

Data-Driven Next-Generation Wireless Networking: Embracing AI for Performance and Security

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Abstract—New network architectures, such as the Internet of Things (IoT), 5G, and next-generation (NextG) cellular systems, put forward emerging challenges to the design of future wireless networks toward ultra-high data rate, massive data processing, smart designs, low-cost deployment, reliability and security in dynamic environments. As one of the most promising techniques today, artificial intelligence (AI) is advocated to enable a data-driven paradigm for wireless network design. In this paper, we are motivated to review existing AI techniques and their applications for the full wireless network protocol stack toward improving network performance and security. Our goal is to summarize the current motivation, challenges, and methodology of using AI to enhance wireless networking from the physical to the application layer, and shed light on creating new AI-enabled algorithms, mechanisms, protocols, and system designs for future data-driven wireless networking.

Index Terms—Wireless network, AI, Machine learning, Performance, Security.

I. INTRODUCTION

The rapid advancement of wireless technology leads to a revolution in daily life. The deployment of Internet of Things (IoT) [1], [2], intelligent networking [3], [4], cloud computing [5], [6], 5G and next-generation (NextG) cellular networks [7], [8] make new demands on the capabilities for efficient and secure network operations. Conventional methods for wireless networking have been generally based on theoretical models, pre-defined operational procedures, or empirical guidelines [9], [10]. Considering the complicated structures and operational protocols of modern wireless networks, conventional methods may not be always efficient, robust, or secure in handling dynamic network operational environments with massive data exchange [9], [11], [12].

Recently, the wide applications of artificial intelligence (AI) and machine learning have drawn increasing attention in the area of wireless networking. New research areas have already emerged to apply AI techniques to enhance wireless network performance and security [13]–[20]. In particular, network operations generate various data of large volume. Without relying on specific mathematical modeling or operational guidelines, AI techniques have enabled a data-driven paradigm to process wireless signals and network traffic in an efficient and secure manner. For example, AI has been adopted in different network layers to improve the network throughput, communication efficiency, and reduce energy consumption and various costs [13]–[15]; and many system designs have also embraced AI

to enhance the confidentiality, integrity, and availability of wireless networks [16]–[18].

In this paper, we aim to provide an overview of existing applications of data-driven AI in the wireless network. We study them from two perspectives: performance and security, and discuss the advantages of using data-driven AI approaches compared with conventional approaches toward wireless network performance and security. In particular, we discuss the following major topics in this paper.

- We classify existing popular AI techniques into supervised learning, unsupervised learning, and reinforcement learning, and briefly introduce common algorithms associated with them.
- We comprehensively present the use of AI techniques to improve the performance and security in wireless network designs throughout the full protocol stack. We begin with the physical (PHY) and medium access control (MAC) layers, which are the main focuses of the recent AI-enabled research. Then, we summarize substantial efforts that have recently applied AI techniques to mechanisms at the network layer and above.
- Based on the state-of-the-art, we discuss what the challenges lie on the path ahead in adopting and creating AI techniques for future wireless network designs.

The remaining sections of this paper are organized as follows. In Section II, we briefly summarize AI techniques. In Sections III and IV, we discuss the use of AI for wireless networking in lower layers (PHY and MAC) and higher layers (network layer and above), respectively. We summarize the future challenges of AI for wireless networking in Section V and conclude this paper in Section VI.

II. BRIEF SUMMARY OF AI TECHNIQUES

Before we discuss AI techniques for wireless network designs, we briefly introduce and classify AI and machine learning techniques. Fig. 1 shows the classification of machine learning techniques into three main categories: supervised learning, unsupervised learning, and reinforcement learning [21], [22], along with common algorithms in each category.

- Supervised learning involves techniques that are trained by explicit labels. Supervised learning includes classification and regression algorithms. Common algorithms include support vector machines (SVM), K-nearest neighbors (K-NN), random forest, linear regression, neural

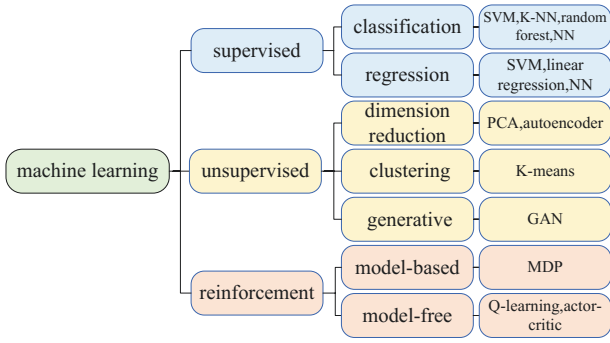


Fig. 1. Taxonomy of AI/machine learning techniques, along with commonly used models.

network (NN) based deep learning such as feedforward neural network (FNN), recurrent neural network (RNN), and convolutional neural network (CNN) [23].

