International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Ingénierie des Systèmes d'Information
Vol. 28, No. 4, August, 2023, pp. 959-967
Journal homepage: http://iieta.org/journals/isi

A Comprehensive Survey of Machine Learning Techniques in Next-Generation Wireless Networks and the Internet of Things

Mohammad Aftab Alam Khan[1*], Hazilah Mad Kaidi[2]

[1] Malaysia-Japan International Institute of Technology, Universiti Teknologi Malaysia, Kuala Lumpur 54100, Malaysia
[2] Razak Faculty of Technology and Informatics, Universiti Teknologi Malaysia, Kuala Lumpur 54100, Malaysia

Corresponding Author Email: hazilah.kl@utm.my

https://doi.org/10.18280/isi.280416

Received: 10 April 2023
Revised: 12 June 2023
Accepted: 23 July 2023
Available online: 31 August 2023

Keywords:
Internet of Things (IoT), Machine Learning (ML), quality of service, deep learning, reinforcement learning, 5G and beyond, next-generation wireless networks

ABSTRACT

The advent of next-generation wireless networks and the Internet of Things (IoT) has introduced numerous challenges in terms of quality of service (QoS), user data rates, throughput, and security. These challenges necessitate innovative solutions to optimize performance and ensure robust security. Machine Learning (ML) has emerged as an influential tool in this regard, offering the potential to fully harness the capabilities of next-generation wireless networks and the IoT. With an ever-increasing number of connected devices and the commensurate data proliferation, ML presents an effective means of analyzing and processing this data. One significant challenge addressed by ML is network optimization. Through the analysis of network traffic patterns, congestion points are identified, and potential network performance issues are predicted. Security, a critical concern in next-generation wireless networks and the IoT, is another facet where ML proves instrumental by detecting and mitigating security breaches. This is achieved by analyzing data to identify anomalous behaviour and potential threats. Moreover, ML facilitates informed decision-making in IoT systems. By scrutinizing real-time data generated by IoT devices, ML algorithms reveal valuable insights, trends, and correlations. This capability enables IoT-enabled systems to make data-driven decisions, thus enhancing the efficiency of various applications such as smart cities, industrial automation, healthcare, and environmental monitoring. This study undertakes a systematic review of the impact of ML techniques, such as reinforcement learning, deep learning, transfer learning, and federated learning, on next-generation wireless networks, placing a particular emphasis on the IoT. The literature is reviewed systematically and studies are categorized based on their implications. The aim is to highlight potential challenges and opportunities, providing a roadmap for researchers and scholars to explore new approaches, overcome challenges, and leverage potential opportunities in the future.

1. INTRODUCTION

The landscape of wireless communication systems has undergone substantial evolution over the past decades, primarily fuelled by technological advancements and the escalating demand for mobile computing and pervasive connectivity. The genesis of this evolution can be traced back to the establishment of commercial mobile telephony in the 1980s, followed by the widespread adoption of Wi-Fi in the 1990s, and subsequently, the expansion of mobile broadband and the Internet of Things (IoT) in the 21st century [1, 2]. The present study embarks on a comprehensive and systematic review of Machine Learning-based methodologies applied in various facets of next-generation telecommunication networks, with a particular emphasis on the IoT paradigm. The amalgamation of IoT and next-generation networks unveils a multitude of potential arenas where Machine Learning (ML) can make significant contributions. For instance, the spatial and temporal big data that IoT continuously generates requires transmission over the network for processing, analysis, and inference by edge, fog, and cloud computing servers. This scenario presents a myriad of research gaps and challenges that call for effective solutions from the ML research community.

The most recent milestone in the evolution of wireless communication is the advent of fifth-generation (5G) technology, which stands poised to usher in a new era of connectivity and performance. By enabling previously impossible applications and services, 5G networks promise higher data rates, lower latency, and enhanced reliability compared to their predecessors. Furthermore, 5G networks have been engineered to cater to the growing connectivity demands of IoT devices, which are anticipated to proliferate exponentially due to the introduction of smart and wearable devices, wireless sensor networks (WSNs), and mobile ad-hoc networks (MANETs). As such, the evolution of wireless communication has revolutionized our lifestyle and work culture, providing constant connectivity and real-time access to information [3].

The IoT, constituting a network of interconnected physical devices, vehicles, buildings, and other entities embedded with sensors, software, and network connectivity, facilitates data collection and exchange. The role of IoT devices in wireless communication systems is pivotal in providing a seamless communication experience for users [4]. Given the exponential growth in the number of connected devices and the escalating demand for higher data rates, IoT-enabled wireless communication systems are becoming indispensable to contemporary society.

These systems are expected to provide reliable and secure communication links between IoT devices and other communication networks, thereby facilitating the delivery of innovative services and applications. The integration of IoT devices with wireless communication systems is anticipated to stimulate the growth of smart cities, the industrial Internet, and other IoT-based applications, thus paving the path towards a more connected and intelligent future [5-7].

IoT devices are designed to generate vast volumes of data from diverse sensors continuously. However, the local computational resources required to process this data are typically lacking in IoT networks. As a result, the data is transmitted via robust communication links to edge, fog, or cloud servers for further processing. It is in this context that Machine Learning (ML) plays a crucial role, helping to discern hidden patterns and trends in this big data. The insights derived from ML algorithms are subsequently used to inform decision support and expert systems.

The remainder of this paper is structured as follows: Section 2 introduces the taxonomy of the literature review, followed by a comprehensive review of the literature in Section 3. Section 4 presents challenges and opportunities for ML in IoT and next-generation wireless communication systems. Finally, Section 5 provides the conclusion.

2. TAXONOMY OF LITERATURE REVIEW

The architecture of this systematic literature review is depicted in a hierarchical flow that is further classified by the taxonomy presented in this section. The review commences with an exploration of the evolution of wireless communication systems, detailing the progression of their generations, the data rates supported, and the temporal developments. This forms the base of the review's pyramid structure.

