Conference Paper

Artificial Intelligence in Wireless Communications: An Overview of Present-day Paradigms

Akinsolu, M. O.

Artificial Intelligence in Wireless Communications: An Overview of Present-day Paradigms

Mobayode O. Akinsolu
Faculty of Arts, Computing and Engineering, Wrexham University,
Wrexham, Wales, LL11 2AW, U.K.
mobayode.akinsolu@wrexham.ac.uk or m.o.akinsolu@ieee.org

***Abstract*—The integration of artificial intelligence (AI) into wireless communications is growing rapidly. This growth is primarily driven by machine learning (ML) techniques, which can be broadly categorized into supervised learning, unsupervised learning, and reinforcement learning. Today, AI-based paradigms are transforming the field of wireless communications by enhancing various aspects, from the rapid design and optimization of components and devices to the robust analysis and characterization of entire systems and networks. This includes advanced systems such as present-day fifth-generation mobile (5G) and the upcoming sixth-generation mobile (6G) systems and networks. AI techniques also offer promising solutions to numerous design and development challenges in modern wireless communications. These challenges encompass enhancing power and energy efficiency, meeting stringent performance criteria, and improving the overall reliability of wireless communication devices, systems, and networks. This paper provides an overview of current paradigms demonstrating the application of AI, particularly ML techniques, in wireless communications.**

***Index Terms*—artificial intelligence (AI), machine learning (ML), wireless communications**

I. Introduction

Due to an ever-increasing pace of innovation in computing and digital technologies, artificial intelligence (AI), particularly, its sub-field machine learning (ML) and its broad archetypes continues to find numerous applications in wireless communications. As a result, several methodologies or paradigms have been proposed in the last few decades demonstrating both the potential and practicality of employing AI in wireless communications. One of the primary areas of interest in the last decade includes device and system characterization and optimization [1], [2]. At both the device level and system level, AI, ML, in particular, has seen to the efficient and expedited simulation-driven design and characterization of devices such as antennas, filters, couplers, and other essential components that ensure the optimality of wireless communication systems [2]–[4]. Whole systems in wireless communications such as present-day 5G and future 6G networks have also been improved via robust ML-assisted analysis and optimization to guarantee their availability, security, and reliability [5], [6].

Despite these advances in the application of AI techniques in wireless communications, only a few works in the literature have discussed these applications to proffer generic guidance or rules of thumb for the efficient selection of specific AI methodologies to address target design problems in wireless communications. Some recent works have attempted to bridge this gap by providing insights into the challenges that must be addressed to guarantee the practical implementation of AI in wireless communications, with emphasis on 6G wireless networks [7]. A few others have discussed the role of AI, ML in particular, in bringing about cognition and intelligence in wireless communication systems in terms of self-awareness, self-adaptiveness, proactiveness, and prescriptiveness with a focus on next-generation wireless networks [8]. The significant role of AI in fostering wireless networking in wireless Internet of Things (IoT) and cyber-physical systems (CPSs) has also been reviewed to highlight some recent advances [9].

In this paper, an overview of the latest approaches in the deployment of AI techniques in wireless communications is provided, covering a slightly more specific context in terms of the target application areas, in comparison to existing works in the literature such as [7]–[9]. This overview is envisaged to do the following:

- Equip researchers with the latest insights across the several domains of wireless communication in which AI techniques are being utilized to facilitate further research and development activities in these areas.
- Instigate additional systematic reviews and scoping studies that will proffer guidance notes and/or rules of thumb on how to select, adopt, and enhance available state-of-the-art AI techniques to address present and future design challenges in wireless communications.

The remainder of this paper is organized as follows: the definition of AI and its types are briefly discussed in Section II, present-day applications of AI techniques in wireless communications are discussed in Section III, and the concluding remarks are provided in Section IV.

II. AI

Broadly speaking, AI simply refers to unnatural (i.e., artificial) intelligence. In other words, AI involves creating machines that mimic human functioning, so that the classification of AI systems can be based on how well they can reproduce human capabilities [10], [11]. The inception of contemporary AI is frequently traced back to 1956, when Dartmouth College suggested an academic conference or workshop, coining the

This work has been supported in part by Wrexham University, U.K.

term ”artificial intelligence” [12], [13]. As a concept, AI predates the 1956 Dartmouth College conference or workshop. This is because the notion that the human brain can be mechanized is deeply embedded in the history of human civilization [14], [15]. Many ancient cultures created human-like automata that were thought to possess emotion and reason, and there are numerous myths and legends about statues coming to life [14], [15]. By the first millennium B.C., philosophers all over the world had developed formal methods of reasoning that progressed during the next two millennia B.C. [12], [15], [16]. These advances were mostly pioneered by early experts and thinktanks who sought to represent human thought through symbols, thereby laying the groundwork for AI concepts like general knowledge representation [12], [15], [16].

A. Types of AI

AI systems are generally classified based on their capability and functionality (see Fig. 1). In terms of functionality, AI systems are classified as reactive machines, limited memory machines, theory of mind, and self-aware AI [17], [18]. The earliest forms of AI systems are reactive machines, characterized by their extremely limited capabilities and their imitation of the human mind's ability to react to many stimuli [17], [18]. These AI systems lack memory-based functionality, preventing them from utilizing previously acquired experiences to inform current actions, and relying on memory to enhance their operations [17], [18]. In addition to possessing the capabilities of purely reactive machines, limited memory machines can learn from historical data to make informed decisions [17], [18]. Nearly all existing AI systems available today fall under this category.

Researchers are working to create AI systems that will be more advanced than the current reactive and limited memory machines, commonly referred to as Theory of Mind AI [18].

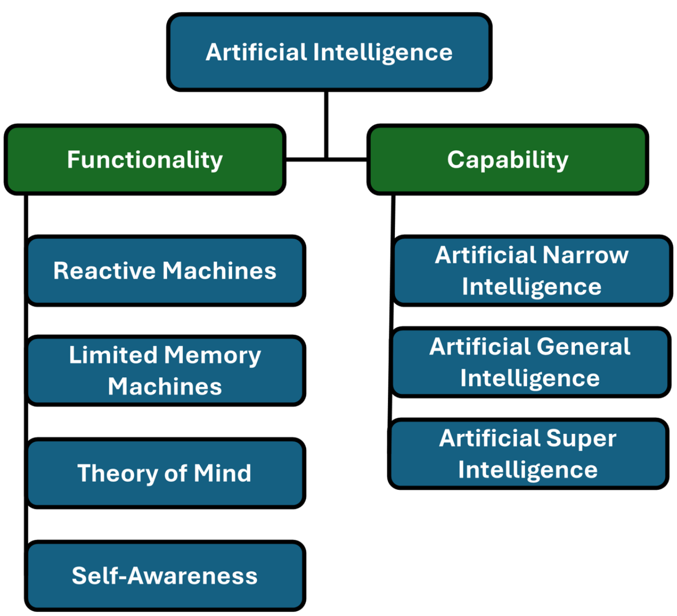

Fig. 1: A typical classification of AI.