- Unsupervised learning does not need labeled data, which is classified into dimension reduction, clustering, and generative algorithms. Principal component analysis (PCA) and autoencoder are two common dimension reduction algorithms. Autoencoder has a similar nature to wireless communication because it has an encoding-decoding structure [24]. K-means is a widely used clustering algorithm. Unlike discriminative classification, generative adversarial network (GAN) is a generative machine learning algorithm [23].
- Reinforcement learning is categorized into model-based and model-free algorithms. One of the most common models for model-based reinforcement learning is based on the Markov decision process (MDP). Model-free algorithms are categorized into value-based algorithms such as the Q-learning, and policy-based algorithms such as the actor-critic algorithm. Besides, deep reinforcement learning is an algorithm that combines reinforcement learning with deep learning. Multi-agent reinforcement learning enables multiple agents in the environment.

III. AI IN PHY AND MAC LAYERS

In a wireless network, the lower layers, including the PHY layer and the MAC layer, are responsible for interacting with the spatially and temporally varying wireless medium to ensure efficient, reliable, and secure wireless communication. Studies have demonstrated that machine learning designs have been successfully integrated into lower-layer designs, enabling wireless networks to (i) adapt to fluctuating environmental conditions (e.g., signal propagation, attenuation, interference) [25]–[33], and (ii) enhance security against various threats, such as the identification of unauthorized access to wireless networks, suspicious behavior, or protecting the confidentiality, integrity, and availability of wireless networks [34]–[40]. In this section, we elaborate on how existing approaches integrate machine learning into wireless networks from two aspects: (i) improving the performance and (ii) enhancing the security.

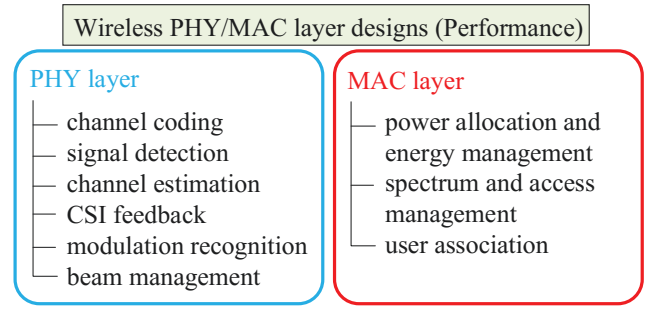


Fig. 2. Machine learning for different mechanisms to improve the PHY and MAC performance

A. Using AI for Performance

Fig. 2 summarizes how AI has been applied to different designs at the PHY and MAC layers to improve the communication performance.

1) *Improving PHY Layer Performance:* In the PHY layer, we discuss how machine learning can be utilized to 1) optimize channel coding, 2) detect high-dimensional signals, 3) advanced channel estimation, 4) optimize CSI feedback procedures, 5) detect modulation without decoding, and 6) improve beam management.

Channel Coding: Channel coding is an essential technique to improve the reliability of wireless communication over a noisy channel (e.g., mitigating wireless collisions [41]). Some studies have used machine learning to design advanced coding processes [13], [24]–[26], [42]. For example, the work of [13] introduced an RNN-based decoder for polar codes in 5G radio. RNN decomposes the iterative operations of the conventional decoder into layers that can significantly reduce memory consumption by sharing the weights of different iterations. Deep learning can train a Tanner graph for error-correcting codes [42]. The deep learning framework improves the performance of the belief propagation decoding algorithm with little extra complexity. Autoencoders have also gained broad attention [24]–[26]. By using autoencoder in the deep generative model, [26] was able to reconstruct the Gray coding before decoding by using the prior information obtained from the channel model.

In addition, machine learning-based modulation and coding schemes for link adaptation were proposed in [43], [44]. Parameters for modulation and coding scheme have a probabilistic model based on signal-to-interference-plus-noise ratio (SINR) [44]. This model is formulated as a multi-armed bandit problem under the reinforcement learning framework. Efficient solutions are used to learn the optimal parameters given the channel state.

Signal Detection: The conventional signal detection method based on the maximum-likelihood estimation can be an NP-hard problem [10]. Recent advances in multiple-input multiple-output (MIMO) technology with high-dimensional signals have even exacerbated the complexity problem at the receiver. To address this issue, existing research has focused on developing AI-based methods for detecting MIMO signals

[11], [27]–[30], [45], [46]. The authors in [46] proposed a deep learning-based MIMO detection called MMNet. MMNet aims to learn the parameter models of an iterative decoder, which eliminates the need to make an impractical assumption that one knows the MIMO channel matrix distribution. In MMNet, parameters can be adaptively adjusted by measuring the channel matrix continuously. Many existing studies on signal detection always assumed that the channel is linear with perfect channel state information (CSI). However, in practice, this assumption does not always hold. The work in [11] replaced the traditional iterative detection algorithm with deep learning to enhance resilience against CSI error and channel non-linearity.