In the subsequent generations of wireless communication systems, particularly in 5G and beyond, the integration of IoT forms the second tier of the pyramid. This incorporation marks a significant milestone in the evolution of wireless communication systems.

The final tier of the pyramid comprises the examination of the implications and applications of various Machine Learning approaches within the IoT and next-generation wireless communication systems. This phase of the literature review is pivotal in understanding the role and impact of Machine Learning in these advanced systems.

Following this systematic review, a compilation of challenges and opportunities is presented, based on the insights gleaned from the reviewed literature. Concluding remarks are then provided, summarizing the key findings and implications of the review. The schematic representation of this literature review is illustrated in Figure 1.

Table 1 elaborates on the taxonomy, focusing on the critical domains within next-generation wireless networks where ML has been deployed. These areas include adaptive communication, Non-Orthogonal Multiple Access (NOMA), and radio resource allocation. The subsequent sections present a series of thematic tables, where relevant studies are catalogued and discussed in relation to their respective topics. This structured approach to the literature review ensures a comprehensive understanding of the role of Machine Learning in next-generation wireless communication systems and IoT.

Figure 1. Flow of literature review

Table 1. Topic-wise taxonomy mapping

Table ID	Topics	Articles
2	ML in Resource Management	[8-13]
3	ML in Adaptive communication	[14-19]
4	ML in NOMA systems	[20-26]

3. SYSTEMATIC LITERATURE REVIEW

This section presents a systematic review of the literature on Machine Learning implications in IoT and next-generation wireless communication systems.

3.1 Evolution in wireless communication

Wireless communication has evolved significantly over the past few decades and has played a critical role in shaping the modern world as we know it today. The evolution of wireless communication can be divided into several generations, each characterized by advances in technology and the development of new standards.

- First Generation (1G) Wireless Communication (1980s): 1G wireless communication refers to the first generation of mobile telephony, which was analog-based and primarily used for voice communication. It was based on Frequency Division Multiple Access (FDMA). The available system bandwidth is divided among the active users equally. That could result in poor radio resource utilization, crosstalk, and a limited number of supported users [27].
- Second Generation (2G) Wireless Communication (1990s): 2G wireless communication introduced digital communication, which improved the quality of voice communication and enabled the transmission of data over cellular networks. The first 2G network was launched in 1991, and by the end of the decade, 2G networks had been deployed globally. The technology used is FDMA plus Time Division Multiple Access (TDMA). Each user signal is assigned a sequence of time and frequency channel slots for communication. It is also known as the Global System of Mobile (GSM) network and land mobile network, one of the most famous and widely used networks across the globe as an alternative to the public switched telephone networks (PSTN). The number of users supported has significantly increased with the only limitation of time synchronization and poor time and frequency slots utilization [28].

- Third Generation (3G) Wireless Communication (2000s): 3G wireless communication brought faster data rates, increased network capacity, and improved multimedia support, enabling a new range of data-intensive applications, such as mobile internet access, video conferencing, and multimedia messaging. It is mainly based on the code division multiple access technology (CDMA) with various other variants and standards. The users were adequately separated in the code domain; hence a huge number of users were supported. The limitations observed were code orthogonality and RAKE receiver complexity [28].
- Fourth Generation (4G) Wireless Communication (2010s): 4G wireless communication brought further improvements in data rate and network capacity, enabling high-speed mobile broadband access, and enabling new applications, such as online gaming, video streaming, and real-time multimedia communication. The technology is mainly based on a combination of multicarrier (MC) CDMA, that is the combination of CDMA, FDMA and TDMA along with space division multiple access (SDMA) enhanced support. It is also known as ultra-wideband (UWB) technology [2].
- Fifth Generation (5G) Wireless Communication (2020s-Present): 5G wireless communication promises to bring even faster data rates, lower latency, and increased network capacity, enabling a new range of applications, such as autonomous vehicles, virtual reality, and the IoT. The main motivation behind the advent and promotion of 5G was enhanced connectivity, data rates, low latency, and the overwhelming number of devices that appeared due to mobile and cloud computing technologies. It is based on non-orthogonal multiple access (NOMA) techniques and millimeter wave (mm) communication [2].

The evolution of wireless communication has been driven by the increasing demand for mobile connectivity and the need to support new and more demanding applications. As technology continues to evolve, future generations of wireless communication will likely bring even more advanced capabilities, enabling new and innovative applications and transforming the way we live and work.

3.2 Mobile computing, IoT and wireless communication

The IoT refers to the interconnected network of physical devices, vehicles, home appliances, and other items embedded with electronics, software, sensors, and network connectivity, allowing these objects to collect and exchange data. IoT devices can communicate and collaborate with the surrounding environment, enabling them to collect and analyze data, make decisions, and perform tasks without human intervention. The IoT has a wide range of applications across various industries and sectors, some of which are:

- Smart Homes: IoT devices are used to automate and control various home appliances, such as lighting, heating, air conditioning, and security systems, from a single device, such as a smartphone.
- Healthcare: IoT devices are used in healthcare to monitor patients remotely, track vital signs, and collect medical data for analysis, helping to improve patient care and reduce hospital stays.
- Manufacturing: IoT devices are used in manufacturing to improve efficiency, monitor production processes, and optimize supply chain management.
- Agriculture: IoT devices are used in agriculture to monitor crops, soil, and weather conditions, helping farmers to optimize crop production and improve yield.
- Transportation: IoT devices are used in transportation to improve traffic management, monitor vehicle performance, and reduce fuel consumption.
- Energy: IoT devices are used in energy to monitor and manage energy consumption, reduce waste, and improve sustainability.
- Retail: IoT devices are used in retail to track inventory, monitor customer behaviour, and improve customer experience.

