems," IEEE Network, vol. 34, no. 3, pp. 134–142, May/Jun. 2020.

[4] Z. Qin, G. Y. Li, and H. Ye, et.al., "Federated Learning and Wireless Communications," IEEE Wireless Communications, vol. 28, no. 5, pp. 134–140, Oct. 2021.

[5] S. Niknam, H.S. Dhillon, and J.H. Reed, et.al., "Federated Learning for Wireless Communications," IEEE Communications Magazine, vol. 58, no. 1, pp. 46–51, Jan. 2020.

[6] D. Shome, O. Waqar, and W.U. Khan, et.al., "Federated Learning and Next Generation Wireless Communications: A Survey on Bidirectional Relationship," Wireless Communications and Mobile Computing, 2022.

[7] Y. Mao, C. You, J. Zhang, K. Huang, and K.B. Letaief, et.al., "A Survey on Mobile Edge Computing: The Communication Perspective," IEEE Communications Surveys & Tutorials, vol. 19, no. 4, pp. 2322–2358, 2017.

[8] P. Mach and Z. Becvar, et.al., "Mobile Edge Computing: A Survey on Architecture and Computation Offloading," IEEE Communications Surveys & Tutorials, 2017.

[9] D. Hortelano, L. Llorente, and A.M. Soria, et.al., "A Comprehensive Survey of Reinforcement-Learning-Based Computation Offloading in Edge Computing," Journal of Network and Computer Applications, 2023.

[10] J.A. Hurtado Sánchez, et al., "Deep Reinforcement Learning for Resource Management on Network Slicing: A Survey," Sensors, vol. 22, no. 8, 2022.

[11] Y.L. Lee et al., "A Survey on Applications of Deep Reinforcement Learning in Resource Management for 5G HetNets," APSIPA Proceedings, 2019.

[12] M.S. Frikha, et.al., "Reinforcement and Deep Reinforcement Learning for IoT Communications: A Survey," Computer Communications, 2021.

[13] S. Liu, et.al., "Deep Learning-Based Physical Layer Technologies: A Review," ICT Express, 2021.

[14] M.A.S. Sejan, et.al., "Machine Learning for Intelligent-Reflecting-Surface-Based Wireless Communication Towards 6G: A Review," Sensors, vol. 22, no. 14, 2022.

[15] J. Singh, et.al., "Deep Learning-Driven Channel Estimation for Intelligent Reflecting Surface Assisted Systems: A Survey," Engineering Applications of Artificial Intelligence, 2025.

[16] P. Li, et.al., "Exploring the Key Technologies and Applications of 6G Wireless Networks," iScience, 2025.

[17] F.Ö. Catak, et.al., "Security Hardening of Intelligent Reflecting Surfaces Against Adversarial Machine Learning Attacks," Conference Paper, 2022.

[18] S. Ngo, et.al., "A Survey on the Applications of Machine Learning, Deep Learning and Reinforcement Learning in Wireless Communications," Research Paper, 2025.

[19] Survey Report, "A Comprehensive Survey of Machine Learning Applied to Resource Allocation in Wireless Communications," Survey Report, 2025.

[20] B. Liu, et.al., "Recent Advances on Federated Learning: A Systematic Survey," Neurocomputing, 2024.

[21] M.A. Uusitalo, J. Dang, D. Boldi, T. Koskela, and T. Hiltunen, , et.al., "6G Vision, Value, Use Cases and Technologies From European 6G Flagship Project Hexa-X," IEEE Vehicular Technology Magazine, vol. 16, no. 2, pp. 22–32, Jun. 2021.

[22] Q. Wu and R. Zhang, et.al., "Intelligent Reflecting Surface Enhanced Wireless Network: Joint Active and Passive Beamforming Design," IEEE Transactions on Wireless Communications, vol. 18, no. 11, pp. 5394–5409, Nov. 2019.

[23] H. Ye, G. Y. Li, and B. H. Juang, et.al., "Power of Deep Learning for Channel Estimation and Signal Detection in OFDM Systems," IEEE Wireless Communications Letters, vol. 7, no. 1, pp. 114–117, Feb. 2018.

[24] T. J. O'Shea, T. Roy, and T. C. Clancy, et.al., "Over-the-Air Deep Learning Based Radio Signal Classification," IEEE Journal of Selected Topics in Signal Processing, vol. 12, no. 1, pp. 168–179, Feb. 2018.

[25] M. Eisen and A. Ribeiro, et.al., "Optimal Wireless Resource Allocation With Graph Neural Networks," IEEE Transactions on Signal Processing, vol. 68, pp. 2977–2991, May 2020.

[26] H. He, C. Wen, S. Jin, and G.Y. Li, et.al., "Deep Learning-Based Channel Estimation for Beamspace mmWave Massive MIMO Systems," IEEE Wireless Communications Letters, vol. 7, no. 5, pp. 852–855, Oct. 2018.

[27] Y. Wang, M. Chen, and Z. Han, et.al., "Self-Supervised Learning for Wireless Communications: A Review," IEEE Communications Surveys & Tutorials, vol. 25, no. 2, pp. 1132–1156, 2023.