Channel Estimation: In wireless networks, channel interference generally incurs a negative impact, particularly in MIMO systems. The interference can significantly reduce the accuracy of channel estimation. Deep learning has been used for improving the channel estimation performance in [7], [31], [47], [48]. While minimum mean square error estimation is the most accurate, it has a high level of complexity, whereas least squares estimation is faster but less accurate. To combine the advantages of both methods, a deep learning method has been proposed in [31], which theoretically proved that noise can be effectively filtered so that least squares estimation can approach the close performance of minimum mean square error estimation. The work in [7] considered a 5G vehicular network where conventional methods use Doppler rate estimation to estimate decision-directed channels, but these methods do not work well in a highly dynamic environment. The work proposed to use deep learning to learn a channel without knowing the exact Doppler rate, enabling more accurate decision-directed channel estimation.

CSI Feedback: It is necessary to perform the sounding process in a beamforming-based multiuser MIMO system, in which each wireless station feedbacks its CSI to the access point for precoding to mitigate interference across different stations. It has been shown that the use of compressed sensing in deep learning can further improve the efficiency of CSI feedback [12], [32], [49], [50]. The CNN-based CsiNet+ framework in [12] has an encoder-decoder structure to compress and quantize the CSI matrix. As opposed to the traditional quantization in deep learning, which requires retraining when changing the bit quantization rate, CsiNet+ is trained by optimizing quantization offset, thus CNN parameters can be fixed without retraining. In [32], a deep learning framework is proposed for extracting CSI features at different resolutions. CSI matrices with different densities require different kernels and resolutions. To extract features at different resolutions, two different convolutional layers are applied in parallel.

Modulation Recognition: Automatic modulation recognition (AMR) is a term used to describe the identification of the modulation scheme used in a communication system without decoding signals. Recently, AI techniques have shown their promising potential in this application [4], [51]. The work in [52] used K-NN combined with genetic programming to

identify four common modulation schemes. K-NN evaluates the fitness of new features generated by genetic programming based on input features. Due to the simplicity of K-NN, the design is low in complexity without compromising the classification accuracy. It is also possible to recognize signal waveforms by transforming complex-valued signals into contour stellar images, then using deep learning methods for image recognition [51], in which the amplitude, frequency, phase, noise, and error are represented by colors and shapes. Simulation results in [51] also validated that such computer vision technology can be applied to AMR.

Beam Management: In 5G/NextG wireless networks, millimeter-wave (mmWave) has been used to support higher data rate transmissions. Due to the directional nature of the mmWave technology, each device uses a dedicated beam to communicate with its connected peer. However, this leads to a complex beam management procedure between the transceivers. Machine learning methods have been proposed for solving a variety of beam management problems. For example, considering the beam selection in a vehicle-to-vehicle network, the dynamic nature of such a network makes it difficult to find a beamforming solution that can accommodate its changes [33], [53], [54]. The work in [33] uses iterative SVM to classify beamforming and select the optimal one. Iterative SVM uses signal power, path loss, and angle of arrival/departures (AoA/AoD) as features for model training, and predicts the analog beam when the link between vehicles is changed.

Tracking beams in a dynamic network is also challenging [55]–[57]. For beam tracking in an unmanned aerial vehicle (UAV) system, drones need to quickly switch beam directions to maximize the SINR when they fly around. Therefore, a fast beam tracking technique is necessary. Although it is difficult to obtain an accurate channel model in a UAV system, Q-learning can learn from the tracking experience without a model to predict tracking [55] by optimizing beam selection by using the SINRs from different beams as rewards.

Beam alignment aims to find and maintain the optimal beam direction between transceivers [58]–[60]. Due to the small antennas used in 5G devices, conventional beam alignment techniques may not be feasible for small devices. The work in [58] uses two machine learning classifiers, i.e., random forest and multilayer perceptron (MLP), for beam alignment. Given a user's location, the work uses exhaustive search to find optimal access points and beamforming, then uses locations as features to train the classifiers. After training, classifiers only need the user's location to predict optimal access points and beamforming. The classifiers are shown robust to the general urban outdoor environment.

2) *Improving MAC Layer Performance:* Machine learning has been used at the MAC layer to optimize the performance by managing a variety of resources as follows.

Power Allocation and Energy Management: Several studies have adopted AI methods for power allocation and energy management [6], [61]–[67]. The work in [64] considered a

cognitive radio network that consists of sensors, primary users, and secondary users. The primary and secondary users share the same spectrum resource. Primary users can adjust their power allocation based on their rules. However, secondary users can not obtain primary users' power allocation information and have to use the strength of the received signal from sensors to change their power allocation. As a result, [64] designed a deep reinforcement learning framework for secondary users to predict primary users' transmission power allocation. In [67], a deep Q-network was developed to learn the optimal sleeping rules for mobile networks to reduce energy consumption. In the proposed deep Q-network method, data traffic from different time periods can be effectively learned, thus reducing the bias caused by current traffic. The method has been shown stable and adaptable in a dynamic environment than conventional Q-learning.

