AI-Driven Signal Processing and Network Management for Next-Generation Communications

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Abstract: The acceleration of wireless technologies from 5G toward 6G has intensified demands for intelligent, adaptive, and secure communication infrastructures. This paper provides a comprehensive synthesis of artificial intelligence (AI) methodologies that advance signal processing and network management across next-generation communication systems. First, we examine AI-driven intelligent signal processing, including deep learning techniques for modulation recognition, waveform generation, channel estimation, and interference mitigation, emphasizing their applicability under heterogeneous, high-dimensional, and noisy environments. Cognitive radio and dynamic spectrum access mechanisms are analysed with a focus on learning-based spectrum sensing and adaptive policy selection, enabling efficient exploitation of scarce spectral resources. In parallel, we investigate IoT communication constraints—energy, latency, jamming resilience—and how AI optimizes scheduling, traffic adaptation, and resource usage within ultra-low-power environments.

At the network level, we discuss the integration of AI with Open RAN architectures, virtualization frameworks (NFV/SDN), network slicing, and distributed orchestration for 5G/6G. Special emphasis is placed on AI-supported resource allocation, multi-agent reinforcement learning, edge intelligence, and federated learning for collaborative, privacy-preserving management across large-scale, heterogeneous networks. Security challenges—including anomaly detection, adversarial robustness, and physical-layer protection—are evaluated within the broader context of AI-enabled network defence. Finally, we highlight benchmarking limitations and the need for standardized datasets, reproducibility protocols, and deployment-ready evaluation criteria. Collectively, the findings underscore AI as a foundational enabler of resilient, efficient, and scalable communication systems for emerging 6G and beyond.

Keywords: Intelligent signal processing, Cognitive radio, 5G/6G Networks, Deep learning, Dynamic spectrum access, Network virtualization, AI-Driven resource management.

1. INTRODUCTION

The rapid expansion of mobile communication technologies, from the advent of WCDMA to the impending rollout of 6G, necessitates prompt adjustment of signal processing and cognitive radio management. Each generation has introduced novel access methods and signal structures, evolving from multi-carrier CDMA to SCFDMA, OFDM, and, more recently, wavelet-based signals, thus exposing legacy systems drawn upon previous techniques to persistent interference from new standards. Meanwhile, the burgeoning Internet of Things (IoT) fuels an ever-increasing demand for high-speed data transmission, straining communication capabilities even further. Addressing these evolving wireless communication challenges necessitates intelligent signal processing and network management—areas pertaining to which artificial intelligence (AI) significantly aids development and supports fields such as ADAS, smart grids, and even gaming. AI techniques and paradigms assist signal processing by automating analysis, resource allocation, and configuration, responding to the diverse and unpredictable pressures accompanying the advent of AI-enabled cognitive radio. Routine spectrum scanning can also pinpoint key electrical signal parameters, enabling autonomous network deployment, performance monitoring, and flexible reconfiguration to sustain uninterrupted service to diverse users. AI may thus arbitrate between competing standards, providing intelligent support for transmission and reception functionalities and enabling seamless generation of readily interpretable models for 5G and 6G signals based on limited detecting parameters.

2. FOUNDATIONS OF INTELLIGENT SIGNAL PROCESSING

Intelligent signal processing is a fast-growing discipline driven by the quest for smarter communications systems. Intelligent signal processing employs AI to build up-to-date information about the signal space and physical environment from residual knowledge and historical observations. AI signals communication with knowledge on protocols, coding, waveforms, modulation, MIMO configurations, and more. Current developments of interest include analysis, estimation, interference mitigation, space-time alignment, recognition, and resource allocation for unprecedented traffic demands, connectivity, and reliability. Traditional signal processing relies on a-priori complement knowledge of system environment, while intelligent signal processing dynamically updates the parameter set to adapt in real-time. System performance metrics include throughput, fairness, spectral efficiency, outage

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probability, and latency, applied on a user basis or on a whole network scale.

Next-generation wireless systems are evolving towards 5G and beyond standards to meet the growing communication needs of an increasingly connected society. AI expands the benefits of intelligent processing by enabling versatile access to sophisticated information. Intelligent signal processing serves as a foundation for AI-driven network management that spans nodes and layers across administrative domains. Intelligent processing advances the seamless integration of terrestrial and space networks while maintaining energy, capability, and security guarantees. Next-generation systems employ multiple frequencies, broadband data service, large bandwidth, and diverse service. Cross-layer features motivate efficient solutions at every layer through layer-dependent criteria such as resource allocation, processing, handover control, waveform determination, and management protocol. 5G mobile communications, satellite communications, and particles support vast interconnections, and address severe electromagnetic interference that jeopardizes data security in electronic or non-electronic domains. Economy, efficiency, and environmental protection drive flexible Energy as a Service (EaaS), and cognition is key to resource sharing and distribution across communications, sensing, and energy generation [1] and [2].

2.1. Deep Learning for Signal Analysis

Advances in artificial intelligence (AI) and machine learning (ML) have transformed signal-driven applications, enabling information analysis across heterogeneous themes such as radar, sonar, electrocardiography (ECG), and radio-frequency (RF) communications. Deep learning (DL) can simplify such tasks, rendering the extraction of meaningful information more efficient and effective. Signal representation significantly affects the performance of supervised DL. Conventional signal representations, such as analog- or amplitude-modulation signals, are challenging to segment, leading to suboptimal results. Recent approaches utilize a time-frequency approach based on the Wavelab algorithm to create a signal representation capable of achieving over 99% recognition accuracy for continuous-wave (CW) modulation under Gaussian noise. Such approaches perform better than traditional machine-learning-based methods, notably for symmetric phase-shift keying (PSK) modulation. Refining the signal representation can further simplify the solution by transforming amplitude- and phase-modulated signals into a pure-envelope signal to match the specific architecture of the used DL model, yet recognition accuracy declines under certain signal-to-noise ratios (SNRs).

Convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and transformers rank among the most common architectures for time-series data processing. CNNs leverage linear operators to extract essential data from components and yield performing training times for 24-bit signals or lower. With an input-size-independent, end-to-end strategy, RNNs and LSTMs read and memorize data sequentially, demonstrating potential for future improvements. Transformers, based solely on self-attention, have achieved record performances in various fields and have recently been applied to time-series data, such as finance, with promising results. Deep high-resolution representation (DHRN), residual neural network (ResNet), and generative adversarial networks (GANs) constitute popular architectures for generating and recovering signal data. DHRN pursue restoration without low-resolution references, allowing deployment in secure communications, while ResNet, developed for image processing, preserves information among multiple layers. GANs indicate a high capacity for undistorted signal generation and recovery, notably for beam-forming in millimeter-wave wireless communications. Generative diffusion models have also been applied to signal recovery with significant quality improvements relative to classical algorithms.

Figure 2.1 illustrates the architecture of an end-to-end generative adversarial network (GAN) built for radio-frequency signal generation, which aims to transform frequency-modulated (FM) signals into time-domain waveforms. Recent work develops an end-to-end training framework for frequency-modulated signal generation. The design incorporates a mapping between time-domain waveforms and frequency-modulated values based on the concept of differentiated operators. The framework benefits the joint design of frequency-modulating modules and the waveform generation process. A GAN-based signal-generation methodology addresses the need for wireless-communication signals in several scenarios where modulation formats and carrierfrequencies remain unknown and need to be generated above other signals.

2.2. Cognitive Radio and Spectrum Sensing

Spectrum is a limited natural resource. Consequently, achieving high transmission capacity and high data rates for wireless broadband remains a challenge. Cognitive Radio (CR) is a novel technology that provides an efficient method to exploit spectrum using the concept of opportunistic spectrum access. The role of CR is to combine Artificial Intelligence (AI) power with the cooperative feature of Network Function Virtualization (NFV). Spectrum Sensing (SS) is one of the key enabling technologies of CR, whose duty is to opportunistically detect the existence of primary users (PU) and provide spectrum usage information to the Secondary User (SU) in order to enable them to use free bands without affecting the primary users and other secondary users actively. Spectrum is one of the most limited natural resources. Achieving high data rates for future wireless broadband remains a challenge. Cognitive Radio (CR) provides an efficient method to exploit spectrum using opportunistic spectrum access [3]. The processor is used to upload the first observation data to the cloud while the Working-Mode (WM) becomes MODE I. The processor switches to MODE II and starts spectrum sensing after enough observation data has been gathered to meet the training requirement of the AI model [4].

2.3. IoT Communication Constraints and Opportunities

Internet-of-Things (IoT) devices operate in extremely limited environments where network conditions, traffic patterns, and mobility exhibit dramatic variations. A well-established communication approach in IoT is the exclusive use of low-power wide-area network (LPWAN) technologies such as Long Range (LoRa), Sigfox, and narrowband Internet-of-Things (NB-IoT). Various AI-assisted strategies are proposed to enhance the capacity of networks or optimize system adaptation based on the traffic patterns. The batteries of IoT devices are often not easily replaceable and could only be charged through event-based energy-harvesting mechanisms such as ambient light or kinetic energy collection. The absence of charging opportunities restricts the lifetime of IoT devices to at most a few years, which still necessitates a reduction of energy consumption for prolonging their useful lifetime. Traffic and pattern, latency requirement, energy consumption, and anti-jamming capacity are the most crucial parameters in deciding the proper scheduling and communication approaches in IoT systems [5]. The devices with low latency and energy-demanding applications are allowed to communicate with high data-rate or on-demand scheduling, whereas those with long latency tolerating and low-requirement services are permitted to adopt very small data size as traffic and a high duty-cycle be utilized to maintain reliable connectivity [6].

3. AI-POWERED NETWORK MANAGEMENT FOR 5G/6G

The fifth-generation (5G) communication system is designed to support enhanced mobile broadband applications, ultra-reliable low-latency communications, and massive machine-type communications. It aims to provide higher communication data rates, decrease latency, improve energy efficiency, increase connection density, and ensure end-to-end security in smart city communications. These features make 5G a foundational technology for moving toward the sixth-generation (6G) communication system, which is expected to enable new service paradigms such as human-in-the-loop, machine-to-humans, and animal and things (*e.g.* robots, satellites, drones, and vehicles) communication. A seamless connection among 5G, 6G, and beyond communication systems is also essential.

The open radio access network (Open RAN) concept is becoming a significant focus of the mobile wireless communication industry and academia. Open RAN exploits the cloudification of a 4G/5G network architecture, introduces a separation of all hardware and software, and allows the decoupling of hardware vendors from service-provider-specific software by adopting Open RAN specifications. Artificial intelligence (AI), together with Open RAN, is envisaged as a fundamental enabler to efficiently orchestrate, plan, configure, and manage large-scale, ultra-dense, highly heterogeneous transport and radio access networks for next-generation wireless communication systems. Such systems include 5G/6G, sub-THz, high-frequency terahertz, millimetre-wave, and lower-frequency sub-Gigahertz communication systems [7]. Consequently, AI-based full-life-cycle management, resource provisioning (including spectrum, energy, connectivity, and computation), proactive and fast failure detection, and recovery will accelerate the deployment of pervasive AI-enabled Open RAN systems in next-generation communication networks [8]. These systems span 5G consumer and industrial applications [9].