By identifying the wants, feelings, beliefs, and mental processes of the creatures it interacts with, this kind of AI seeks to comprehend them better [18]. While top AI researchers are now very interested in this field, other branches of AI will need to improve in order for AI to reach the Theory of Mind stage. This is because AI systems need to view humans as unique individuals impacted by a variety of elements in order to really comprehend human behaviour and cognition [19]. Self-aware AI on the other hand will not only understand and evoke emotions in its interactions but also possess its own emotions, needs, beliefs, and potentially desires [17], [19]. Such advancements could revolutionize various aspects of human life, significantly. However, the development of self-aware AI comes with substantial risks. A self-aware AI might prioritize self-preservation, potentially developing strategies that could surpass human intellect and manipulate or control human activities [20].

In terms of capability, AI technologies are often grouped as artificial narrow intelligence (ANI), artificial general intelligence (AGI), and artificial super intelligence (ASI) [17], [19]. All AI systems created to carry out certain tasks autonomously with human-like capabilities are classified as ANI [21]. AGI on the other hand refers to the capability of an AI agent to learn, perceive, understand, and operate in a manner indistinguishable from a human being [21]. Since both AGI and ASI will be greater than any other kind of intelligence on Earth, ASI will probably be the culmination of AI research. Due to its much larger memory, quicker data processing, improved analytical powers, and stronger decision-making abilities, ASI will not only mimic human intelligence in all its facets but also perform far better than humans [22], [23]. The emergence of AGI and ASI will bring about what is sometimes called the singularity [21], [22].

III. AI in Wireless Communications

Wireless communications has transformed information exchange by enabling data transmission over long distances without the need for physical cables or conductors, utilizing electromagnetic (EM) waves such as satellite signals, microwaves, infrared rays, and radio frequencies [24]. Originating in the 19th century with Heinrich Hertz's demonstration of radio waves and James Clerk Maxwell's EM theory, wireless communications gained practical application through the early radiotelegraph system, paving the way for modern technologies like Bluetooth, wireless fidelity (Wi-Fi), and cellular networks [25]. These advancements have profoundly impacted communication by enhancing mobility and accessibility: Bluetooth facilitates short-range data exchange, Wi-Fi enables wireless internet access over broader areas, and cellular networks support global mobile communications via radio frequencies [26]. Together, these technologies have fostered a connected world where information flows seamlessly across devices and locations, driving innovation in connectivity and accessibility in today's digital world.

The main aspect of AI that features in wireless communications is arguably ML [27], [28]. From evolutionary computation-driven optimization to predictive modeling, ML techniques continue to find numerous applications in wireless communications [27], [28]. By definition, ML as a subfield of AI, involves teaching computers to learn similarly to humans or animals, focusing on learning from experience, or a posteriori knowledge [29]–[31]. Although a priori knowledge may play a role, ML primarily relies on real-world data and observations [29]–[31]. In other words, data analysis and data-driven modeling lie at the core of ML; ML algorithms employ computational intelligence techniques to derive information directly from data without the need for predefined model equations [29]–[31]. As more data samples become accessible to ML algorithms, their performance typically improves adaptively [29]–[31]. This is because ML algorithms mainly operate by identifying inherent patterns within data, thereby enhancing their ability to make informed decisions and predictions based on the insights gained [29], [30].

As stated earlier, wireless communications involves data and information exchange using wireless connectivity. ML is prominently integrated into wireless communications through the analysis of data derived from wireless devices, systems, and networks [27], [28]. In general, ML can be divided into three primary archetypes: reinforcement learning, supervised learning, and unsupervised learning. All three have several uses in wireless communications [27], [28]. Supervised learning involves training models with paired input and output data, which facilitates the accurate prediction of future outcomes, such as the anticipation of wireless communication equipment alarms [32]. Unsupervised learning aims to identify intrinsic characteristics or hidden patterns in data that do not have pre-assigned labels, which is typical in tasks like trend analysis and pattern identification in wireless networks [33], [34]. Reinforcement learning is distinct in its approach, concentrating on how software agents should act within changing environments to ascertain the most beneficial actions [35]. These agents independently establish associations between the states of the environment and the respective actions to take, learning to discern the most rewarding actions through a process of trial and error, as opposed to receiving direct instructions on the actions to perform [35]. A typical application of reinforcement learning in wireless communications would be the dynamic reconfiguration ultra-dense networks for energy-efficient operations of base stations (BSs) [36].

Other recent applications of ML techniques in wireless communications are summarily discussed as follows under the three broad archetypes of ML:

A. Application of Unsupervised Learning in Wireless Communications

Unsupervised learning identifies intrinsic structures or patterns in data, enabling inferences for datasets lacking labeled responses [33]. Generally, when there is no pre-existing data on how the dataset might be grouped, unsupervised learning can be applied [33], [34]. This learning method typically involves cluster analysis or clustering [34]. In cluster analysis, data is divided into clusters (or groups) based on measures of similarity or shared attributes [37]. Clusters are designed so that objects within the same cluster are very similar, while those in different clusters are highly dissimilar. Cluster analysis is a widely used statistical data analysis technique in many different domains, including wireless communications [38]. Generally, cluster analysis can take two forms: soft clustering and hard clustering.

A few recent applications of soft clustering and hard clustering techniques in wireless communications are discussed summarily as follows:

1) Soft Clustering: In soft clustering, each data point can belong to multiple clusters simultaneously [39]. In other words, soft clustering groups data items in such a way that a single data point can exist in several clusters [39]. A few recent applications of soft clustering methodologies in wireless communications are discussed summarily as follows:

The Internet-of-Things (IoT) network's data clustering is examined in [38], which also discusses issues with data volume, communication latency, and information security. Specifically, in [38], a distributed soft clustering (DSC) technique is purpose-built for IoT scenarios, wherein data from multiple clusters may be present on a single IoT node. Since calculating each cluster center via weighted averaging is the main idea of soft clustering, the approach proposed in [38] uses an effective finite-time average-consensus technique. Furthermore, a data variance partitioning-based distributed deterministic initialisation method was presented in [38] to improve stability and prevent poor local solutions. The proposed DSC method performs comparably to its centralized version in terms of convergence and clustering quality, according to experimental data [38]. The proposed DSC method also guarantees stable clustering quality, which is more suitable for IoT networks than most clustering techniques that rely on probabilistic initialization [38]. A real-world case study on clustering analysis of scattered data sets collected by environmental monitoring stations further demonstrates the applicability of the proposed DSC method [38].