Spectrum and Access Management: Spectrum and channel access management can also leverage AI to improve its efficiency [14], [68]–[79]. For example, non-orthogonal multiple access (NOMA) has become a popular design for 5G/NextG networks, which requires comprehensive management of power and spectrum, such that the receiver can successfully decompose signals from users. A multi-task deep learning-based NOMA was proposed in [1], which is able to modulate, spread symbols, and detect. The design is to create a new structure of autoencoder. Each user's bits are modulated to a symbol independently by one of the isolated sublayers. The symbol is spread to a sequence, and then multiple sequences are jointly detected by a neural network. The design was further improved in [74] by introducing a balancing technique among users to avoid some users getting trapped in local optima. Targeting the dynamic spectrum access scenario where wireless devices dynamically and autonomously access and use available spectrum resources in a given frequency band, [69] considered a probability model in multichannel wireless networks. In the model, each user accesses a channel to send data packets with a probability, and will be informed whether the packets are received successfully. A multi-agent deep reinforcement learning was created to learn the best time slot for spectrum access and maximize the data rate on the channel. The study investigated several cases with different rewards and objective functions, including cooperative rewards and global rewards.

User Association: User association is a process to associate a user with an appropriate access point based on geographical, channel, interference, and bandwidth information. Machine learning techniques for user association have been investigated in [80]–[82]. In particular, [80] proposed a multi-agent reinforcement learning model to optimize the association decision. In this model, each user is associated with an agent, and the SINR is used to evaluate the goodness. The experimental results show that this model can achieve up to 99.8% of the optimal performance. In [82], the user association and resource allocation were considered jointly in a large-scale heterogeneous cellular network. When users are associated

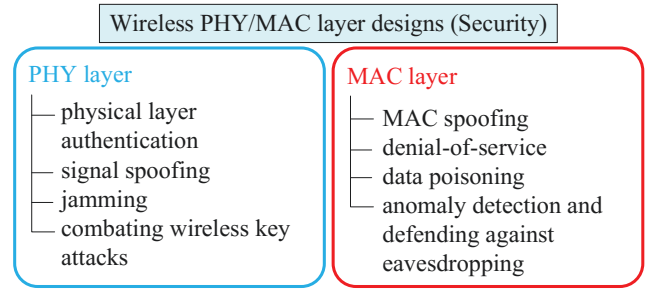


Fig. 3. PHY and MAC security mechanisms leveraging AI.

with different base stations, both network resources and communication quality can be optimized. It is assumed that users do not know the network environment and are selfish to benefit themselves, which is formulated as a stochastic game. By defining the network utility as the reward of each user, their multi-agent deep reinforcement learning framework can find the Nash equilibrium among users.

B. Using AI for Security

In addition to using AI to improve the communication performance, the literature also investigated how to leverage AI to enhance wireless network security against various attacks. Fig. 3 summarizes related major topics at the PHY and MAC layers, which will be discussed in the following.

1) *Security at PHY Layer:* At the PHY layer, various machine learning-based mechanisms have been proposed to enhance authentication, combat spoofing attacks and jamming, and detect anomaly and eavesdropping.

Physical Layer Authentication: It has been demonstrated that secret information can be coupled with random channel responses for secure information exchange without using conventional cryptography. Typically, these designs mainly involve physical-layer authentication (PLA). Some implementations of machine learning on PLA were discussed in [3], [34]–[38]. For example, [37] used logistic regression to predict unique features in the channel matrix as a way for user authentication, showing better performance than using the conventional received signal strength indicators. In [38], a method was proposed to allow Bob using Alice's packets to train one class nearest neighbor algorithm. Packets not classified as belonging to Alice are marked as suspicious. The work in [3] developed a CNN-based radio frequency fingerprinting model by using baseband error signals in the time domain. This method utilizes the frequency offset as a feature during the training process, which is difficult to spoof and therefore can be used to identify attackers.

Signal Spoofing Attacks: Spoofing attack is a common attack to compromise the authentication process [16], [83]–[85]. There are studies specifically targeting spoofing attacks in wireless networks based on AI techniques. For example, the authentication scheme in [16] models the virtual channels of a MIMO system. The sparsity and total energy of users' virtual channels are considered features used by a logistic regression classifier to distinguish spoofing attacks. As the

spoofing attacker can be smart and try to learn from waveform and channel status information to improve the spoofing success probability, [84] proposed a GAN model that allows the spoofing attacker trains deep learning to obtain the best signals against the defense mechanism obtained by training another deep learning model. This GAN-based attacker can generate signals that are easily misidentified as normal users.