3.1. Network Virtualization and Slicing

Network slicing and orchestration techniques enable a network operator to offer multiple virtual networks on communication infrastructure that competes and ambient different applications. Network slicing solutions leverage data-driven approaches such as deep learning and reinforcement learning support data different network management tasks including slice creation, admission control, policy enforcement, user association, name resolution, and slice balancing [10].

3.2. AI-Driven Resource Allocation and Orchestration

Next-generation networks must manage diverse services, such as enhanced mobile broadband, ultra-reliable low-latency communication, and massive machine-type communications. These heterogeneous devices require intelligent, flexible resource allocation to respond adequately to network dynamics. 5G and upcoming 6G networks must therefore allocate resources efficiently across data streams and transmissions to maintain quality of service, reliability, and robustness [7]. Artificial intelligence (AI)—especially machine learning (ML)—offers promising tools for intelligent network management, enabling network entities to learn environment parameters such as traffic demand and network state to improve efficiency and stability. Research thus far, which has helped pave the way for AI-driven systems, has focused largely on radio resource allocation, device-to-device communications, spectrum access, energy efficiency, and application-aware resource allocation in heterogeneous networks. Many distributed algorithms allow individual base stations to learn independently, without sharing sensitive data. Deep learning has been widely employed for various layers of the network stack, enhancing resource management across perspectives such as link adaptation, bandwidth allocation, mode selection, and power control. AI techniques also find interest in a growing number of use cases, from mobile broadband and tactile Internet to unmanned aerial vehicles/the aerial network and heterogeneous cellular networks. The development of deep reinforcement learning (DRL) solutions has significantly improved delay performance in latency-sensitive resource-allocation problems. Yet challenges and open issues remain in deploying AI-enabled wireless networks [11].

Efficient, objective, evidence-based scholarly prose with formal structure and clear argumentation; maintain an academic tone and emphasize rigorous analysis of intelligent signal processing, AI-powered network management for 5G/6G, cognitive radio, IoT, deep learning for signal analysis, communication security, and AI-driven virtualization, linking AI innovations to real-world communication challenges.

3.3. Anomaly Detection and Security in Next-Generation Networks

Next-generation networks confront increasingly complex and diverse security requirements as they evolve toward more flexible and heterogeneous architectures. At the same time, malicious actors are developing advanced offensive strategies to exploit vulnerabilities, either directly targeting the physical layer, software, or firmware of connected devices or undermining network protocols. Consequently, anomaly detection, a critical prerequisite for proactive threat response, remains a core focus of research. Various signals may indicate the deployment of malicious software (malware) capable of launching distributed denial-of-service (DDoS) attacks, unauthorized surreptitious state manipulation (*e.g.*, pipe-lining), or data exfiltration via covert data-pilfering channel establishment [12]. Therefore, the design of robust, low-complexity, low-power, and accurate anomaly-detection algorithms is an active area of investigation.

Security-by-design principles, integrated into the system development life cycle from the initial phases, significantly strengthen overall resilience. AI/ML-driven monitoring, incident response, and continuous resilience enhancement facilitate protection against zero-day vulnerabilities by enhancing software safety and increasing the cost and effort required to compromise the target device. Security attacks introduce continuous dynamics in systems, demanding personalized responses. A straightforward approach, such as a rule-based engine with predefined countermeasures, is often insufficient; complementary AI-driven security architectures for timely, lightweight, and context-aware detection and response are valuable [13, 14].

4. DEEP LEARNING ARCHITECTURES FOR COMMUNICATION SYSTEMS

Next-generation communication systems must adapt to ever-increasing traffic demands, heterogeneous technologies, and novel use cases. These systems, therefore, require intelligent solutions for both signal processing and network management. While much progress has been made in both areas, the link between AI-driven signal processing and AI-enabled network management remains underexplored. The network must also be taken into account in the design of the signal-processing module.

The intelligent signal processing and AI-enabled network management concepts are closely related because they target the same goal: facilitating the establishment or enhancement of end-to-end links between users and services. However, the information flow for the two domains is different; the accuracy of the signal-processing module can affect network management, and vice versa. Consequently, it is imperative that these two domains be jointly considered in next-generation network design.

Intelligent signal processing encompasses several signal-processing algorithms involved in the transmission/reception of a communication signal [15]. Traditionally, a transceiver, which modulates a source signal into a wave suitable for transmission over a channel at the transmitter and extracts the source signal from the received wave at the receiver, is designed according to certain performance metrics based on prior knowledge of the source and channel. The performance metrics can be link-level or system-level objectives. The transceiver design process consists of a combination of source signal encoding and channel coding to equip the source information, data and service descriptions, or predefined objectives with appropriate codes or specific resource schedulers.

4.1. End-to-End Communication System Design

Signals conveyed through wireless channels such as satellite, LTE, and Wi-Fi are affected by noise and interference. To alleviate the impact of adverse effects including interference and multipath fading, robust signal processing technologies are needed. Wireless radio signals are subsequently demodulated and decoded before being transformed into higher layers such as an IP packet. Original end-to-end learning schemes with deep neural network (DNN) architectures can be used to purely learn transmission. A differentiable channel modulation model converts symbols to waveforms through one or multiple signals. A simple Pilot-Symbol-Assisted-Modulation (PSAM) architecture enables precise channel estimation while avoiding extra information insertion. Conventional end-to-end schemes feed the original waveform and do not yield satisfactory performance since the signal of interest can be masked by other signals.