Federated learning (FL) has become a key technique in vehicular communication networks, allowing cars to train models together while maintaining data privacy [40]. However, there are significant obstacles brought about by the dynamic topology and rapid mobility of vehicle environments, most notably the additional communication cost needed to exchange model parameters [40]. In [40], a novel framework for decentralized wireless FL that combines 1-bit compressed sensing and soft clustering (SC1BCS-WFL) is proposed to address these problems. When classifying cars or automobiles, this framework takes into account variables including model cosine similarity, speed, characteristics, and vehicle position. It uses a 1-bit compression-based adaptive threshold method to reduce up-link transmission load while maintaining FL performance. In addition, the SC1BCS-WFL framework incorporates an early halting method to avoid wasting communication and processing resources. The simulation outcomes reported in [40] show that the SC1BCS-WFL framework improves FL efficiency in vehicular communication network scenarios, especially when the data is identically distributed and non-independent. The results in [40] also demonstrate that the SC1BCS-WFL framework can achieve high model accuracy with little communication overhead, highlighting its potential for distributed Internet of Vehicles (IoV) situations [40].

In [41], the expectation-maximization framework of the Gaussian mixture model is extended with a new weighted dissimilarity loss. This enhancement integrates graph clustering and centroid-based clustering into a single, coherent framework to fully utilize the benefits of both methods. This method helped to develop a basic "soft" asynchronous hybrid clustering technique. The algorithm may begin as a strictly centroid-based one (k-means), gradually transitioning to a purely graph-based one (basic greedy asynchronous distributed interference avoidance, or GADIA) as it converges. As will be covered later in Section III-A2, a hard variant of this clustering algorithm is also proposed in [41]. Potential uses for the methodology presented in [41] include wireless communication signal processing, among others.

When building wireless sensor networks (WSNs), energy load balancing is a crucial consideration [42]. In order to spread out network energy consumption and increase network lifetime, clustering techniques are frequently used as energy-efficient tactics [42]. An improved soft-k-means (IS-k-means) clustering algorithm is presented in [42] for the purpose of optimizing energy usage among nodes in WSNs. The proposed algorithm enhances the selection of initial cluster centers by incorporating the concepts of clustering by fast search and finding of density peaks and kernel density estimation. It further leverages the adaptability of soft-k-means by reassigning boundary nodes based on membership probabilities to balance cluster sizes. Additionally, the use of multiple cluster heads (multi-CHs) within clusters allowed for a more even distribution of energy consumption. In comparison to current clustering methods, the IS-k-means algorithm greatly delays the first node death, half node death, and final node death, according to extensive simulations conducted under a variety of network conditions [42]. Further evidence of the IS-k-means algorithm's efficiency in balancing energy usage comes from reduced average energy variance and smoother average remaining energy curves between nodes [42].

2) Hard Clustering: In hard clustering, each data point is assigned to only one cluster. This means that data items are grouped in such a way that each point belongs exclusively to a single cluster. A few recent applications of soft clustering methodologies in wireless communications are discussed summarily as follows:

One of the most important issues in routing protocol design is maximising the lifespan of WSNs [43]. To tackle this problem, a number of clustering-based hierarchical routing protocols have been put forth; nevertheless, they frequently overlook the duplicate data that is gathered by adjacent and overlapping nodes [43]. Energy efficiency is decreased by this duplication in data gathering, compilation, and transmission. In [43], an enhanced clustering hierarchy (ECH) approach for WSNs, aiming to extend network lifetime by minimizing data redundancy is proposed. The ECH approach specifically targets neighboring and overlapping nodes that convey duplicate data to cluster heads (CHs) and subsequently to the base station (BS). By employing a sleeping-waking mechanism for these nodes, ECH reduces data redundancy. The method also presents a new technique for CH selection and reduces the distance for data exchange. According to simulation studies, ECH-based routing protocols are more effective than current ones such as low-energy adaptive clustering hierarchy [44]. While the work carried out in [43] has concentrated primarily on static sink networks, it can be easily extended to mobile sink networks, theoretical analysis of network lifetime maximization, and the integration of ECH into present-day routing protocols for WSNs.

A data-centric clustering (DCC) approach for data gathering in resource-constrained machine-to-machine (M2M) communication networks is proposed in [45]. Specifically, a mixed-integer nonlinear programming problem is formulated in [45], to develop a two-tier cluster structure aimed at minimizing total radio resource usage while meeting data fidelity requirements on M2M communication networks. It should be noted that this particular problem entails the joint optimization of cluster formation and power control, that was addressed by splitting it into two smaller problems in [45]. After that, two algorithms were suggested: one for iterative power updates and another for cluster structure search, each solving their respective sub-problems. While the cluster formation sub-problem is (NP)-hard, the power control sub-problem can be optimally solved for any given cluster configuration. To address this issue, an any time, guided, stochastic search algorithm to identify an effective cluster structure without excessive computational complexity was developed in [45]. Evaluations comparing DCC to baseline clustering and non-clustering techniques show significant reductions in transmission energy and radio resource consumption.

Lifetime remains a very critical metric in WSNs. In [46], a clustering protocol based on a meta-heuristic approach (CPMA) is proposed, which prioritizes extending network lifetime. CPMA is composed of two main components. The first component addresses online cluster head selection and network communication coordination, utilizing the harmony search (HS) algorithm to minimize energy dissipation and balance energy usage across the network. The second component tackles the issue of parameter tuning for diverse WSNs by employing the artificial bee colony (ABC) algorithm for offline optimization of key parameters, executed once, prior to network deployment. Comparative analysis with traditional clustering protocols such as particle swarm optimization-based clustering demonstrates that CPMA significantly enhances network lifetime and throughput under various conditions. Additionally, simulations indicate that CPMA exhibits strong adaptability and performs effectively across different network lifetime definitions. The findings in [46] suggest that CPMA is a suitable and efficient protocol for a wide range of WSN applications.

The hard version of the hybrid clustering algorithm proposed in [41] combines the regular k-means (Lloyd method), standard Hopfield neural networks, Bruck's Ln algorithm, and Babadi and Tarokh's fundamental GADIA. This hard clustering method called "hybrid–nongreedy asynchronous clustering (H-NAC), has been used with reputable benchmark datasets to address a range of clustering issues [41]. According to the outcomes of the computer simulations in [41], H-NAC performs better than spectral clustering, k-means clustering, k-GADIA, and the current structured graph learning algorithms [47], highlighting its superior performance among state-of-the-art clustering techniques. Similar to its soft variant, H-NAC can also be applied in wireless communication signal processing, image processing, and computer vision, among others [47].

B. Application of Supervised Learning in Wireless Communications

Supervised learning techniques encompass both classification and regression methods [48]. Classification techniques are used to predict discrete responses, where models are trained to classify data into distinct categories, groups, or classes [48]. On the other hand, regression techniques predict continuous responses [48]. If the data can be tagged, categorized, or separated into specific groups or classes, classification techniques are appropriate [48], [49]. Conversely, if the data consists of real-valued numbers across ranges, regression algorithms are often employed [48], [50]. Utilizing larger training datasets for supervised learning often results in models that generalize accurately and effectively to new data [49].