These are just a few examples of the many areas where IoT is being used to improve efficiency, reduce costs, and create new and innovative solutions. As technology continues to evolve, IoT will likely have an even greater impact on our daily lives and the way we work and interact with the world around us. All the said technological advances require and set the room of 5G and beyond the network. That is mainly due to the inherent need for connectivity, speed, data rates and low latency with support to excessively increase the number of connected devices.

The wireless sensor network (WSN) is a specific type of IoT technology that uses wireless communication to connect many low-power, small sensors, and devices. The WSNs are designed for applications in which many small sensors are deployed to collect data and send it to a central location for processing and analysis. WSNs can be used in a wide range of applications, including environmental monitoring, industrial process control, healthcare, military, and many others [4, 29]. The WSNs are a crucial part of the IoT ecosystem and are used in many IoT applications.

The WSNs have several advantages over traditional wired sensor networks. They are easy to install and maintain, as there are no wires to run or cables to connect. They can be deployed in remote or hard-to-reach locations, and they can be reconfigured on-the-fly to adapt to changing conditions. WSNs are also energy-efficient, as they are designed to use low power, allowing the sensors to run for long periods on batteries. However, WSNs also have some challenges, including limited bandwidth, interference, security, and scalability. Researchers and engineers are constantly working to address these challenges and improve the performance of WSNs. As technology continues to evolve, WSNs are becoming increasingly popular and widely used for a variety of applications [4, 30].

Wearables are also a specific type of IoT device that can be worn on the body and are designed to be used near the user. Examples of wearables include smartwatches, fitness trackers, and smart glasses. Wearables are equipped with sensors, computing power, and wireless connectivity, which enables them to collect and exchange data with other devices. Wearables are a growing part of the IoT ecosystem and are used in many applications, including health and fitness tracking, mobile payments, and hands-free control of other devices. They allow users to access and control information and perform tasks without having to physically interact with a device. Mobile computing technologies play a crucial role in enabling the IoT and its various applications. That is under such communication systems the said technologies can be affordable at a user level. Some of the mobile computing technologies used in IoT include, but are not limited to:

- Wireless Connectivity: IoT devices require wireless connectivity to exchange data and communicate with each other. Mobile computing technologies such as Wi-Fi, cellular networks, and Bluetooth provide the wireless connectivity infrastructure needed for IoT devices to function.

- Mobile Operating Systems: Mobile operating systems, such as Android and iOS, are used to create and manage IoT devices. These operating systems provide a platform for developers to create and deploy IoT applications, and for users to interact with and control their devices.
- Cloud Computing: Cloud computing technologies, such as Amazon Web Services (AWS) and Microsoft Azure, provide a scalable and secure platform for storing, processing, and analyzing large amounts of data generated by IoT devices.
- Mobile Devices as Controllers: Mobile devices such as smartphones and tablets can serve as controllers for IoT devices. Users can use their mobile devices to monitor and control their IoT devices, as well as to access and analyze the data generated by these devices.
- Mobile Data Analytics: Mobile computing technologies, such as mobile data analytics, provide the tools needed to analyze the vast amounts of data generated by IoT devices. These tools can help organizations to uncover new insights, make better decisions, and improve their operations.

The impact of mobile computing technologies on wireless communication systems has been significant in recent years. The integration of mobile computing technologies into wireless communication systems has led to the creation of smart and connected devices that can communicate with each other, resulting in new opportunities for innovation and growth in various industries [31, 32]. The rise of the IoT has been a key driver for this development, as more and more devices are being connected to the Internet to collect, process, and exchange data. This has created the need for wireless communication systems that can support many devices, have low power consumption, and low latency [33, 34]. To meet these requirements, new mobile computing technologies, such as 5G, have been developed to improve wireless communication capabilities and support the growth of IoT applications. The combination of IoT and mobile computing technologies has enabled the development of new use cases, such as smart homes, smart cities, and connected vehicles, among others [35]. Overall, the impact of mobile computing technologies on wireless communication systems has been transformative, providing new opportunities and driving innovation in a variety of industries.

The integration of IoT devices, wireless communication systems, and mobile computing technologies is expected to play a major role in enabling the next generation of smart and connected applications [36]. IoT devices can collect and exchange data with each other and with other communication networks through wireless communication systems. These systems are designed to provide reliable and secure communication links between IoT devices, enabling the delivery of innovative services and applications. Mobile computing technologies, on the other hand, provide the computational power and storage needed to process and analyze the vast amounts of data generated by IoT devices. The combination of IoT devices, wireless communication systems, and mobile computing technologies is expected to drive the growth of various applications, including smart cities, industrial Internet, and wearable technologies. These applications require low-latency, high-bandwidth, and reliable communication links, which can only be provided by the integration of IoT devices, wireless communication systems, and mobile computing technologies, thus paving the way for a more connected and intelligent future [29].

Moreover, the impact of mobile computing technologies on wireless communication systems has been significant in recent years. The integration of mobile computing technologies into wireless communication systems has led to the creation of smart and connected devices that can communicate with each other, resulting in new opportunities for innovation and growth in various industries. The rise of the IoT has been a key driver for this development, as more and more devices are being connected to the internet to collect, process, and exchange data. This has created the need for wireless communication systems that can support many devices, have low power consumption, and have low latency. To meet these requirements, new mobile computing technologies, such as 5G, have been developed to improve wireless communication capabilities and support the growth of IoT applications. The combination of IoT and mobile computing technologies has enabled the development of new use cases, such as smart homes, smart cities, and connected vehicles, among others. Overall, the impact of mobile computing technologies on wireless communication systems has been transformative, providing new opportunities and driving innovation in a variety of industries. In conclusion, mobile computing technologies play a key role in enabling the IoT and its various applications and will continue to shape the future of IoT and other emerging technologies [37, 38].