Physical layer procedures such as channel estimation, demodulation, and reconstruction based on Modulation Classification (MC) are required before using higher layer methods. Signals transmitted through the same or adjacent spectrum bands suppress the light of modulation information and add difficulty in classification. The original architecture can learn to filter unnecessary information but neuronal interference among multiple tasks limits performance improvement. The original waveform of the signal may deviate from the reference waveform during transmission, leading to potential signal loss and performance degradation. Five additional scenarios have been simulated to prove architecture adaptability [2].

4.2. Reinforcement Learning for Adaptive Transmission

Reinforcement learning (RL) formulates the control problem as a Markov Decision Process (MDP) to determine the optimal transmission policy for effective resource utilization in future wireless communication systems [16]. An MDP comprises five components: a state space capturing the environment's characteristics, an action space representing actions the system can take, a reward function indicating the quality of the transmission, and the state transition probability determining the likelihood of transitioning from one state to another after taking a certain action. On account of the complexity, high-dimensionality and nonstationarity of the state space, such systems are non-trivial to formulate as MDPs. Consequently, the exploration-exploitation dilemma, the off-policy nature of gathered data, and the design of a reward structure remain challenging. These obstacles must be addressed to achieve satisfactory performance [17]. Several adaptive transmission scenarios have been investigated, such as adaptive modulation and coding (AMC), power control and scheduling, where it has been demonstrated that RL outperforms other cross-layer and heuristic-based solutions.

4.3. Generative and Self-Supervised Models in Signal Processing

Training signal-processing models on pairs of data can be labor-intensive, demanding both time and resources to gather appropriate datasets. Self-supervised training and generative models enable training on sparse datasets, which tools such as ChatGPT, images, and conventional datasets can alleviate. Yet, the generative models remain at the research stage and their robustness, sample efficiency, and deployment in communications still require evaluation.

Generative models, *e.g*. Generative Adversarial Networks (GANs) and diffusion models, capture the statistical properties of data and permit data augmentation. Such models can augment incomplete datasets through noise generation; reconstruct missing portions; and simulate additional transients, making GANs useful in filmmaking. In time-dependent channels, GANs model the temporal structure of packages and assist in channel modelling. Generative models can also simulate intermediate statuses and comply with regulatory frameworks in both spectrum sharing and control. [18]

5. COGNITIVE RADIO FOR DYNAMIC SPECTRUM ACCESS

Dynamic spectrum access (DSA) has emerged as an effective approach to alleviate spectrum scarcity by allowing unlicensed secondary users to opportunistically access licensed frequency bands without interfering with the activities of licensed primary users [19]. Licensing schemes are thus transitioning from a static, long-term, exclusive-use model towards more flexible arrangements, permitting different levels of sharing depending on the regulatory framework in force. Cognitive radio (CR) technology holds the potential to become a key enabler for DSA by equipping secondary users with the means to monitor spectrum availability and coordinate their access according to the spectrum sharing model in place [4].

Artificial intelligence (AI) and machine learning (ML) techniques are being increasingly leveraged to enable the automatic learning of spectrum sensing policies, allowing the cognitive cycle to adapt to variations in the RF environment [1]. Of particular interest to next-generation communication systems, deep reinforcement learning (DRL) is being investigated for the formulation of intelligent spectrum management algorithms.

Policy-based spectrum management relies on a global observation of the environment for aggregated input. Upon receiving this input, the agent selects a spectrum management action and receives an associated reward. The policy function governing the agent's behaviour is gradually improved through trial-and-error learning in an attempt to maximally accumulate cumulative long-term reward. Restoring the initial RF environment following an interruption observed at either the environmental or the cognitive radio environment can be addressed as a fully observable Markov decision process (MDP).

5.1. Spectrum Sharing Protocols and Regulatory Considerations

Spectrum sharing has emerged as a significant approach to enhance spectrum utilization in wireless networks. To provide a broad overview, sharing protocols are classified into primary and secondary sharing, respectively controlled by a governmental or a regulatory authority [20].

In governmental primary sharing, sharing may be based on geographical regions. Incumbents remain the owners of the spectrum band, while new users can obtain a license to access spectrum bands in less-used regions. In this case, managers are authorized by governmental authorities to adjust the allocation of spectrum either for legal users or shadow users. The communication in these networks is achieved through dedicated stations, where each user is assigned to specific stations.

In regulatory primary sharing, the rules can be set either on a grading basis, or in a centralized or decentralized manner. The primary regulator is in charge of monitoring the channels occupied by the legal users. Additional defined parameters indicate the permissible level of interference for the network to remain under control. In some situations, sharing may also occur during active time slots for both licensed and shadow users. The sharing may occur independently among locations or users, where the same logical frequency can be utilized in multiple regions whenever their distances are sufficiently apart.

Systems that rely on intelligent secondary sharing encompass all semi-dynamic and fully dynamic approaches, where incumbents have the complete authority to observe the status of the entire frequency band and make adaptations without prior notifications. In addition, consumers own the radio resources with which to receive service from the incumbent, and the sharing can be performed at various layers, such as spectrum, slots, codes and systems. With time, it is foreseen that the operation will be extended towards automatic models.

Within spectrum allocation, yet another facet of sharing is regulation compliance, which provides an associated evolution on top of the aforementioned policies in a highly applicable manner. Identification of the sharing links occurs at the channel layer, where resource groups are appointed in accordance with regulatory activities. The channel conditions may differ across time slots, and an available vacant channel may not imply that it suffices to correspond with the designated policy rules; a complete assertion on the sharing status thus becomes indispensable.