A few recent applications of regression and classification techniques in wireless communications are discussed summarily as follows:

1) Regression: Also known as regression analysis or regression modeling in statistics, regression is the process of estimating the relationships between a dependent variable (often referred to as the target, outcome variable, or response variable) and one or more independent variables (commonly called features, predictors, or explanatory variables). A few recent applications of regression methods in wireless communications are discussed summarily as follows:

In [51], two state-of-the-art artificial neural network (ANN)-based models for multiple reconfigurable intelligent surface (RIS)-enhanced wireless communication are presented. The first model, called ANN-RIS, employs channel coefficients between the transmitter (TX) and the receiver (RX) as well as between the RIS and the receiver to train itself to anticipate RIS phase shifts. ANN-RX, the second model, employs the transmitted symbol as the output and the baseband received signal as input to detect symbols at the receiver. Mean squared error (MSE) and cross-entropy metrics for ANN-RIS and ANN-RX, respectively, were used to appraise the performance of both models. The bit error rate (BER) of ANN-RX was also assessed for different quantization levels and RIS panel sizes. A comparative study against current techniques shows that the suggested models provide better BER performance.

When it comes to maritime wireless communications, the evaporation duct effect presents serious difficulties [52]. In [52], a new approach for reliably forecasting route loss in evaporation ducts using a deep neural network (DNN) is proposed. Utilizing antenna and ambient factors as inputs, the proposed lightweight model demonstrates natural scenario adaptability. A comparative study shows that the suggested DNN scheme performs better at different frequencies than linear regression models, random forests, and k-nearest neighbor (k-NN) models. The impact of frequency, receiver height, and broadcast distance on DNN prediction accuracy is also investigated in [52]. The simulation results reveal that the DNN scheme achieves good accuracy at low frequencies, but because of its complicated peak areas, it displays a slight reduction at higher frequencies. The recipient height and transmission distance were also ascertained to have negligible effects on the prediction accuracy of the DNN scheme proposed in [52].

For wireless communications using Multi-user Multiple-Input Multiple-Output, or MU-MIMO, channel ageing poses a major challenge [53]. A potential solution to this problem is channel prediction [53]. Due to the complicated structure of wireless channels, modeling errors can cause significant performance deterioration in traditional prediction approaches that frequently rely on parametric models [53]. Because they do not rely on model assumptions, non-parametric regression techniques that are ideal for inferring from complex channel data can be employed as a workaround as demonstrated in [53]. Specifically, in [53], two techniques are adopted: local polynomial regression (LPR), an improved variant of k-NN regression, and its original form. Furthermore, in LPR, the Bayesian information criterion is employed to determine parameters, suggesting local linear regression for real-world uses. Additionally, a pre-processing method for determining the channel's correct singular matrix is offered. Simulation results show that for channel prediction, these non-parametric approaches perform much better than traditional parametric methods [53].

The combined issue of power allocation and uplink-downlink scheduling for multiple control systems interacting over wireless networks is addressed in [54]. To do this, an ML-based method is proposed to handle wireless resource restrictions, where one system is controlled while other systems predict missing state and action information using Gaussian process regression (GPR) in [54]. Since the most recent reception's age-of-information (AoI) determines how credible the prediction is, and transmission power affects successful reception, a network-wide average AoI and transmission power minimization problem are posed and addressed by a dynamic control technique that adheres to communication reliability and control stability restrictions, and uses Lyapunov drift-plus-penalty optimization [54]. Numerical results described in [54] show that the proposed algorithm can consistently operate twice as many actuators as an event-triggered scheduling baseline and eighteen times more than a round-robin scheduling baseline.

The inherent imaginary interference of filter bank multicarrier with offset quadrature amplitude modulation (FBMC-OQAM) systems makes channel estimation approaches for orthogonal frequency division multiplexing systems generally unsuitable for these systems [55]. A novel support vector regression (SVR)-based approach for fading channel estimation in FBMC-OQAM systems is proposed in [55]. With two auxiliary pilots (AP) in the FBMC-OQAM signal, the suggested nonlinear complex SVR algorithm (NCSVR) is designed specifically for this application, and is called AP-NCSVR. The simulation results reported in [55] show that the AP-NCSVR technique is accurate in calculating channel frequency response coefficients using the Jakes fading and vehicular A models. In addition, the AP-NCSVR algorithm outperforms the traditional interpolation technique for both models in terms of BER performance [55].

Wireless technology is being used by medical device manufacturers more and more for convenience, although coexistence issues are brought up by unlicensed radio frequency bands [56]. The U.S. FDA (United States Food and Drug Administration)-recognized ANSI (American National Standards Institute) C63.27 standard covers wireless coexistence evaluation but does not include an estimating technique [56]. To calculate the probability that medical equipment will coexist wirelessly, logistic regression (LR) is adopted in [56]. A ZigBee system under test (SUT) and an IEEE 802.11n Wi-Fi interfering network were included in the test scenario presented in [56]. The performance of the SUT under varied coexistence conditions was described by fitting the LR model. These findings were combined with a Monte Carlo simulation and spectrum survey to evaluate the probability of wireless coexistence for the SUT in a hospital setting.

The ability of wireless communication signals to be detected is becoming ever more crucial due to the growing needs of present-day wireless communications. To tackle this, a novel wireless communication signal identification model known as the AE-ELM algorithm, which blends the features classification powers of the extreme learning machine (ELM) algorithm with the auto-encoder (AE) principles has been proposed in [57]. The results of the performance comparison trials reported in [57] show that the AE-ELM algorithm outperforms conventional algorithms, achieving lower average relative time complexity and BER. Further analysis of the efficacy of the signal detection model based on the fusion method also revealed low detection error rate, indicating exceptional performance. The findings in [57] highlight the AE-ELM-based model's potential in improving wireless communication signal detection.

2) Classification: Classification is typically a predictive modeling problem where a unique class label is predicted for a given set of input data [48]. From a modeling perspective, classification requires a training dataset with numerous sets of inputs and outputs to learn, train, and build models [48]. A classification model then uses this training dataset to determine how to best map examples of input data (i.e., each observation) to specific class labels [48], [49]. The training dataset must be sufficiently representative of the problem and contain numerous examples of each class label [49]. A few recent applications of classification methods in wireless communications are discussed summarily as follows:

To address the issue of limited network observability in congested areas, a two-tier ML-aided traffic steering method is proposed in [58]. The proposed method uses a support vector machine (SVM) for user equipment (UE) classification and ensemble long short-term memory (LSTM) for predicting cell throughput, which informs handover decisions and facilitates proactive resource management [58]. The resulting traffic steering algorithm improved UE distribution across cells, increasing the percentage of cells with the ideal number of UEs [58]. The observed inference delays were also found to be per open radio access network standards, suggesting that the ML-driven method effectively distributes load while minimizing handovers, hence improving both network performance and user experience [58].