Jamming: Jamming is a common strategy of sending wireless signals with the same frequency in order to disrupt ongoing communication [86]. Some machine learning-based anti-jamming methods have been developed in [17], [87]–[92]. In [17], the attacker’s goal is to disrupt secondary users in a cognitive radio network. Secondary users leverage spatial diversity to transmit signals at different locations to avoid attackers. This study proposes to use deep reinforcement learning to learn the optimal location for the secondary user at each time slot. The work in [87] investigated a multi-channel cognitive radio network where secondary users’ access is not protected, thus making them vulnerable to jamming attacks. The secondary user’s defense strategy is to switch channels in order to hide from the attacker when the attacker is searching for different channels. In this study, the channel hopping is modeled as a Markov decision process (MDP) where the transition probability describes the action of the secondary user.

Combating Wireless Key Attacks: The varying wireless channel state can be leveraged to generate a random secret key. A defense method against wireless key attack was considered in [93]. In a wireless network, the wireless secret key generation technique enables key agreement protocols to ensure safe encryption. The performance of wireless secret key generation can be evaluated by the secret key rate. However, both hardware impairment and the forged signal can downgrade the secret key rate. Secret key generation requires randomness distillation that uses pilot signals, thus attackers can inject forged pilot signals. Hardware impairment leads to the mismatch of randomness observation, which can be fixed by deep learning. The attacker is defended against by using RNN to predict the source of common randomness and enhance the randomness distillation. The defense method in [93] has up to 30% improvement compared with others.

2) *Security at MAC Layer:* At the MAC layer, we discuss how AI techniques have been used in security topics related to spoofing, data poisoning, denial-of-service (DoS), and eavesdropping.

MAC Spoofing: Spoofing attacks at the MAC layer are studied in [39], [40], [94]. It is possible to use CSI to detect MAC spoofing [39]. When two packets are sent from different MAC addresses, the proposed deep learning classifier in [39] can identify whether MAC addresses are associated with the same device even when two devices of the same model are sending messages at the same location and their CSI still has variances. The work in [40] uses sequence numbers of frames associated with identifies features to train a machine learning model. The experiment conducted in a real-world environment shows it is

effective in noisy IEEE 802.11 networks.

DoS Attacks: DoS attacks targeting the MAC layer are discussed in [95] to undermine the frame formatting and flow control. The study showed that attackers can flood forged IEEE 802.11 management frames in WiFi. Management frames are essential for the initialization of WiFi setup. A forged management frame can de-authenticate and disconnect devices. Without upgrading protocol or hardware, machine learning-based classifiers can classify de-authentication frames based on the traffic features, such as the number of different frames and their exchange.

Data Poisoning: Data poisoning attacks have been proposed in [96]–[98] to circumvent multi-access mechanisms. In particular, in a cooperative spectrum sensing scenario, in which sensing devices can send their results to a data fusion server to determine whether a channel is free. Malicious devices can send poisonous data to the fusion center, which may lead to the server making incorrect decisions. Different from traditional statistics-based methods, this line of research has developed surrogate models based on adversarial machine learning for attackers to mimic the fusion center’s decision process, based on which to generate poisonous data in a precise way. Experimental results show that the success probability of adversarial machine learning-based attacker achieves up to 82% attack success rate.

Anomaly Detection and Defending against Eavesdropping: Anomaly detection is a method against malicious access or anomalous phenomena [99], [100]. In [99], an anomaly detection algorithm for a wireless sensor network implemented in a microgrid is considered. The algorithm adopts machine learning to detect data integrity with a low false alarm rate during the experiments. The study in [101] trained a machine learning model with the traffic features under IEEE 802.11 protocol to detect an anomaly. Detecting eavesdropping [102], [103] is a challenge because it is a passive attack and does not need to actively transmit signals. Some anti-eavesdropper defense strategies were developed in [104], [105]. The idea in [104] is to mix signals with artificial noise to confuse any eavesdropper. FNN is used to optimize the secrecy throughput, which is evaluated by the power of artificial noise power, the time taken by transferring power, and the redundancy of wiretap code.

IV. AI IN NETWORK LAYER AND ABOVE

While the PHY and MAC layers are always the focus of wireless network research, considerable efforts have also been devoted to using AI for the wireless network layer and above. In this section, we aim to summarize such research efforts toward improving the wireless performance and security. Fig. 4 summarizes existing machine learning-based mechanism designs toward improving the performance and enhancing security at the network layer and above.

A. AI for Performance

We first review existing methods of applying AI techniques to improve the network performance.