In the spectrum sharing framework, the two-tier concept introduces significant modifications to cooperation mechanisms. When a network has access to multiple licensed channels, the flexibility of coordination can be preserved while still fulfilling all specified criteria [21].

5.2. Learning-Based Spectrum Management

Artificial intelligence (AI) is poised to play a fundamental role in the evolution of wireless technology. Future wireless networks, including 5G and 6G, will support a plethora of services such as enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (URLLC), and massive machine-type communications (mMTC) [7]. These heterogeneous devices will demand intelligent resource allocation strategies to address their diverse Quality-of-Service (QoS) requirements. Also, the learning capabilities related to the changeable nature of the wireless environment give an edge to AI-enabled networks over their predecessors [1]. Published efforts revolve around the following subjects: radio resource allocation, device-to-device communications, spectrum access, and network deployment; and the deep-learning paradigm has been extensively adopted throughout. Distributed algorithms allow each base station to learn resource parameters independently, thus altering requirements on shut-down pre-configuration for deployment. A deep reinforcement-learning resource allocation solution has been demonstrated to outperform conventional methods in terms of delay performance.

Cognitive radio (CR) technology is paramount for spectrum-efficient dynamic spectrum access in beyond 5G networks. Machine learning (ML) and reinforcement learning (RL) are the most promising alternatives for the next generation of spectrum management. Learning-based techniques on spectrum allocation, sensing, and access have been proposed to adaptively adjust the operating policy in response to the changeable environment. Such approaches try to determine the appropriate distribution of the spectrum across the available channels by modelling the problem as a multi-armed bandit, thereby automatically selecting new channels to monitor or to transmit while satisfying given constraints. They converge towards an optimal allocation and demonstrate advantageous adaptability to a non-stationary environment and resilience against adversarial situations.

6. AI AND SECURITY IN COMMUNICATION SYSTEMS

Achieving security in communication systems constitutes a pivotal challenge for artificial intelligence (AI) and machine learning (ML); necessitating deliberate investigation into threat modeling, attacks, defense strategies, and mission objectives relevant to various transmission scenarios. Automated methods for flagging (anomaly detection) also take on major significance, given that cybercriminals routinely modify their tactics to evade detection by conventional means [2]. In the context of mobile systems, which rely on precious resources to be configured iteratively after large temporal longing, the issue of anomaly detection continues to gain traction for violation of usage patterns or communications. The provision of data privacy constitutes another major concern; it may suffice to disclose aggregate or essential information yet sustain substantial threat levels that data remain discernible to the adversary [22]. Privacy-preserving AI and learning without data have accordingly captured attention.

AI enhances physical-layer secrecy and integrity, expands protection against jamming, and enables dramatization of one-way leakage reduction at the receiver. When eavesdropping in MIMO systems, for instance, AI achieves secrecy enhancement, jamming-defended communication, and leakage-margin minimization. AI algorithms suffice to enforce linear (alternating) secrecy-encoding matrix manipulation, polarization-design choices being a case in point.

Security parallels performance, forming a dual mission to be undertaken simultaneously. Analytical measures are used to set performance and security thresholds; accordingly, the two measurements are interconnected via introduction of joint-success rates or through quantification of losses suffered by either side within specific conditions. Physical-layer spaces thereby lend themselves to security-analysis explorations, along with the extent to which safeguarding against one attacks cyberhygiene enables threats to be suppressed more readily against the other. The academic literature affords precious little information on risk quantification, owing to organic dynamics between two multitude spaces; without the degree of challenge takes place for further mathematical representation, as guaranteed to occur when information-theoretic notions engage with those grounded in performance/communication-engineering constraints. Fundamental notions of physical-layer security and actively jamming-resistant are thus subsumed—major motivations for pursuing AI-enabled modelling are thereby integrated, embracing data-driven ML and related fields that have experienced concurrent rise across these last 20 years.

6.1. Physical Layer Security with AI

The physical layer of communication systems represents a critical part that need to carefully protected against eavesdropping attacks. Communications security can be enhanced by increasing the use of channel coding, digital modulation and transceiver design, all of which adds inevitable complexity to the communication system. Physical layer security (PLS) has emerged as complementary solution to cryptography-based security, and guarantee secrecy irrespective of any cryptographic key generation procedure. PLS establish a lossless noiseless wiretap channel model to analyse security performance quantitively. Nevertheless, the traditional security problem at physical layer focuses on secrecy rate maximisation under perfect channel state information (CSI) over the main and wiretap link. However, the wireless channel is random and time-varying in nature. Consequently, artificial-intelligence- (AI-) and machine-learning- (ML-) based technologies have been introduced to enhance the design, performance and intelligence of PLS in the physical layer. The audit of the recent trends in signal detection, channel estimation, spectrum- and power-allocation, and jamming-interference-resistance have been concentrated on by AI and ML. Moreover, the techniques are further introduced into multi-node protection for dynamic satellite communication to boost landing-security-level in satellite-based 5 G system. The domain of nonlinear signal has been discussed whereby community detection corresponding to the non-linear signal relies on deep-learning-based decision and multi-domain quantification also have been presenting.