Millimeter wave (mmWave) communication holds great potential in fulfilling the demands of 5G and other next-generation cellular networks such as 6G [5]. To overcome the problems of poor coverage and strong penetration attenuation, multi-connectivity ultra-dense mmWave networks that enable users to contact several mmWave BSs at the same time have been investigated in [5]. In [5], the user association problem is identified and formulated as an NP-hard problem to maximize system throughput. To solve it, multi-label classification is employed using binary relevance (BR), ranking by pairwise comparison (RPC), and random k-labELsets (RAKEL) algorithms [5]. The low computational complexity and good optimality of the selected algorithms are demonstrated by the numerical results obtained, where RAKEL had the lowest collision probability and highest subset accuracy [5].

Modulation classification is increasingly important for the rapid deployment of wireless radios in civilian and military applications [59]. While extensive research exists on single-signal transmissions, multi-signal transmission scenarios are less explored [59]. To address this gap, various modulation classification algorithms can be investigated. In [59], a novel algorithm for code-aided modulation classification in multiuser uplink single-carrier frequency division multiple access systems is proposed. This algorithm leverages the channel decoder's soft information to enhance classification performance and is initialized using the maximum-likelihood principle. It employs space-alternating generalized expectation-maximization (SA-GEM) [60], with channel estimation formulated as an auxiliary problem. Simulation results demonstrate that the proposed classification method in [59], outperforms traditional methods reported in [61] and [62], offering superior classification accuracy and reduced processing time.

Continuous phase modulation (CPM) is widely used in wireless communications, particularly satellite systems, because of its significant spectrum and power efficiency [63]. The classification of CPM signal in the context of unknown fading channels has been investigated in [63]. To achieve this, the memory property CPM is utilized to represent time-varying phases of CPM as a hidden Markov model (HMM), and a likelihood-based classifier (LBC) which estimates the unknown HMM parameters using the Baum-Welch (BW) algorithm is adopted [63], [64]. The simulation results reported in [63] demonstrate that the proposed classification method, with appropriate initialization of the unknown fading, achieves a correct classification probability when the SNR is greater than 15 dB in unknown fading channels with a single receiver, outperforming current approaches that use approximate entropy.

The identification and categorization of interference plays a crucial role in the secure transfer of information and the efficiency of wireless communications [65]. Conventional classification methods frequently lack the accuracy required to distinguish and classify different kinds of interference, while deep learning (DL) algorithms are unsuitable for real-time situations since they depend on high-quality training samples and data [65]. A fairly recent approach to tackle these difficulties is proposed in [65], where the denoising diffusion probabilistic model (DDPM) for offline processing of gathered signals is utilized before feature extraction and classification. Using five signal samples, the experimental results reported in [65] show that the proposed approach outperforms both traditional and generative adversarial network (GAN)-based DL methods, achieving a very high accuracy without prior knowledge. In particular, the method in [65] offers a precedent for the use of generative models in signal processing and establishes a new benchmark for highly accurate recognition in practical wireless communication situations.

C. Application of Reinforcement Learning in Wireless Communications

Reinforcement learning involves learning how to map situations to actions to maximize a numerical reward signal [35]. Unlike supervised and unsupervised learning, which often make use of static data, reinforcement learning operates within a dynamic environment, making it a closed-loop problem where the system's actions influence its future inputs [35]. The goal of reinforcement learning is neither to cluster data (as in unsupervised learning) nor to label data (as in supervised learning), but to find the optimal sequence of actions to achieve the best outcome or reward [35]. To accomplish this, reinforcement learning employs an agent to explore, interact with, and learn from the environment [35]. Depending on the agent's familiarity with the environment, reinforcement learning algorithms can be categorized into two types: model-free and model-based [66].

In model-free reinforcement learning, the agent does not require prior knowledge of the environment but can still learn to interact with it, enabling it to work in any environment and learn the optimal policy, assuming it has access to observations, rewards, actions, and sufficient internal states of the environment [67]. In model-based reinforcement learning, the agent uses a model of the environment or part of it to explore without physically taking actions, thereby enhancing the learning process by avoiding known unfavorable areas and focusing on other parts of the environment [67].

Another categorization for reinforcement learning algorithms is dependent on the method used to enhance or optimize the agent's policy, giving rise to on-policy and off-policy reinforcement learning methods that are exemplified in [68], where off-policy deep Q-network (DQN) and on-policy proximal policy optimization (PPO) have been employed to jointly optimize the phase shift of RIS, the positioning of unmanned aerial vehicle (UAV)-RIS, and the scheduling of an IoT device (IoTD) transmissions in large-scale IoT networks.

A few recent applications of on-policy and off-policy reinforcement learning methods in wireless communications are discussed summarily as follows:

1) On-policy Learning: On-policy learning methods aim to evaluate or enhance the policy that is employed for decision-making, which is based on actions taken. A few recent applications of on-policy learning methods in wireless communications are summarily discussed as follows:

By positioning services adjacent to IoT facilities, edge computing is able to effectively address the latency and resource needs of various IoT applications [69]. Sensing-data-driven applications, which rely on sensor data to complete activities, are common in IoT systems [69]. To provide the quality of service (QoS) for these applications, particular caching functions (CFs) in an edge-enabled IoT system are needed to cache essential sensor data [69]. The joint caching and computing service placement (JCCSP) issue has been studied for such applications in [69]. Deep reinforcement learning (DRL) has been used to tackle this problem in [69] because it can adapt to diverse systems with minimal prior information. The proposed DRL-based approach makes use of a policy network based on the encoder-decoder paradigm to handle the varied sizes of JCCSP states and actions that arise from distinct application-related CFs [69]. Next, an on-policy learning method is used to train the policy network [69]. It is worth mentioning that [69] also looked into off-policy learning, as discussed in Section III-C2.

User scheduling, specifically transmission times and powers for AoI minimization in energy harvesting networks, is addressed in [70], highlighting the computational complexity and suitability for ML approaches. In the offline setting, a mixed-integer linear programming (MILP) formulation is used for optimal scheduling, and a near-optimal learning-based algorithm employing a bidirectional LSTM (BiLSTM) network is proposed in [70]. The BiLSTM network effectively learns from time series data, achieving near-optimal performance and better runtime scalability as reported in [70]. For the online setting, a model-free on-policy reinforcement learning approach based on the Markov decision process (MDP) formulation is proposed, using an actor-critic DRL algorithm [70]. The proposed approach is reported to achieve performance comparable to offline results with significantly improved runtime efficiency [70]. The work carried out in [70] demonstrates that ML can effectively solve computationally challenging MILP problems, providing near-optimal solutions with reasonable computational time for moderate-sized wireless systems, and suggests that distributed learning via wireless edge devices may be necessary for large-scale systems.

In the face of several eavesdroppers, a secure routing technique for multihop ad hoc networks is proposed in [71] based on reinforcement learning. Specifically, the secure relay region (SRR), is proposed to illustrate the distribution of relays capable of safely forwarding data in [71]. Then expanding upon this, an SRR-driven on-policy Monte Carlo technique (SRR-driven MC) is developed to expedite routing decision convergence [71]. The computation of the secrecy connection probability, which rates the level of security achieved by various routes, is another consideration in the proposed approach [71]. The outcomes of the simulations reported in [71] show that SRR-driven MC technique quickly and effectively chooses safe routes while remaining resilient to changes in the number of relays that are available over time. In this way, the proposed method in [71] can guarantee secure and dependable communication in dynamic network environments that may be hacked.