3.3 ML in IoT-enabled wireless communication

Traditional optimization techniques have been investigated in the literature for optimizing wireless communication systems. But there are limitations such as the complexity of the techniques such as convex optimization, secondly, no closed-form formula is usually available. Moreover, traditional techniques are applied to earlier communication systems with relatively fewer variables and a better degree of freedom. Nonetheless, for modern wireless communication systems traditional optimization techniques are either impractical or nearly impossible to investigate or relied upon. A sample optimization problem has been depicted in Eq. 1. The overall system's data rate is being enhanced subject to the fulfilment of two constraints. Namely, the bit error and transmit power. The mathematically constrained optimization problem for the communication system can be given as:

$$max\ R_{Total} = \sum_{i=1}^{N_{sc}} r_i \tag{1}$$

$$such\ that, BER_{Total} \leq BER_T$$

and

$$P_{Total} \leq \sum_{i=1}^{N_{sc}} P_i < P_T \tag{2}$$

where, $r_i = (\log_2(M))_i R_{c,i}$ the bit rate of the i^{th} subcarrier, which is a product of code rate and modulation order used, P_T is the available power and BER_T is the target BER that depends upon the quality of service (QoS) or application requirements while N_{sc} is several subcarriers in NOMA.

Here comes ML which is a subfield of artificial intelligence (AI) that provides systems with the ability to automatically improve their performance through experience. In the context of IoT-enabled wireless communication, ML has the potential to greatly enhance the performance and efficiency of these networks by optimizing various aspects such as network management, resource allocation, and security [39]. This can be achieved using ML algorithms such as supervised and unsupervised learning, deep learning, and reinforcement learning. In supervised learning, the algorithms are trained on a labelled dataset and the goal is to make predictions on new, unseen data. In unsupervised learning, the algorithms work with an unlabeled dataset and the goal is to discover patterns or structures in the data. In reinforcement learning, the algorithms learn through trial-and-error interactions with an environment [40].

These algorithms can be applied to various problems encountered in IoT wireless communication systems such as energy efficiency, data accuracy, and network reliability. By leveraging ML, IoT-enabled wireless communication systems can better handle the large amounts of data generated by IoT devices and provide more robust and efficient communication services. ML is used in a wide range of applications, including image and speech recognition, natural language processing, recommendation systems, and predictive modeling. It has revolutionized many industries, including healthcare, finance, marketing, and transportation, and continues to play a crucial role in the development of AI and the IoT such as medical IoT (IoMT) [41, 42].

ML has a significant role in wireless communication, particularly in the design and optimization of communication systems. ML techniques are used to tackle complex problems in wireless communication, such as interference management, resource allocation, and network optimization. ML has also played a crucial role in the development of 5G wireless communication networks. With the increase in the number of connected devices and the growing demand for high-speed data transfer, 5G networks require sophisticated techniques to optimize performance and ensure efficient utilization of resources. ML algorithms are used in 5G networks to perform functions such as network slicing, traffic management, and congestion control [43-45].

ML has a key role in wireless communication, providing new and innovative solutions to complex problems in the field. It is expected to continue to play a crucial role in the evolution of wireless communication networks, especially with the advent of the IoT and the growing demand for high-speed data transfer. ML is a subfield of AI that focuses on the development of algorithms and models that can learn from and make predictions on data. ML algorithms use statistical techniques to model and understand the relationships between the input data and output predictions, enabling the models to improve over time with experience [46].

Moreover, ML can also help in reducing the complexity of network management by enabling autonomous decision-making, reducing the need for manual intervention, and enabling real-time responses to change network conditions. Additionally, ML can also be used to detect and prevent security threats by analyzing the behaviour of IoT devices and detecting anomalies in real-time. This helps to ensure the security and privacy of sensitive data and protects the network from potential cyber-attacks [47].

Another important aspect where ML can play a crucial role is in optimizing the utilization of network resources. ML algorithms can be used to predict network congestion and dynamically allocate network resources such as bandwidth and power to the devices that need it most. This results in improved network performance and reduces the need for manual intervention. ML has the potential to significantly improve the performance and efficiency of IoT-enabled wireless communication systems. The integration of ML with IoT and wireless communication technologies is a rapidly growing area of research, and numerous advancements have been made in recent years. Though, there is still much room for improvement, and ongoing research efforts are aimed at further refining the use of ML in these systems and developing new ML-based solutions for the various challenges faced by IoT-enabled wireless communication [48].

3.4 Summary of literature review on ML in wireless communication

This study has a specific aim to evaluate the impact of ML techniques in the upcoming generation of wireless networks while considering the IoT as a crucial factor. To achieve this aim, a systematic review of the existing literature is conducted. This study will provide an in-depth analysis of the role of ML in next-generation wireless networks and its potential impact on the design and optimization of these networks, particularly in the context of IoT devices. The systematic review of the literature enables us to gain a comprehensive understanding of the current state of the art in ML-based wireless communication and the opportunities and challenges in this area. The results of this study will provide valuable insights for researchers, engineers, and practitioners in the field of wireless communication and help in future research and development in this area. From the literature review, the following can be summarized.

(1) IoTs have been becoming an essential component in information and communication technologies because of the tremendously growing popularity of wearable and sensory devices.

(2) Communication systems have been evolving rigorously to meet the expectations of the demanding information and communication technologies of the current era.

(3) ML has been playing a significant role in optimizing the communication systems utilization and fulfilment of the enhanced speed and data rate needs.

(4) Together the IoT and communication systems have been obtaining the limitless benefits of ML in various aspects whether it is radio resources utilization or elasticity of the demand.

Moreover, Table 2 contains a summary of the selected literature for ML in wireless communication systems such as device-to-device (D2D) communication emphasizing radio resource optimization such as for spectrum and energy efficiency (EE).

Likewise, Table 3 summarizes the studies involving ML such as Gaussian Radial Basis Function (GRBF) neural networks, Fuzzy Rule-Based System (FRBS) and Genetic algorithms (GA) in adaptive communication.