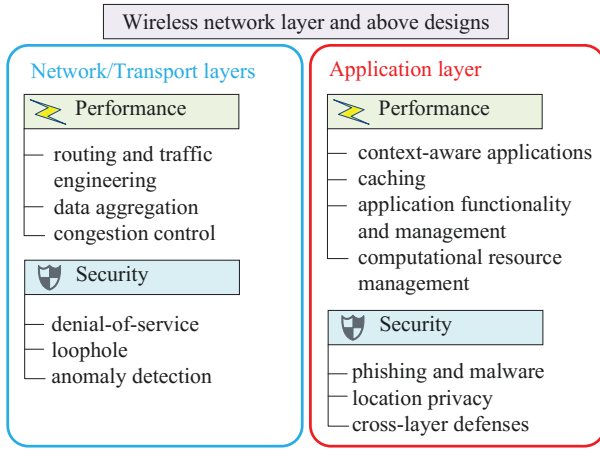


Fig. 4. Machine learning to improve performance and security of mechanisms at the network layer and above.

1) *Network and Transport Layers:* Existing studies have been focused on AI-enabled routing, traffic engineering, and data aggregation at the network layer and intelligent congestion control at the transport layer.

Routing and Traffic Engineering: Routing is one of the major tasks in the network layer. Leveraging machine learning methods can help routers determine when and where the data traffic should be sent efficiently [19], [106]. For example, the work in [19] considered that an IoT network serves High Volume Flexible Time (HVFT) applications. HVFT needs to transfer a large volume of data to the cloud server such as prefetching videos with ultra-high bit rate. A deep reinforcement learning-based policy was created to coordinate HVFT with other time-sensitive applications such as video streaming for the IoT network. HVFT is scheduled to avoid time-sensitive applications by deep reinforcement learning with the reward set to be the total HVFT throughput. This design is able to transmit 14.7% more data without downgrading time-sensitive applications.

Data Aggregation: Data aggregation can improve the efficiency of wireless networks by reducing redundant data [107], [108]. Conventional aggregation techniques may not be flexibly efficient as they were generally built on fixed routes. In [108], a reinforcement learning-based data aggregation design was created for a mobile vehicular network (VANET) scenario. Every vehicle in the VANET uses distributed MDP model to learn from nearby vehicles' actions and rewards. Every vehicle adds a delay before transmitting data as action. The reward is the distance between data in different route nodes. Therefore, data from different vehicles can arrive at the same time and then be aggregated, achieving a good trade-off between delay and redundancy with the number of redundant data reduced without causing a long delay.

Congestion Control: A variety of machine learning algorithms have been applied for congestion control at the transport layer, including K-means [109], SVM [110], neural network [111], and reinforcement learning [15], [112]–[116]. Rein-

forcement learning has received more attention recently. For example, [112] considered a mobile network with varying link bandwidths. Users can switch between links with different channel capacities, which leads to a large-scale dynamic reinforcement learning state space. The congestion window size is defined as the action and network throughput as the reward. Then, Kanerva coding in reinforcement learning is applied to speed up the convergence rate by adequately choosing a part of the state space to approximate the full space.

2) *Application Layer:* We briefly discuss common applications where machine learning techniques have been proposed to improve the performance.

Context-aware Applications: Context-aware applications can adapt to serve users based on the context of users. Various machine learning-based applications have been proposed in [2], [117]–[120]. For example, [117] proposes a location-based mobile computing application by using deep learning. It can predict users' tracking or user identification based on biometric motion. Global interactions are obtained by merging local interactions from different sensing modalities. Features such as frequency are extracted to train deep learning. It can handle both regression and classification in a unified way. Another popular context-aware application is indoor localization [118]. Multiple machine learning algorithms are trained, and their predictions are fused to improve accuracy.

Caching: Machine learning-based content caching methods have been proposed in [8], [121], [122]. One of the implementations is the intelligent base station with caching [122]. It has a placement delivery array system in the base station that uses the double-coded caching technique. It is formulated as an optimization problem that minimizes the delay and power consumption. The wireless network is modeled as an MDP with unknown transition probabilities because it is not available in a real-world scenario. Deep reinforcement learning is used to solve the MDP by taking the action of scheduling decisions and optimizing the reward of the transmission delay and power.

Application Functionality and Management: Traffic classification is another important application of AI techniques [106], [123]. The work in [123] developed Atlas on wireless networking at HP Labs. Atlas is a traffic classifier that can check the data traffic and identify its source software and applications. However, it is challenging to obtain training datasets for machine learning because massive and various network flow samples are hard to label. Atlas addresses this problem by using the mobile agents installed on some dedicated testing devices to collect the network logs, which are then used as the training data.

Network function virtualization (NFV) is a key function in a software-defined network (SDN) [20], [124]. A software-defined radio was proposed in [20] to control IoT network parameters. NFV maps the transmission requests to virtual requests at the software level, which is modeled as MDP. MDP is solved by multi-agent deep reinforcement learning where every agent learns to select devices to form optimal

routes and allocate proper power to devices. The study in [125] considered SDN management to support mobile edge clouds for video streaming. The functions of SDN such as video quality, transcoding, and caching are controlled by the virtual appliances of NFV. Both bandwidth allocation and power consumption of virtual appliances are optimized by deep reinforcement learning.