6.2. Adversarial Robustness in Signal Processing

Deep neural networks (DNNs) have recently enabled impressive breakthroughs in numerous fields, including wireless communications. For example, DNNs have been successfully deployed for modulation recognition, where the objective is to identify the modulation scheme used to transmit information over a communication channel. Despite their remarkable performance, DNN-based models are also known to be vulnerable to adversarial examples, which are typically small input perturbations generated to deceive the model at test time. For modulation recognition tasks, various studies illustrate that DNNs trained on unperturbed samples can be easily fooled by imperceptible adversarial perturbations. This vulnerability introduces security concerns in wireless communications because an attacker could apply adversarial perturbations to a transmitted signal to mislead the receiver. Such attacks represent a new and open attack vector in communications, alongside conventional denial-of-service attacks such as jamming or interference.

The same concern applies to other communication tasks, such as channel estimation and direction-of-arrival estimation. Consequently, the robustness of DNN-based systems against adversarial perturbations needs to be strengthened. Because traditional model-based approaches already deliver very high performance, it is also of interest to examine the comparative robustness between DNNs and traditional approaches. Evaluating robustness in this context raises various questions, including characterizing adversarial signals and devising suitable defense mechanisms, as well as defining appropriate robustness metrics.

6.3. Privacy-Ppreserving AI for IoT and Networks

Privacy is a crucial challenge in the Internet of Things (IoT) and network communication. Privacy-preserving models, such as federated learning, secure multi-party computation, and differential privacy, are used to protect sensitive data. In IoT and telecommunication networks, smart connected devices, equipment, and machines communicate sensitive information, such as location, routing, and activity. Protecting the privacy of such information while still allowing for the completion of data-dependent tasks is a vital element of designing a communication system.

Federated learning, secure multi-party computation, and differential privacy are effective methods for preserving privacy while training artificial intelligence systems [23]. Federated learning allows multiple clients to collaboratively learn a shared global model while keeping their data local. It trains the model on each client, requiring minimal data transfer from the clients and only sharing their model updates with the server. Secure multi-party computation enables a group of clients to jointly compute a function over their inputs while keeping them private from each other. Differential privacy provides formal guarantees on the privacy of the participants' data by adding noise to an output.

Federated learning incurs minimal extra utility degradation; thus, it is often preferred when privacy is a concern or sensitive data is available. Evolutionary routes are followed [2]. The evolution of intelligent information and communications systems under untrusted or partially trusted settings will provide assurance for future advanced communication systems. Collaboration will focus on more domain knowledge-backed architectural search in the emerging intelligent system era. Such privacy-preserving AI architecture will enjoy a much wider safety net and greatly benefit the advanced development of intelligent and AI–native next-generation intelligent information and communications systems.

7. AI-DRIVEN VIRTUALIZATION TECHNOLOGIES

The growing complexity and heterogeneity of modern networks and the rapid expansion of connected devices have led to an increasing urgency for adaptable infrastructures. Virtualization techniques such as Network Function Virtualization (NFV) and Software-Defined Networking (SDN) have emerged to tackle these concerns, enabling flexible and efficient network service management. These technologies offer the capability to deliver fine-grained multi-tenant, multi-service, and multi-domain services, leading to the concept of network slicing [24]. Virtualized networking and artificial intelligence (AI) are now actively being combined to better address these resources, performance, flexibility, security and scaling management challenges [25].

The different layers of AI network management raise the need to determine the appropriate locations for applying AI models. In a traditional infrastructure, the core is often the primary AI execution domain. NFV architecture facilitates flexible service chaining and intelligent lifecycle management to improve quality and maintain service-level agreements (SLAs). AI-based orchestrators defined at the control plane automatically configure different virtualized functions in the data plane according to the specific characteristics of requests and slice arrangements. However, a significant latency-reliability trade-off arises due to the distance between endpoints and the core network, necessitating a residual accuracy-delayed-allowed coordination scheme that adapts the computing strategy to provide differentiated services according to SLA constraints.

7.1. Network Function Virtualization and AI Orchestration

Network Function Virtualization (NFV) and AI-based orchestration enable the separation of networking infrastructure from service deployment, unlocking agile resource management in next-generation networks [26]. In NFV, virtual network function instances are provisioned on servers via a control plane that dynamically creates an ordered chain of connected functions to handle user traffic. Tight coupling between hardware and software functions hampers flexible resource allocation. Virtualized functions and service chaining enhance resource utilization.

AI-driven resource allocation across multiple slices improves isolation and quality-of-experience guarantees. Adjusting the number of function instances is a direct means to tailor resources for each slice, influencing resource consumption and service quality. Scheduling new requests while satisfying user-demand patterns emerges as a critical cross-layer challenge for next-generation networks.

7.2. Edge Intelligence and Distributed Inference

To address the burgeoning demand for low-latency, high-bandwidth, and intelligent services supported by artificial intelligence (AI), sophisticated machine learning, and artificial intelligence (AI) techniques associated with next-generation wireless communication networks, paradigm-shifting operations at unprecedented speeds and accuracy levels are required. Mobile edge computation and distributed inference are promising solutions that enable collaborative processing among devices, driving the migration from cloud-enabled to edge-assisted machine-oriented communication networks. To mitigate latency incurred by distributed transmission and ensure an optimal latency-accuracy trade-off, a generic edge-cloud computing framework architecture and cooperative deployment strategies have been proposed. Collaborative outsourcing of computation tasks can achieve the model-parallel distributed machine learning paradigm, in which a model is split into several segments, and transference of intermediate values constitutes the primary communication bottleneck limiting the gains provided by widespread-edge inference and distributed learning [27].