Similarly, Table 4 summarizes ML in the NOMA-based systems in the power domain (PD) as well as code domain (CD) for various radio networks.

Table 2. Machine Learning based resource management

Ref	Objective	Method	Conclusion
[8]	A power allocation scheme is utilized to optimize the D2D transmit power and maximize the EE	ML-based power control algorithm	It was shown that the spectrum and energy efficiency of a network can be enhanced by maximizing EE and optimizing the transmit power.
[9]	To maximize the sum throughput of D2D links, while at the same time ensuring the QoS	Deep Reinforcement Learning (DRL)	The simulation results reveal that POPS outperforms DDPG, DDQN, and DQN by 16.67%, 24.98%, and 59.09%.
[10]	Optimize system spectral efficiency	Joint utility and strategy estimation-based learning	The proposal can achieve near-optimal performance in a distributed manner
[11]	Optimize a long-term utility that is related to task execution delay, task queuing delay, and so on.	DRL	Improved computation offloading performance significantly compared to several baseline policies
[12]	Optimize system sum rate	K-nearest neighbours (KNN)	Raise system performance compared to a state-of-the-art approach.
[13]	BDMA can overcome the scarcity of time and frequency to share spectrum and OFDM is used as 5G modulation techniques.	Beam Division Multiple Access (BDMA)	Does not support adaptivity which is a feature of OFDM

Table 3. Machine Learning in adaptive communication

Ref	Objective	Method	Conclusion
[14]	ACM using Product code and QAM	FRBS	Flat power distribution
[15]	Adaptive modulation	Fuzzy Logic	Only adaptive modulation
[16]	ACM and power	FRBS and GA.	Complex system
[17]	ACM and power using GA and product codes with QAM compared to the water-filling principle	FRBS, Water-filling principle, GA	Huge complexity in decoding product codes
[18]	Adaptive communication	GRBF Neural Network	For satellite communication only.
[19]	Adaptive communication	FRBS and differential evolution algorithm	For satellite communication only.

Table 4. Machine Learning in NOMA systems

Ref	Objective	Method	Conclusion
[20]	Optimal power allocations for m-user uplink/ downlink NOMA systems	Evolutionary computing	CD not considered
[21]	An overview of the latest NOMA research and innovations and applications.	Survey on various ML NOMA applications	Missing ACM rather than surveying challenges and trends.
[22]	PD multiplexing NOMA with an emphasis on amalgams of multiple antenna (MIMO) techniques and NOMA	Survey on various ML methods in PD-multiplexing-aided NOMA	Focused on MIMO and NOMA mainly while ACM was missing.
[23]	CD-NOMA performance was found better than classical ALOHA	Compare the performance of CD-NOMA with classical ALOHA protocol.	Focused on CD NOMA while PD NOMA was not considered
[24]	Power allocation policies are discussed for the proposed scheme	ML in NOMA for centralized radio networks	The application of FD in NOMA has been studied
[25]	The superiority of NOMA-enabled F-RANs over conventional OMA-enabled F-RANs is verified.	ML was used as monotonic optimization approach	Limited to adaptative power
[26]	Investigated the error performance of NOMA schemes in the presence of channel estimation errors in addition to imperfect SIC	Derive exact bit error probabilities (BEPs) in closed forms and technical analysis is validated via simulations	Limited to optimum power allocation

4. CHALLENGES AND OPPORTUNITIES

The role of ML in IoT-enabled next-generation wireless communication systems is a complex and dynamic field, with several challenges that need to be addressed. Some of the main challenges include:

- Data privacy and security: IoT devices generate a large amount of sensitive data, and preserving the privacy and security of this data is critical.
- Limited computation and storage: Many IoT devices have limited computational and storage resources, making it challenging to deploy ML algorithms on these devices.
- Network heterogeneity: IoT devices are connected to the network through different communication technologies such as Wi-Fi, Zigbee, and others, leading to network heterogeneity. This can make it challenging to deploy ML algorithms seamlessly.
- Heterogeneous data sources: IoT devices can generate data from various sources, making it challenging to integrate and analyze data from multiple sources.
- Lack of standardization: There is currently a lack of standardization in the deployment of ML algorithms for IoT devices, making it challenging to deploy ML algorithms in a scalable manner.

- IoT and big data: The huge data continuously generated/produced by the IoT devices need to be processed. However, the IoT devices themselves can not do that due to limited resources and sometimes just comprised of sensors and transmitters. That data need to be transmitted to some edge, fog or cloud server for processing and analyses with the help of ML-based algorithms.
- Real-time processing: IoT devices generate real-time data, and there is a need to process this data in real time to enable real-time decision-making. This can be challenging for ML algorithms that require significant computational resources.
- Lack of data: ML algorithms require massive amounts of data to train accurate models. There may be a lack of adequate data from IoT devices to develop ML solutions.
- Concept drift: The relationships between input data and outputs may change over time, reducing the accuracy of ML models. ML solutions for IoT and wireless networks need to adapt to concept drift.
- Lack of explainability: ML models are often opaque and complex, lacking explainability. This can reduce the trust and adoption of ML solutions. Interpretable ML is needed.

Despite these challenges, there are huge opportunities in applying ML for the IoT in next-generation wireless communication systems are numerous and include:

- Improved network performance: ML can be used to optimize network resources, manage traffic, and improve network efficiency and coverage.
- Predictive maintenance: ML algorithms can analyze data from IoT devices to predict potential failures, allowing for proactive maintenance to prevent outages.
- Increased security: ML algorithms can identify and mitigate potential security threats, such as cyber-attacks, in real time.
- Customization and personalization: ML can be used to personalize services for individual users based on their preferences and behaviour.
- Enhanced user experience: ML algorithms can provide real-time recommendations and personalized services, improving the overall user experience.
- Efficient resource allocation: ML algorithms can optimize the use of network resources, reducing energy consumption and increasing the overall efficiency of the system.
- Real-time data analysis: ML algorithms can analyze large amounts of data from IoT devices in real time, providing valuable insights and enabling better decision-making.
- Automated network optimization: ML can automatically optimize network configurations and parameters to maximize performance. This reduces manual effort and improves network efficiency.
- Predictive modeling: ML models can predict future network demands, traffic patterns and failures. This enables a proactive rather than reactive approach to network monitoring and management.
- Personalized QoS: ML techniques can predict the QoS needs of different IoT applications and allocate network resources to meet those needs. This results in improved QoS for end users.