Computational Resource Management: AI techniques can also help computational resource allocations in wireless networks [126]–[129]. In mobile edge computing, it is important to determine how to allocate the workload to mobile edges based on their available computing resources. A reinforcement learning-based framework for each edge to maximize each user’s energy consumption and computing time is proposed in [128]. The work of [127] considered an energy-saving model in IoT networks to reduce energy consumption based on a reinforcement learning model that allows every edge device to learn offloading decisions locally without accurate global information.

B. AI for Security

We then review existing studies related to using AI techniques to enhance the wireless network performance.

1) *Network Layer:* At the network layer, attacks mainly focus on disruptions to normal operations of network traffic.

DoS Attacks: The DoS attack is a common attack at the network layer [18], [130], [131]. 5G network slicing is a technology that divides a network into multiple virtual networks, which can be targeted by DoS attacks [18]. A deep learning framework has been proposed in [18] to jointly predict DoS attacks and slice traffic. The detection of DoS attacks is based on packet features including flow duration, internet protocol (IP) addresses, ports, and protocols. Deep learning with Kalman backpropagation was also proposed to detect DoS attacks in [130]. Features used in [130] include flow duration and flow inter-arrival time. The Kalman filter shows its capability to predict and detect DoS attacks by adjusting deep learning weights.

Loophole Attacks: A new insider attack called loophole attack was proposed in [132]. The attacker can be launched at a malicious gateway node. By intercepting and rerouting data in a loop to delay traffic, it can attack the IPv6 routing protocol for low-power and lossy networks. To counter attackers, traffic features such as rank, topology inconsistency, and rerouting procedures are used to train a deep learning framework. Simulations in [132] show that the deep learning framework achieves more than 90% accuracy to identify such attackers.

Anomaly Detection: Machine learning-based anomaly detection has become a common way to detect anomaly in network traffic based on packet features. A general comparison of machine learning-based anomaly detection was given in [133], which tested various machine learning algorithms, including SVM, decision tree, random forest, and K-means; and common network attacks, including SYN flooding, land, UDP flood, ping of death, smurf, IP sweeping, and port scan. Generally,

those machine learning algorithms can be used to detect suspicious features of network traffic. Tree-based methods were observed with better performance than others in [133].

2) *Application Layer:* Recently, there are also substantial efforts focusing on using AI for application layer security.

Phishing and Malware: A strategy against phishing in fog networks was designed in [134] and built upon a neural network-based fuzzy detector. In the detector, 27 features are selected from uniform resource locator information and web information, and then are fuzzed as three classes and provided to a neural network to detect phishing. Machine learning has been proposed to detect malware at the application layer [135]–[137]. For example, Q-learning has been used in [135], [137] for malware detection in mobile and IoT networks, respectively.

Location Privacy: Location privacy [138], [139] has become an increasingly important topic recently with new attacks emerging to infer a mobile user’s location. For example, [140] showed that attackers can target the application layer to steal the geographical information of users. The use of machine learning towards location privacy has been discussed in [141]–[143]. Anonymizing the spatiotemporal trajectory data is an effective method to protect privacy before publishing data [142], in which trajectories are clustered by k-means to confuse adversaries without information loss measured by generalization hierarchy trees.

Cross-layer Defenses: Some methods can work across layers to defend against attacks [144], [145]. In [144], DDoS attacks across the PHY layer and application layers were taken into consideration. Three kinds of DDoS attacks were analyzed: silent call attacks, message spamming attacks, and signaling attacks, all leading to changes in network traffic features. A deep learning framework in [144] was trained by a large volume of data to accurately detect such attacks. In [145], distributed DoS of TCP, HTTP, and UDP protocols were considered. Decision trees were used to distinguish the features of flow because distributed DoS on different protocols will lead to some specific changes, such as the TCP SYN, HTTP GET, or POST requests.

V. SUMMARY OF CHALLENGES GOING FORWARD

Based on our review, we find that the application of AI on wireless networks is under rapid development, and there still exist challenges to be solved on the path ahead.

- **Interpretability of operational wireless data.** Many existing machine learning frameworks work like black boxes, which lack interpretability. They need experts to determine which features are dominant and should be used to train models [19], [27], [51]. How to select wireless network features, why these features are important, and accordingly lead to accurate classification for an AI-based design worth more research efforts.
- **Model Adaptation to Dynamics.** A distinguishing feature of the wireless network is the dynamically-changing environmental data, such as user mobility and time-varying channel fading. They cause confusion, noise, and

unreliability in data. Some models are designed typically to process certain kinds of data [13], [42]. Generally, it is worthy of more studies regarding how a trained machine learning model based on wireless data for one environment for a time period can be reliably applied to a different environment at another time period.