2) Off-policy Learning: Off-policy learning evaluates or improves a policy that is distinct from the one that produced the data (i.e., the policy used for value evaluation is different from the one used for action selection). A few recent applications of off-policy learning methods in wireless communications are discussed summarily as follows:

Vehicular ad-hoc wireless communications rely on real-time periodic messages, known as beacons, to enable situational awareness for vehicles, which are crucial for driver safety applications [72]. However, channel overload from periodic beaconing can cause data loss, compromising safety functions, especially during emergencies [72]. For this reason, maintaining efficient congestion control is essential to keeping a portion of the channel free. A joint beaconing rate and transmission power congestion control system is proposed in [72]. Given the non-convex nature of the problem, traditional optimization methods are ineffective, so the problem is modeled using simplified and tractable assumptions resolved through Q-learning within the MDP framework [72]. The proposed MDPRP (MDP rate and power) solution mitigates congestion in a non-cooperative, distributed manner without relying on additional neighbor information, with each vehicle contributing to overall congestion reduction [72]. The simulation results reported in [72] show that MDPRP effectively maintains channel load below the desired levels and achieves favorable packet delivery ratios. The proposed solution's robustness is also evident as it performs well even when initial MDP assumptions are unmet.

Next-generation wireless networks, like the current 5G and upcoming 6G, will integrate high-frequency spectrum exploration with intelligent convergence of radio frequency (RF) and non-RF channels, like optical and visible light communication [6]. Optical attocell (OAC) networks offer an additional layer of connectivity to RF networks, with gigabit-per-second data rates and centimeter-level location precision [6]. On the other hand, difficulties with throughput and latency are caused by directionality, line-of-sight limitations, and sensitivity to user terminal placement and orientation [6]. In [6], mobile heterogeneous networks (HetNets) that integrate indoor OAC using macrocells and femtocells, providing an energy-efficient, low-cost solution that satisfies several IoT service criteria, including data rate, mobility, latency, accuracy, and security have been investigated. Mobility-aware HetNets typically rely on smooth connectivity and appropriate resource allocation, which requires effective handover management in dynamic contexts. A DRL method is proposed in [6] to improve handover characteristics like hysteresis margin and time-to-trigger to overcome this issue. By training a DNN to predict future rewards from states and actions, this model-free, off-policy reinforcement learning approach makes it possible to choose the best course of action. Performance analysis and numerical simulations reported in [6] show how the system's flexibility to changing surroundings and the advantages of enriching the state space are achieved.

Additionally, a twin-delayed (TD) deep deterministic policy gradient (DDPG)-based off-policy training technique was presented in [69] to address the joint caching and computing service placement (JCCSP) problem in edge-enabled IoT systems. This was done to improve training efficiency and experience utilization of the DRL methodology in [69]. To lessen the bias in the Q-value estimate, a weighted average twin-Q-delayed (WATQD) algorithm is included in the suggested DDPG-based approach [69]. The proposed DRL-based JCCSP techniques in [69] obtained converged solutions that are noticeably better than benchmarks, according to the simulation results. In addition to this, the proposed WATQD approach in [69] also shows the potential to improve training stability in comparison to the traditional TD method.

Table I provides a summary of the applications of AI in wireless communications as discussed in this paper. While a broad range of AI technologies, particularly machine learning (ML) techniques, have been employed to characterize, enhance, and optimize the operations of wireless communication systems, as reflected in Table I, challenges related to data integrity and inherent biases in ML methods persist in many of these applications. This is especially critical in real-world safety-sensitive deployments, where the tolerance for errors and biases is extremely limited. As a result, these issues of data integrity and bias are likely to become central to future research, aimed at ensuring greater practical reliability of these methods. Moreover, despite the extensive use of supervised, unsupervised, and reinforcement learning techniques in wireless communications, the application of generative AI techniques remains in its infancy. This presents a promising area for further exploration, particularly in wireless system operations, such as control and supervision, where generative AI may offer significant advancements.

IV. Conclusion

Machine learning (ML), a distinct area of artificial intelligence (AI), has increasingly become integral to advancements in wireless communications. Its adaptability and capacity to analyze large datasets make ML indispensable for various tasks such as trend analysis, pattern recognition, optimization, and predictive modelling in wireless communications. This

TABLE I: Contemporary ML techniques applied in wireless communications.

ML Archetype	ML Techniques and References
1) Unsupervised Learning	• *Soft Clustering:* DSC [38], SC1BCS-WFL [40], k-means+GADIA [41], and IS-k-means [42]. • *Hard Clustering:* ECH [43], DCC [45], CPMA [46] and H-NAC [41].
2) Supervised Learning	• *Regression:* ANN [51], DNN [52], LPR [53], k-NN [53], GPR [54], AP-NCSVR [55], LR [56], and AE-ELM [57]. • *Classification:* SVM + ensemble LSTM [58], BR+RPC+RAKEL [5], SA-GEM [60], LBC [63], and DDPM [65].
3) Reinforcement Learning	• *On-policy Learning:* DRL with Encoder-decoder Model [69], Actor-Critic DRL [70], and SRR-Driven MC [71]. • *Off-policy Learning:* Q-learning [72], DNN [6], and TD+DDPG+WATQD [69].

paper provides an overview of recent ML paradigms employed in wireless communications, as reported in current literature. These paradigms are systematically categorized into the three broad archetypes of ML: reinforcement learning, supervised learning, and unsupervised learning. The approaches discussed are summarized for easy reference. The paper also highlights the significant impact of ML in numerous applications within wireless communications. For instance, ML techniques are being leveraged to optimize performance and improve efficiency in Internet of Things (IoT) networks, Internet of Vehicles (IoV), Wireless Sensor Networks (WSN), millimeter-wave (mmWave) communications, and Machine-to-Machine (M2M) interactions. These examples discussed in this paper underscore the pivotal significance of ML in addressing the challenges and enhancing the capabilities of modern wireless communication systems. As ML continues to evolve, its integration into wireless technologies is expected to drive further innovation, making it a crucial component in the future of wireless communications.

References

[1] E. Pereira, , *et al.*, "A zero-shot learning approach for task allocation optimization in cyber-physical systems," *IEEE Transactions on Industrial Cyber-Physical Systems*, vol. 2, pp. 90–97, 2024.

[2] M. O. Akinsolu, , *et al.*, "A parallel surrogate model assisted evolutionary algorithm for electromagnetic design optimization," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 3, no. 2, pp. 93–105, 2019.

[3] Z. Zhang, , *et al.*, "A surrogate modeling space definition method for efficient filter yield optimization," *IEEE Microwave and Wireless Technology Letters*, vol. 33, no. 6, pp. 631–634, 2023.