5. CONCLUSION

In conclusion, the integration of Machine Learning techniques with IoT and wireless communication systems has the potential to bring about significant advancements in the next generation of wireless networks. But, to fully realize the potential of ML for IoT in wireless communication, several challenges need to be addressed, including the development of algorithms that can effectively process large amounts of data in real-time, the creation of secure and reliable communication infrastructure, and the design of efficient and effective ML models. However, despite the numerous benefits, there are also several challenges associated with applying ML in IoT-based systems. These challenges include data privacy and security, computational complexity, and interpretability. To fully realize the potential of ML in IoT-based systems, it is crucial that these challenges are addressed and overcome. Further research in this area can help to expand the capabilities of ML and bring in the next generation of wireless communication systems that are more efficient, secure, and scalable.

It can further be concluded that next-generation networks are among the hottest areas of research where ML can be incorporated to solve complex problems more adequately. Nonetheless, ML techniques exhibit inherent complexity in the training phase, more research is needed to address this problem and make the solution real time. In the IoT inclusion, fog and cloud computing becomes more evident and consequently, the problems become more diversified and multifaceted. In this case, different variants of ML can be investigated such as transfer learning, federated and fusion-based learning [49, 50]. That is still an open area of research to comprehend ML-based optimization in next-generation wireless networks, especially in the IoT and cloud computing paradigms. In particular smart applications, such as wearables, smart homes, smart cities and industrial automation such as Industry 4.0 and Healthcare 5.0 are a few among many potential application areas.

REFERENCES

[1] Shah, A.S., Qasim, A.N., Karabulut, M.A., Ilhan, H., Islam, M.B. (2021). Survey and performance evaluation of multiple access schemes for next-generation wireless communication systems. IEEE Access, 9: 113428-113442. https://doi.org/10.1109/access.2021.3104509

[2] Budhiraja, I., Kumar, N., Tyagi, S., Tanwar, S., Han, Z., Piran, M.J., Suh, D.Y. (2021). A systematic review on NOMA variants for 5G and beyond. IEEE Access, 9: 85573-85644. https://doi.org/10.1109/access.2021.3081601

[3] Khanh, Q.V., Hoai, N.V., Manh, L.D., Le, A.N., Jeon, G. (2022). Wireless communication technologies for IoT in 5G: Vision, applications, and challenges. Wireless Communications and Mobile Computing, 2022: 1-12. https://doi.org/10.1155/2022/3229294.

[4] Borza, P.N., Machedon-Pisu, M., Hamza-Lup, F. (2019). Design of wireless sensors for IoT with energy storage and communication channel heterogeneity. Sensors, 19(15): 3364. https://doi.org/10.3390/s19153364