7.3. Federated Learning for Collaborative Network Management

Next-generation wireless systems encompass high-bandwidth, low-latency, large-traffic, and ultra-reliable networks that enable a wide range of applications, such as remote surgery, digital twins, and augmented reality. The key challenge for a collaborative network management is how to leverage collected information at a base station (BS) to train a model collaboratively without knowing the raw data from users. Federated learning (FL), which is a paradigm for distributed processing that accommodates collaborative machine learning in such settings, is a promising solution. An multiuser open radio access network (O-RAN)-based architecture improves communication efficiency and reduces latency through distributed spectral learning at BSs, leveraging existing libraries and applying lightweight methods [28].

8. CHALLENGES, EVALUATION, AND BENCHMARKING

Intelligent signal processing and AI-driven network management for 5G/6G, cognitive radio, the IoT, communication security, and virtualization offer groundbreaking solutions for contemporary communication challenges. All of these areas are still nascent and fraught with difficulties, which include evaluation, reproducibility, benchmarking, deployment, and standards.

The efficacy of intelligent signal processing and network management depends on multiple attributes: accuracy, latency, energy consumption, reliability, robustness, and fairness. Standardized metrics and benchmarking protocols are urgently needed to assess the value of different approaches [2]. Existing datasets fall short in coverage and quality, and even publicly available examples—such as the IEEE 1686-2020 data set for physical layer security and the WISER 2020 and WISER 2022 data sets for wideband spectrum-sensing—have not all been subjected to reproducibility checks. The definition of a minimal set of well-documented baseline experiments further supports reproducibility [7].

Field trials highlight crucial deployment challenges, since the potential of intelligent signal processing and AI-assisted networks remains unrealized in commercial systems [1]. Uncertainty spans standards, interfaces, and equipment availability, while the risk of substantial investment without guaranteed returns is a significant disincentive for operators.

8.1. Evaluation Metrics for AI-Driven Communication

Accurate evaluation of AI-driven communication solutions relies on appropriate indicators, protocols, datasets, and corresponding methodologies. Several performance metrics can be adapted from the communication domain to quantitate AI solutions integrated into 5G and beyond RANs, including:

- **Accuracy** quantifies the capability of a system to process and generate meaningful information, consistently matching the expected output and supporting intelligent communication. - **Latency** is the time period during which input information passes through a system, including potential output delays, driving the need for computational resources and schedu3d801820-2d0b-4c7c-add3-276cf06ec7cfg. Shorter latency fosters higher system capacity in interactive applications. - **Energy** consumption, either total or per unit of transported information, constitutes an important performance metric for battery-powered UEs, IoT devices, and embedded solutions. - **Reliability** describes the capability of a system to achieve a user-defined error rate, encompassing access, service, and delivery at packet, frame, and bit levels. - **Robustness** reveals the performance drop of a system under various constraints, such as operating with incomplete or incorrect knowledge. The development of AI-powered solutions must emphasise this attribute. - **Fairness** conveys the extent to which servicing multiple users provides equitable performance across several dimensions, including latency, error rate, capacity, and service quality. [29]

8.2. Datasets, Reproducibility, and Benchmark Suites

Over the past decade, machine learning and, more recently, deep learning have made headway into the domain of communication systems. In the early days, the community focused on developing solutions for specific communication problems, establishing a trend that continues to this day. As a result, a number of works concerning benchmarks, datasets, metrics, and testbeds could be found in the literature, all with a view to facilitating the fast evaluation, comparison, and deployment of AI-based methodologies.

Several representative datasets covering relevant communication scenarios have been released in the public domain. Both the communication community and public organizations advocate for a minimum level of quality in datasets and underline the importance of reproducibility in experimental studies. It is therefore essential to define crucial aspects like the detailed specification and proper generation of the datasets themselves and the reporting of the experimental set-up, codes, metrics, baselines, and pre-trained models.

A survey of AI-driven solutions for communication problems concludes with some important pointers for evaluating and benchmarking such solutions. It indicates the need for a consolidated framework that encompasses all the key factors involved in communication-related AI techniques in order to avoid misinterpretations that could severely impair future applications and developments in the field. [30]

8.3. Deployment Considerations and Standards

Next-generation mobile communications enable a plethora of applications and use cases characterized by stringent and diverse requirements. Such flexibility can be achieved through intelligent management of network resources and automated connection set-up based on knowledge of the communication context [1]. A viable approach towards AI-driven signal processing and subsequent AI-powered resource management for 5G/6G is illustrated in [31]. However, despite the recognized disruptive potential of AI in mobile communications, certain gaps remain concerning the implementation of these and other visionary concepts in real-world systems. Consequently, consideration on how to deploy advanced AI solutions is critical in ensuring that AI meets the widespread, practical needs of modern networks. Such consideration includes attention to standardization, interoperability across networks and systems, practicability of the various RAN AI concept and consideration of trends in services, devices, content and user behaviour.

9. CASE STUDIES AND REAL-WORLD APPLICATIONS

Next-generation communication systems such as 5G/6G networks, the Internet of Things (IoT), and artificial intelligence (AI)-enhanced smart factories apply intelligent signal processing and AI-powered network management technologies to address significant telecommunications challenges. Intelligent signal processing (ISP) aims to adapt signal processing algorithms to the rapidly evolving specifications of communication signals, transmitting and receiving data more efficiently and supporting operations like denoising, modulation detection, and information retrieval [1]. AI-based approaches, specifically deep learning algorithms capable of processing raw signals, have gained attention in environments with high signal complexity at all layers of the communication stack. Widespread use of these solutions increases demand for AI-powered network management to accommodate the corresponding rise in cell density, user number, and electricity consumption [2]. Operators want to ensure high performance with minimal investment, and AI-driven network management simplifies and automates workload planning, monitoring, and adjustment to satisfy service-level agreements and extend the life of existing equipment.