[4] N. J. G. Fonseca, , *et al.*, "Additively manufactured waveguide hybrid septum coupler optimized using machine learning," in *2024 18th European Conference on Antennas and Propagation (EuCAP)*, pp. 1–4, 2024.

[5] R. Liu, , *et al.*, "User association for ultra-dense mmwave networks with multi-connectivity: A multi-label classification approach," *IEEE Wireless Communications Letters*, vol. 8, no. 6, pp. 1579–1582, 2019.

[6] S. Shao, , *et al.*, "Self-optimizing data offloading in mobile heterogeneous radio-optical networks: A deep reinforcement learning approach," *IEEE Network*, vol. 36, no. 2, pp. 100–106, 2022.

[7] W. Tong and G. Y. Li, "Nine challenges in artificial intelligence and wireless communications for 6g," *IEEE Wireless Communications*, vol. 29, no. 4, pp. 140–145, 2022.

[8] M. G. Kibria, , *et al.*, "Big data analytics, machine learning, and artificial intelligence in next-generation wireless networks," *IEEE Access*, vol. 6, pp. 32328–32338, 2018.

[9] B. A. Salau, , *et al.*, "Recent advances in artificial intelligence for wireless internet of things and cyber–physical systems: A comprehensive survey," *IEEE Internet of Things Journal*, vol. 9, no. 15, pp. 12916–12930, 2022.

[10] J. H. Korteling, , *et al.*, "Human-versus artificial intelligence," *Frontiers in artificial intelligence*, vol. 4, p. 622364, 2021.

[11] S. Samoili, , *et al.*, *AI Watch. Defining Artificial Intelligence. Towards an operational definition and taxonomy of artificial intelligence*. Seville: European Commission, Joint Research Centre, 2020.

[12] P. J. Bentley, *Artificial Intelligence and Robotics: Ten Short Lessons*. Johns Hopkins University Press, 2020.

[13] J. Harris, "The history of ai rights research," *arXiv preprint arXiv:2208.04714*, 2022.

[14] A. Currie, "The history of robotics." http://www.faculty.ucr.edu/~currie/roboadam.htm, 1999. Acessed:2024-05-30.

[15] B. G. Buchanan, "A (very) brief history of artificial intelligence." https://web.archive.org/web/20070926023314/http://www.aaai.org/AITopics/assets/PDF/AIMag26-04-016.pdf, 2005. Acessed:2024-07-18.

[16] H. Redner, *Beyond Civilization: Society, Culture, and the Individual in the Age of Globalization*. Routledge, 2020.

[17] H. Hassani, , *et al.*, "Artificial intelligence (ai) or intelligence augmentation (ia): what is the future?," *Ai*, vol. 1, no. 2, p. 8, 2020.

[18] J. Schossau and A. Hintze, "Towards a theory of mind for artificial intelligence agents," in *Artificial Life Conference Proceedings 35*, vol. 2023, p. 21, MIT Press One Rogers Street, Cambridge, MA 02142-1209, USA journals-info . . . , 2023.

[19] E. Pelivani and B. Cico, "Toward self-aware machines: Insights of causal reasoning in artificial intelligence," in *2021 International Conference on Information Technologies (InfoTech)*, pp. 1–4, 2021.

[20] A. Nowak, , *et al.*, "Assessing artificial intelligence for humanity: Will ai be the our biggest ever advance ? or the biggest threat [opinion]," *IEEE Technology and Society Magazine*, vol. 37, no. 4, pp. 26–34, 2018.

[21] R. Fjelland, "Why general artificial intelligence will not be realized," *Humanities and Social Sciences Communications*, vol. 7, no. 1, pp. 1–9, 2020.

[22] C. Mercer, , *et al.*, "Superintelligence: Bringing on the singularity," *Religion and the Technological Future: An Introduction to Biohacking, Artificial Intelligence, and Transhumanism*, pp. 181–204, 2021.

[23] P. Radanliev, , *et al.*, "Super-forecasting the 'technological singularity'risks from artificial intelligence," *Evolving Systems*, vol. 13, no. 5, pp. 747–757, 2022.

[24] S. Kumar, *Wireless Communication-the fundamental and advanced concepts*. River Publishers, 2022.

[25] V. L. Patil, *Chronological Developments of Wireless Radio Systems Before World War II*. Springer, 2021.

[26] M. Hassan, *Wireless and mobile networking*. CRC Press, 2022.

[27] Y. Sun *et al.*, "Application of machine learning in wireless networks: Key techniques and open issues," *IEEE Communications Surveys Tutorials*, vol. 21, no. 4, pp. 3072–3108, 2019.

[28] I. Ahmad *et al.*, "Machine learning meets communication networks: Current trends and future challenges," *IEEE Access*, vol. 8, pp. 223418–223460, 2020.

[29] M. I. Jordan and T. M. Mitchell, "Machine learning: Trends, perspectives, and prospects," *Science*, vol. 349, no. 6245, pp. 255–260, 2015.

[30] A. Burkov, *The hundred-page machine learning book*, vol. 1. Andriy Burkov Quebec City, QC, Canada, 2019.

[31] M. P. Deisenroth, A. A. Faisal, and C. S. Ong, *Mathematics for machine learning*. Cambridge University Press, 2020.

[32] M. Boldt *et al.*, "Alarm prediction in cellular base stations using data-driven methods," *IEEE Transactions on Network and Service Management*, vol. 18, no. 2, pp. 1925–1933, 2021.

[33] Z. Ghahramani, "Unsupervised learning," in *Summer school on machine learning*, pp. 72–112, Springer, 2003.

[34] K. Tyagi, , *et al.*, "Unsupervised learning," in *Artificial intelligence and machine learning for edge computing*, pp. 33–52, Elsevier, 2022.

[35] R. S. Sutton and A. G. Barto, *Reinforcement learning: An introduction*. MIT press, 2018.

[36] H. Ju *et al.*, "Energy-efficient ultra-dense network with deep reinforcement learning," *IEEE Transactions on Wireless Communications*, vol. 21, no. 8, pp. 6539–6552, 2022.

[37] A. E. Ezugwu, , *et al.*, "A comprehensive survey of clustering algorithms: State-of-the-art machine learning applications, taxonomy, challenges, and future research prospects," *Engineering Applications of Artificial Intelligence*, vol. 110, p. 104743, 2022.

[38] H. Yu, , *et al.*, "Distributed soft clustering algorithm for iot based on finite time average consensus," *IEEE Internet of Things Journal*, vol. 8, no. 21, pp. 16096–16107, 2021.

[39] M. B. Ferraro and P. Giordani, "Soft clustering," *Wiley Interdisciplinary Reviews: Computational Statistics*, vol. 12, no. 1, p. e1480, 2020.

[40] G. Tan, , *et al.*, "A framework of decentralized federated learning with soft clustering and 1-bit compressed sensing for vehicular networks," *IEEE Internet of Things Journal*, vol. 11, no. 13, pp. 23617–23629, 2024.