[5] ALRikabi, H.T.S., Alaidi, A.H., Nasser, K. (2020). The Application of wireless communication in IOT for saving electrical energy. International Journal of Interactive Mobile Technologies (IJIM), 14(1): 152-160. https://doi.org/10.3991/ijim.v14i01.11538
[6] Celebi, H. B., Pitarokoilis, A., Skoglund, M. (2020). Wireless communication for the industrial IoT. Industrial IoT: Challenges, Design Principles, Applications, and Security, Springer, Cham, 57-94. https://doi.org/10.1007/978-3-030-42500-5_2
[7] Singh, R.K., Berkvens, R., Weyn, M. (2020). Energy efficient wireless communication for IoT enabled greenhouses. In International Conference on Communication Systems and Networks, pp. 885-887. https://doi.org/10.1109/comsnets48256.2020.9027392
[8] Khan, M.A.A., Kaidi, H.M., Ahmad, N. (2021). Joint time and power control scheme for NOMA-enabled D2D users with energy harvesting in IoT environment. In 2021 IEEE Symposium on Future Telecommunication Technologies (SOFTT), Bandung, Indonesia, pp. 28-34. https://doi.org/10.1109/SOFTT54252.2021.9673146
[9] Khan, M.A.A., Kaidi, H.M., Ahmad, N., Rehman, M.U. (2023). Sum throughput maximization scheme for NOMA-Enabled D2D groups using deep reinforcement learning in 5G and beyond networks. IEEE Sensors Journal, pp. 1-1. https://doi.org/10.1109/JSEN.2023.3276799
[10] Sun, Y., Peng, M., Poor, H.V. (2018). A distributed approach to improving spectral efficiency in uplink device-to-device-enabled cloud radio access networks. IEEE Transactions on Communications, 66(12): 6511-6526. https://doi.org/10.1109/TCOMM.2018.2855212
[11] Chen, X., Zhang, H., Wu, C., Mao, S., Ji, Y., Bennis, M. (2018). Optimized computation offloading performance in virtual edge computing systems via deep reinforcement learning. IEEE Internet of Things Journal, 6(3): 4005-4018. https://doi.org/10.1109/JIOT.2018.2876279
[12] Wang, J.B., Wang, J., Wu, Y., Wang, J. Y., Zhu, H., Lin, M., Wang, J. (2018). A Machine Learning framework for resource allocation assisted by cloud computing. IEEE Network, 32(2): 144-151. https://doi.org/10.1109/MNET.2018.1700293
[13] Dalela, P.K., Bhave, P., Yadav, P., Yadav, A., Tyagi, V. (2018). Beam Division Multiple Access (BDMA) and modulation formats for 5G: Heir of OFDM? In 2018 International Conference on Information Networking (ICOIN) Chiang Mai, Thailand, pp. 450-455. https://doi.org/10.1109/ICOIN.2018.8343158
[14] Qureshi, I.M., Muzaffar, M.Z. (2011). Adaptive coding and modulation for OFDM systems using product codes and fuzzy rule base system. International Journal of Computer Applications, 35(4): 41-48. https://doi.org/10.5120/4393-6099
[15] Qureshi, I.M., Naseem, M.T., Muzaffar, M.Z. (2012). A fuzzy rule base system aided rate enhancement scheme for OFDM systems. In 2012 International Conference on Emerging Technologies Islamabad, Pakistan, pp. 1-6. https://doi.org/10.1109/INMIC.2012.6511444
[16] Qureshi, I.M., Salam, M.H., Naseem, M.T. (2013). Efficient link adaptation in OFDM systems using a hybrid intelligent technique. In 13th International Conference on Hybrid Intelligent Systems, Gammarth, Tunisia, pp. 12-17. https://doi.org/10.1109/HIS.2013.6920471
[17] Islam, S.R., Avazov, N., Dobre, O.A., Kwak, K.S. (2016). Power-domain non-orthogonal multiple access (NOMA) in 5G systems: Potentials and challenges. IEEE Communications Surveys & Tutorials, 19(2): 721-742. https://doi.org/10.1109/COMST.2016.2621116
[18] Rahman, A. (2023). GRBF-NN based ambient aware realtime adaptive communication in DVB-S2. Journal of Ambient Intelligence and Humanized Computing, 14(5): 5929-5939. https://doi.org/10.1007/s12652-020-02174-w
[19] Rahman, A.U., Dash, S., Luhach, A.K. (2021). Dynamic MODCOD and power allocation in DVB-S2: A hybrid intelligent approach. Telecommunication Systems, 76: 49-61. https://doi.org/10.1007/s11235-020-00700-x
[20] Ali, M.S., Tabassum, H., Hossain, E. (2016). Dynamic user clustering and power allocation for uplink and downlink non-orthogonal multiple access (NOMA) systems. IEEE Access, 4: 6325-6343. https://doi.org/10.1109/ACCESS.2016.2604821
[21] Ding, Z., Lei, X., Karagiannidis, G.K., Schober, R., Yuan, J., Bhargava, V.K. (2017). A survey on non-orthogonal multiple access for 5G networks: Research challenges and future trends. IEEE Journal on Selected Areas in Communications, 35(10): 2181-2195. https://doi.org/10.1109/JSAC.2017.2725519
[22] Liu, Y., Qin, Z., Elkashlan, M., Ding, Z., Nallanathan, A., Hanzo, L. (2017). Nonorthogonal multiple access for 5G and beyond. Proceedings of the IEEE, 105(12): 2347-2381. https://doi.org/10.1109/JPROC.2017.2768666
[23] Duchemin, D., Gorce, J.M., Goursaud, C. (2018). Code domain non orthogonal multiple access versus aloha: A simulation-based study. In 2018 25th International Conference on Telecommunications (ICT) Saint-Malo, France, pp. 445-450. https://doi.org/10.1109/ICT.2018.8464836
[24] Chen, X., Liu, G., Ma, Z., Zhang, X., Fan, P., Chen, S., Yu, F.R. (2019). When full duplex wireless meets non-orthogonal multiple access: Opportunities and challenges. IEEE Wireless Communications, 26(4): 148-155. https://doi.org/10.48550/arXiv.1905.13605
[25] Liu, B., Liu, C., Peng, M., Liu, Y., Yan, S. (2020). Resource allocation for non-orthogonal multiple access-enabled fog radio access networks. IEEE Transactions on Wireless Communications, 19(6): 3867-3878. https://doi.org/10.1109/TWC.2020.2978843
[26] Ferdi, K.A.R.A., Hakan, K.A.Y.A. (2020). Error probability analysis of non-orthogonal multiple access with channel estimation errors. In 2020 IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom) Odessa, Ukraine, pp. 1-5. https://doi.org/10.1109/BlackSeaCom48709.2020.9234956
[27] Akbar, A., Jangsher, S., Bhatti, F.A. (2021). NOMA and 5G emerging technologies: A survey on issues and solution techniques. Computer Networks, 190: 107950. https://doi.org/10.1016/j.comnet.2021.107950
[28] Agrawal, R. (2022). Comparison of different mobile wireless technology (From 0G to 6G). ECS Transactions, 107(1): 4799-4839. https://doi.org/10.1149/10701.4799ecst
[29] Eeshwaroju, S., Jakkula, P., Ganesan, S. (2020). IoT based empowerment by smart health monitoring, smart