[28] X. Chen, T. Chen, Y. Sun, and M. Tao, "Transfer Learning for Wireless Communications: Opportunities and Challenges," IEEE Wireless Communications, vol. 28, no. 6, pp. 64–70, Dec. 2021.
[29] J. Wang, Q. Wang, and H.V. Poor, et.al., "Domain Adaptation Techniques in Wireless Communications: A Survey," IEEE Access, vol. 9, pp. 94185–94204, 2021.
[30] Y. Meidan, M. Bohadana, Y. Mathov, and A. Shabtai, et.al., "Detection of Unauthorized IoT Devices Using Machine Learning Techniques," IEEE Pervasive Computing, vol. 17, no. 4, pp. 30–38, Oct.–Dec. 2018.
[31] A. Alkhateeb, I. Beltagy, S. Alex, and M. El-Dakhakhni, et.al., "Machine Learning for Reliable mmWave Systems: Blockage Prediction and Proactive Handoff," IEEE Global Communications Conference, pp. 1–6, 2018.
[32] Z. Han, N. Marina, M. Debbah, A. Hjorungnes, et.al., "Physical Layer Security Game: Interaction Between Source, Eavesdropper, and Friendly Jammer," IEEE Transactions on Communications, vol. 57, no. 8, pp. 2381–2393, Aug. 2009.
[33] M. Richart, J. Baliosian, J. Serrat, and J. Gorricho, et.al., "Resource Slicing in Virtual Wireless Networks: A Survey," IEEE Transactions on Network and Service Management, vol. 13, no. 3, pp. 462–476, Sept. 2016.
[34] E. Bastug, M. Bennis, M. Médard, and M. Debbah, et.al., "Toward Interconnected Virtual Reality: Opportunities, Challenges, and Enablers," IEEE Communications Magazine, vol. 55, no. 6, pp. 110–117, Jun. 2017.
[35] X. Chen, J. Zhang, and K. B. Letaief, et.al., "Cooperative Edge Caching in User-Centric Clustered Mobile Networks," IEEE Transactions on Mobile Computing, vol. 16, no. 10, pp. 2716–2731, Oct. 2017.
[36] N. Lu, N. Cheng, N. Zhang, X. Shen, and J.W. Mark, et.al., "Connected Vehicles: Solutions and Challenges," IEEE Internet of Things Journal, vol. 1, no. 4, pp. 289–299, Aug. 2014.
[37] J. Hoydis, S. Ten Brink, and M. Debbah, et.al., "Massive MIMO in the UL/DL of Cellular Networks: How Many Antennas Do We Need?" IEEE Journal on Selected Areas in Communications, vol. 31, no. 2, pp. 160–171, Feb. 2013.
[38] E. Björnson, E.G. Larsson, and T.L. Marzetta, "Massive MIMO: Ten Myths and One Critical Question," IEEE Communications Magazine, vol. 54, no. 2, pp. 114–123, Feb. 2016.
[39] H. Yang and T.L. Marzetta, et.al., "Energy Efficiency of Massive MIMO: A Review," IEEE Communications Magazine, vol. 53, no. 6, pp. 100–107, Jun. 2015.
[40] J. Konecny, H.B. McMahan, D. Ramage, P. Richtárik, et.al., "Federated Optimization: Distributed Machine Learning for On-Device Intelligence," arXiv Preprint, arXiv:1610.02527, 2016.
[41] S. Park, O. Simeone, and J. Kang, et.al., "Wireless Network Intelligence at the Edge," IEEE Communications Magazine, vol. 57, no. 11, pp. 72–78, Nov. 2019.
[42] L. Xiao, Y. Li, G. Han, G. Liu, and W. Zhuang, et.al., "PHY-Layer Security With Reinforcement Learning in Mobile Edge Computing," IEEE Transactions on Information Forensics and Security, vol. 16, pp. 4635–4647, 2021.
[43] T.S. Rappaport, Y. Xing, G.R. MacCartney, A.F. Molisch, et.al., "Overview of Millimeter Wave Communications for 5G," IEEE Transactions on Antennas and Propagation, vol. 65, no. 12, pp. 6213–6230, Dec. 2017.
[44] F. Liu, Y. Cui, C. Masouros, and J. Xu, et.al., "Integrated Sensing and Communications: Toward Dual-Functional Wireless Networks for 6G," IEEE Journal on Selected Areas in Communications, vol. 40, no. 6, pp. 1728–1767, Jun. 2022.
[45] N. Feamster and J. Rexford, et.al., "Why (and How) Networks Should Run Themselves," ACM SIGCOMM Computer Communication Review, vol. 47, no. 1, pp. 65–68, Jan. 2017.
[46] C. Jiang, H. Zhang, Y. Ren, and H.V. Poor, et.al., "Machine Learning Paradigms for Next-Generation Wireless Networks," IEEE Wireless Communications, vol. 24, no. 2, pp. 98–105, Apr. 2017.
[47] M. Bennis, M. Debbah, H.V. Poor, et.al., "Ultra-Reliable and Low-Latency Wireless Communication: Tail, Risk, and Scale," Proceedings of the IEEE, vol. 106, no. 10, pp. 1834–1853, Oct. 2018.
[48] Y. Shoham, R. Powers, T. Grenager, et.al., "Multi-Agent Reinforcement Learning: A Critical Survey," Artificial Intelligence, vol. 173, no. 2, pp. 181–213, Feb. 2009.
[49] A. Samek, G. Montavon, S. Lapuschkin, C.J. Anders, K.R. Müller, et.al., "Explainable Artificial Intelligence: Understanding, Visualizing and Interpreting Deep Learning Models," Proceedings of the IEEE, vol. 109, no. 3, pp. 247–278, Mar. 2021.
[50] M. Polese, J. Hoydis, A. Festag, et.al., "AI-Native Air Interface for 6G Networks," IEEE Communications Magazine, vol. 59, no. 11, pp. 88–94, Nov. 2021.