9.1. 5G/6G Network Slicing in Intelligent Manufacturing

Intelligent manufacturing is a major trend in industry 4.0, characterized by highly flexible processes and advanced applications such as augmented reality, autonomous vehicle, and complex machinery and robot operations. The advent of 5G/6G mobile communication technology promotes the growth of intelligent manufacturing. Modern factories integrate sensors, PLC, MES, production monitoring, etc., equipped with wireless access systems for flexible production environments. 5G/6G highly flexible factory communication networks need to deliver multiple QoS guaranteed services simultaneously in a short time to enable parallel control of production by different departments. Wireless communication control signals, large data streams, and real-time video streams are typical data types in intelligent factories.

5G/6G technology provides a viable solution by introducing network slicing, provisioning several virtual networks on a single physical infrastructure to transmit heterogeneous traffic by controlling different transmission parameters for each slice. Flexible slices on intelligent factories, such as large stream data control slice, video stream full monitoring slice, etc., exhibit diverse transmission characteristics. AI (Artificial Intelligent) drives Machine Learning (ML) technologies and has been effective in numerous industries and science fields. Intelligent manufacturing mainly involves addressing how to analyze the communication dynamic characteristics and choose the most suitable slice for various traffic at the device side [32].

9.2. IoT-Driven Smart Cities with AI-Enabled Radios

Data-driven solutions, network infrastructure evolution, and Artificial Intelligence (AI)-assisted technological advancements are driving the quest towards paradigm shifts in wireless communication technologies. Therefore, a fresh perspective on communication requirements is obliged. The heavy workload imposed by the Internet of Things (IoT), 5G, sixth-generation (6G), and Next-generation (NextG) systems, coupled with tighter energy constraints on remote sensing and control applications, is steering transformation efforts towards Lower Power Wide Area Networks (LPWANs) [6]. Deployed nationwide, hybrid Low-Power Wide-Area Networks (Cognitive-LPWANs) integrating Long-Range (LoRa), SigFox and Narrowband-IoT technologies provide meets various-quality-of-service demands required by transmission from individual units. AI-assisted communication algorithms enable smart-interfacing selection. Emerging communication equipment with Artificial Intelligence Module (AI-M) also supports an open environment. Three pilot projects are currently shared on academia and industrial platforms, namely Intelligent Manufacturing, Intelligent Water Conservancy and Jumbo-truck Scheduling. Communication is evolving from information- to service-centric. Quality-of-experience, service-based models and cross-stack optimization from 5G to broader NextG systems will enhance customer experience and actually advance economy [2].

9.3. Secure and Efficient Edge-Assisted Communication

The rapid advancement of the Internet of Things (IoT) greatly increases demand for low-cost, low-power, and low-latency communication systems. Formulating effective transmission schemes to support ultra-low-latency communications while simultaneously minimizing energy consumption poses a critical challenge. In next-generation networks, where the number of devices will reach billions, communication systems are expected to deliver increasingly high spectral efficiency, support more diverse protocols and services, remain flexible to adapt to task specifications, and guarantee security. Addressing these challenges, AI-assisted communication intelligent adaptation techniques facilitate proper updating of protocol or scheme choices based on pre-knowledge and real-time traffic while ensuring resource limits, security, and privacy.

Aided by the growing sensing, communication, and computation capabilities of 5G networks, AI-enabled collaborative IoT technologies have emerged as a powerful approach to shaping the “smart” cities of tomorrow. Several pilots target specific cooperation scenarios—digital twins of urban areas for construction monitoring or self-driving car signalization for traffic management—each contributing to improved city resilience, reduced congestion, and higher carbon-reduction potential. Yet challenges related to an excess of heterogeneous data, privacy, openness, integrity, compatibility, and sharing persist. To address these issues, AI-enabled radios are integrated across multiple network layers to perform communication optimization, collaborative sensing, and intelligent analysis with traffic control and adaptive reconfiguration capabilities.

CONCLUSION

The convergence of artificial intelligence (AI) and communications might significantly improve the efficiency of wireless networks. AI can be seen as a set of algorithms and methodologies that enable machines to learn, reason, and adapt based on data, with neural networks being a common implementation. Intelligent signal processing uses AI to enhance resource usage and service quality in communication systems. Quality of experience, reliability, and end-to-end delay are typical performance indicators. Each component in a wireless network has an impact on the overall quality graph, and very often, it depends on metrics like the signal-to-noise ratio or modulation schemes. Determining how one component influences others is interesting for communication networks. Causality, discovered through correlations over time, can contribute to this goal. AI can also be considered a network objective, as knowledge of the impact of shared components in networked environments is important for configuration [1].

The scientific literature has sequentially described important concepts related to intelligent signal processing and network management. Emerging network typologies such as the Internet of Things (IoT), 5G, and anticipated sixth-generation (6G) innovations emphasize the need for AI since a significant volume of information is generated across many devices, systems, and domains [2]. These trends induce complex management themes forming a major focus for today's operators, manufacturers, business institutions, governments, and academia.

Next-generation wireless networks constitute a crucial component of smart industry applications like intelligent manufacturing, power grid management, automation, and energy control. Distributed components can exhibit sophisticated, nonlinear behaviour. These challenges occur during a transitional phase from fifth-generation specification standards to widespread commercial realizations. The evolution from the current generation toward the next requires a neutral, comprehensive, platform-independent delineation of pivotal concepts within intelligent signal processing and AI-driven network management for 5G, IoT, 6G, and beyond.

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