education and smart jobs. In 2020 International conference on computing and information technology (ICCIT-1441), Tabuk, Saudi Arabia, pp. 1-5. https://doi.org/10.1109/iccit-144147971.2020.9213754
[30] Ali, M.H., Kamardin, K., Maidin, S.N., Hlaing, N.W., Kaidi, H.M., Ahmed, I.S., Taj, N. (2022). Agricultural production system based on IOT. International Journal of Integrated Engineering, 14(6): 313-328. https://doi.org/https://doi.org/10.30880/ijie.2022.14.06.028
[31] Frank, M., Drikakis, D., Charissis, V. (2020). Machine-learning methods for computational science and engineering. Computation, 8(1): 15. https://doi.org/10.3390/computation8010015
[32] Zhong, S., Zhang, K., Bagheri, M., Burken, J.G., Gu, A., Li, B.K., Ma, X.M., Marrone, B.L., Ren, Z.J., Schrier, J., Shi, W., Tan, H.Y., Wang, T.B., Wang, X., Wong, B.M., Xiao, X.S., Yu, X., Zhu, J.J., Zhang, H.C. (2021). Machine Learning: New ideas and tools in environmental science and engineering. Environmental Science & Technology, 55(19): 12741-12754. https://doi.org/10.1021/acs.est.1c01339
[33] Alqahtani, A., Aldhafferi, N., Atta-ur-Rahman 0001, Sultan, K., Khan, M.A.A. (2018). Adaptive communication: A systematic review. Journal of Communications, 13(7): 357-367. https://doi.org/10.12720/jcm.13.7.357-367
[34] Atta-ur-Rahman, Musleh, D., Aldhafferi, N., Alqahtani, A., Alfifi, H. (2018). Adaptive communication for capacity enhancement: A hybrid intelligent approach. Journal of Computational and Theoretical Nanoscience, 15(4): 1182-1191. https://doi.org/10.1166/jctn.2018.7191
[35] Kaur, M.J., Mishra, V.P., Maheshwari, P. (2020). The convergence of digital twin, IoT, and machine learning: Transforming data into action. Digital twin technologies and smart cities, Springer, Cham, 3-17. https://doi.org/10.1007/978-3-030-18732-3_1
[36] Daya Sagar, K.V. (2019). Implement of smart health care monitoring system using mobile IoT and cloud computing technologies, International Journal of Innovative Technology and Exploring Engineering, 9(2S5): 67-72. https://doi.org/10.35940/ijitee.b1015.1292s519
[37] Khan, M.A.A., AlAyat, M., AlGhamdi, J., AIOtaibi, S.M., ALZahrani, M., AIQahtani, M., ur Rahman, A., Altassan, M., Jan, F. (2022). WeScribe: An intelligent meeting transcriber and analyzer application. In Proceedings of Third International Conference on Computing, Communications, and Cyber-Security: IC4S 2021, Singapore: Springer Nature Singapore, pp. 755-766. https://doi.org/10.1007/978-981-19-1142-2_59
[38] Khan, M.A.A., Alsawwaf, M., Arab, B., ALHashim, M., Almashharawi, F., Hakami, O., Olatunji, S.O., Farooqui, M., ur Rahman, A. (2022). Road damages detection and classification using deep learning and UAVs. In 2022 2nd Asian Conference on Innovation in Technology (ASIANCON), Ravet, India, pp. 1-6. https://doi.org/10.1109/ASIANCON55314.2022.9909043
[39] Khan, M.A.A., Kaidi, H.M., Alam, N., Rehman, M.U. (2021). Sum throughput maximization scheme for NOMA-Enabled D2D groups using deep reinforcement learning in 5G and beyond networks. IEEE Sensors Journal, 23(13): 15048-15057. https://doi.org/10.1109/JSEN.2023.3276799
[40] Dash, S., Biswas, S., Banerjee, D., Rahman, A.U. (2019). Edge and fog computing in healthcare-A review. Scalable Computing: Practice and Experience, 20(2): 191-206. https://doi.org/10.12694/scpe.v20i2.1504
[41] Nasir, M.U., Khan, S., Mehmood, S., Khan, M.A., Rahman, A.U., Hwang, S.O. (2022). IoMT-based osteosarcoma cancer detection in histopathology images using transfer learning empowered with blockchain, fog computing, and edge computing. Sensors, 22(14): 5444. https://doi.org/10.3390/s22145444
[42] Rahman, A.U., Nasir, M.U., Gollapalli, M., Alsaif, S.A., Almadhor, A.S., Mehmood, S., Khan, M.A., Mosavi, A. (2022). IoMT-based mitochondrial and multifactorial genetic inheritance disorder prediction using Machine Learning. Computational Intelligence and Neuroscience, Article ID: 2650742, https://doi.org/10.1155/2022/2650742
[43] Alhaidari, F., Rahman, A., Zagrouba, R. (2020). Cloud of Things: Architecture, applications and challenges. Journal of Ambient Intelligence and Humanized Computing, 14: 5957-5975. https://doi.org/10.1007/s12652-020-02448-3
[44] Dash, S., Ahmad, M., Iqbal, T. (2021). Mobile cloud computing: A green perspective. In Intelligent Systems: Proceedings of ICMIB 2020, Springer, Singapore, 185: 523-533. https://doi.org/10.1007/978-981-33-6081-5_46
[45] Rahman, A., Sultan, K., Dash, S., Khan, M.A. (2018). Management of resource usage in mobile cloud computing. International Journal of Pure and Applied Mathematics, 119(16): 255-261.
[46] Basheer Ahmed, M.I., Zaghdoud, R., Ahmed, M.S., Sendi, R., Alsharif, S., Alabdulkarim, J., Saad, B.A.A., Alsabt, R., Rahman, A., Krishnasamy, G. (2023). A real-time computer vision-based approach to detection and classification of traffic incidents. Big Data and Cognitive Computing, 7(1): 22. https://doi.org/10.3390/bdcc7010022
[47] Bhati, B.S., Rai, C.S., Balamurugan, B., Al-Turjman, F. (2020). An intrusion detection scheme based on the ensemble of discriminant classifiers. Computers & Electrical Engineering, 86: 106742. https://doi.org/10.1016/j.compeleceng.2020.106742
[48] Chettri, L., Bera, R. (2019). A comprehensive survey on Internet of Things (IoT) toward 5G wireless systems. IEEE Internet of Things Journal, 7(1): 16-32. https://doi.org/10.1109/jiot.2019.2948888
[49] Gafni, T., Shlezinger, N., Cohen, K., Eldar, Y.C., Poor, H.V. (2022). Federated learning: A signal processing perspective. IEEE Signal Processing Magazine, 39(3): 14-41. https://doi.org/10.1109/MSP.2021.3125282
[50] Asif, R. N., Abbas, S., Khan, M. A., Sultan, K., Mahmud, M., Mosavi, A. (2022). Development and validation of embedded device for electrocardiogram arrhythmia empowered with transfer learning. Computational Intelligence and Neuroscience, Article ID: 5054641. https://doi.org/10.1155/2022/5054641