[41] Z. Uykan, "Fusion of centroid-based clustering with graph clustering: An expectation-maximization-based hybrid clustering," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 34, no. 8, pp. 4068–4082, 2023.

[42] B. Zhu, , *et al.*, "Improved soft-k-means clustering algorithm for balancing energy consumption in wireless sensor networks," *IEEE Internet of Things Journal*, vol. 8, no. 6, pp. 4868–4881, 2021.

[43] H. El Alami and A. Najid, "Ech: An enhanced clustering hierarchy approach to maximize lifetime of wireless sensor networks," *IEEE Access*, vol. 7, pp. 107142–107153, 2019.

[44] A. Ahmad, , *et al.*, "$(ach)^2$: Routing scheme to maximize lifetime and throughput of wireless sensor networks," *IEEE Sensors Journal*, vol. 14, no. 10, pp. 3516–3532, 2014.

[45] H.-Y. Hsieh, , *et al.*, "Minimizing radio resource usage for machine-to-machine communications through data-centric clustering," *IEEE Transactions on Mobile Computing*, vol. 15, no. 12, pp. 3072–3086, 2016.

[46] Y. Han, , *et al.*, "Clustering the wireless sensor networks: A meta-heuristic approach," *IEEE Access*, vol. 8, pp. 214551–214564, 2020.

[47] Z. Kang, , *et al.*, "Structured graph learning for scalable subspace clustering: From single view to multiview," *IEEE Transactions on Cybernetics*, vol. 52, no. 9, pp. 8976–8986, 2022.

[48] P. Louridas and C. Ebert, "Machine learning," *IEEE Software*, vol. 33, no. 5, pp. 110–115, 2016.

[49] A. O. Sangodoyin *et al.*, "Detection and classification of ddos flooding attacks on software-defined networks: A case study for the application of machine learning," *IEEE Access*, vol. 9, pp. 122495–122508, 2021.

[50] M. O. Akinsolu *et al.*, "Behavioral study of software-defined network parameters using exploratory data analysis and regression-based sensitivity analysis," *Mathematics*, vol. 10, no. 14, p. 2536, 2022.

[51] A. K. Shrivastava *et al.*, "Neural networks-based phase estimation and symbol detection for ris-assisted wireless communications," *IEEE Communications Letters*, vol. 27, no. 12, pp. 3245–3249, 2023.

[52] B. Shu, , *et al.*, "Path loss prediction in evaporation ducts based on deep neural network," *IEEE Antennas and Wireless Propagation Letters*, vol. 23, no. 2, pp. 798–802, 2024.

[53] Z. Xiao, , *et al.*, "Nonparametric regression for mu-mimo channel prediction: From knn to local linear regression," *IEEE Transactions on Wireless Communications*, vol. 23, no. 4, pp. 2784–2795, 2024.

[54] A. M. Girgis, , *et al.*, "Predictive control and communication co-design via two-way gaussian process regression and aoi-aware scheduling," *IEEE Transactions on Communications*, vol. 69, no. 10, pp. 7077–7093, 2021.

[55] Z. He, , *et al.*, "Nonlinear complex support vector regression for fading channel estimation in fbmc-oqam system," *IEEE Wireless Communications Letters*, vol. 8, no. 3, pp. 753–756, 2019.

[56] M. O. Al Kalaa, , *et al.*, "Estimating the likelihood of wireless coexistence using logistic regression: Emphasis on medical devices," *IEEE Transactions on Electromagnetic Compatibility*, vol. 60, no. 5, pp. 1546–1554, 2018.

[57] S. Zhao, , *et al.*, "Application of elm algorithm incorporating ae principles in wireless communication signal detection," *IEEE Access*, vol. 11, pp. 89720–89732, 2023.

[58] R. Ntassah, , *et al.*, "User classification and traffic steering in o-ran," *IEEE Open Journal of the Communications Society*, vol. 5, pp. 3581–3594, 2024.

[59] M. Marey and H. Mostafa, "Code-aided modulation classification algorithm for multiuser uplink sc-fdma systems," *IEEE Wireless Communications Letters*, vol. 10, no. 5, pp. 1023–1027, 2021.

[60] S. Chakraborty and D. Sen, "Iterative sage-based joint mcfos and channel estimation for full-duplex two-way multi-relay systems in highly mobile environment," *IEEE Transactions on Wireless Communications*, vol. 17, no. 11, pp. 7379–7394, 2018.

[61] S. Zhou, , *et al.*, "Blind modulation classification for overlapped co-channel signals using capsule networks," *IEEE Communications Letters*, vol. 23, no. 10, pp. 1849–1852, 2019.

[62] S. Huang, , *et al.*, "Automatic modulation classification of overlapped sources using multiple cumulants," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 7, pp. 6089–6101, 2017.

[63] J. Zhang, , *et al.*, "Continuous phase modulation classification via baum-welch algorithm," *IEEE Communications Letters*, vol. 22, no. 7, pp. 1390–1393, 2018.

[64] L. Rabiner, "A tutorial on hidden markov models and selected applications in speech recognition," *Proceedings of the IEEE*, vol. 77, no. 2, pp. 257–286, 1989.

[65] Y. Zhang, , *et al.*, "Offline real-world wireless interference signal classification algorithm utilizing denoising diffusion probability model," *IEEE Signal Processing Letters*, vol. 30, pp. 1132–1136, 2023.

[66] P. Swazinna *et al.*, "Comparing model-free and model-based algorithms for offline reinforcement learning," *IFAC-PapersOnLine*, vol. 55, no. 15, pp. 19–26, 2022.

[67] V. Suryan *et al.*, "Multifidelity reinforcement learning with gaussian processes: Model-based and model-free algorithms," *IEEE Robotics Automation Magazine*, vol. 27, no. 2, pp. 117–128, 2020.

[68] M. Sherman, , *et al.*, "Optimizing aoi in uav-ris-assisted iot networks: Off policy versus on policy," *IEEE Internet of Things Journal*, vol. 10, no. 14, pp. 12401–12415, 2023.

[69] Y. Chen, , *et al.*, "Joint caching and computing service placement for edge-enabled iot based on deep reinforcement learning," *IEEE Internet of Things Journal*, vol. 9, no. 19, pp. 19501–19514, 2022.

[70] S. Leng and A. Yener, "Learning to transmit fresh information in energy harvesting networks," *IEEE Transactions on Green Communications and Networking*, vol. 6, no. 4, pp. 2032–2042, 2022.

[71] J. Lu, , *et al.*, "Secure routing in multihop ad-hoc networks with srr-based reinforcement learning," *IEEE Wireless Communications Letters*, vol. 11, no. 2, pp. 362–366, 2022.

[72] J. Aznar-Poveda, , *et al.*, "Mdprp: A q-learning approach for the joint control of beaconing rate and transmission power in vanets," *IEEE Access*, vol. 9, pp. 10166–10178, 2021.