- Balancing between Complexity and Performance. Machine learning frameworks, in particular neural networks, can incur a higher complexity than conventional methods, indicating that IoT devices with limited cost budgets still have difficulty in adopting them. Low-complexity neural network implementation and deployment can provide one feasible way for AI-empowered IoT devices.
- Balancing between AI and Conventional Methods. AI may not be the optimal choice for every wireless network task as conventional methods can provide more stable and interpretable results sometimes. Therefore, we think adequately adopting AI to balance between AI-based and conventional methods is important in wireless network operations.
- Adversarial Machine Learning and Effective Defense. Using machine learning unfortunately creates a new dimension of security risks. Adversarial machine learning can attack existing machine learning models by maliciously manipulating the learning process with small perturbations [97]. As a result, AI-based methods need to be carefully reviewed to address the risk of adversarial examples in wireless networking.

VI. CONCLUSION

In this paper, we surveyed the literature on a rapidly growing area of AI for wireless networking. We summarized the use of AI techniques from the PHY layer to the application layer in two major aspects: improving performance and enhancing security. We also discuss the challenges on the path ahead. As we have seen, different AI techniques can be applied or re-designed for various wireless algorithms, mechanisms, architectures, and systems, making AI for wireless networking a challenging and promising research area.

REFERENCES

- [1] N. Ye, X. Li, H. Yu, A. Wang, W. Liu, and X. Hou, "Deep learning aided grant-free NOMA toward reliable low-latency access in tactile Internet of Things," *IEEE TII*, 2019.
- [2] J. Santos, J. J. Rodrigues, J. Casal, K. Saleem, and V. Denisov, "Intelligent personal assistants based on Internet of things approaches," *IEEE Systems Journal*, 2016.
- [3] K. Merchant, S. Revay, G. Stantchev, and B. Nossain, "Deep learning for RF device fingerprinting in cognitive communication networks," *IEEE JSTSP*, 2018.
- [4] Y. Wang, M. Liu, J. Yang, and G. Gui, "Data-driven deep learning for automatic modulation recognition in cognitive radios," *IEEE TVT*, 2019.
- [5] J. Xiong, M. Wei, Z. Lu, and Y. Liu, "Warmonger: inflicting Denial-of-Service via serverless functions in the cloud," in *ACM CCS*, 2021.
- [6] Z. Xu, Y. Wang, J. Tang, J. Wang, and M. C. Gursoy, "A deep reinforcement learning based framework for power-efficient resource allocation in cloud RANs," in *IEEE ICC*, 2017.
- [7] M. Mehrabi, M. Mohammadkarimi, M. Ardakani, and Y. Jing, "Decision directed channel estimation based on deep neural network k-step predictor for MIMO communications in 5G," *IEEE JSAC*, 2019.
- [8] A. Sadeghi, F. Sheikholeslami, and G. B. Giannakis, "Optimal and scalable caching for 5G using reinforcement learning of space-time popularities," *IEEE JSTSP*, 2017.
- [9] J. R. Hampton, *Introduction to MIMO communications*. Cambridge university press, 2013.
- [10] S. Yang and L. Hanzo, "Fifty years of MIMO detection: The road to large-scale MIMO," *IEEE COMST*, 2015.
- [11] N. Shlezinger, R. Fu, and Y. C. Eldar, "DeepSIC: Deep soft interference cancellation for multiuser MIMO detection," *IEEE TWC*, 2020.
- [12] J. Guo, C.-K. Wen, S. Jin, and G. Y. Li, "Convolutional neural network-based multiple-rate compressive sensing for massive MIMO CSI feedback: Design, simulation, and analysis," *IEEE TWC*, 2020.
- [13] C.-F. Teng, C.-H. D. Wu, A. K.-S. Ho, and A.-Y. A. Wu, "Low-complexity recurrent neural network-based polar decoder with weight quantization mechanism," in *IEEE ICASSP*, 2019.
- [14] Y. Xu, J. Yu, and R. M. Buehrer, "The application of deep reinforcement learning to distributed spectrum access in dynamic heterogeneous environments with partial observations," *IEEE TWC*, 2020.
- [15] J. Xu and B. Ai, "Deep reinforcement learning for handover-aware MPTCP congestion control in space-ground integrated network of railways," *IEEE Wireless Commun.*, 2021.
- [16] N. Wang, L. Jiao, P. Wang, M. Dabaghchian, and K. Zeng, "Efficient identity spoofing attack detection for IoT in mm-Wave and massive MIMO 5G communication," in *IEEE GLOBECOM*, 2018.
- [17] G. Han, L. Xiao, and H. V. Poor, "Two-dimensional anti-jamming communication based on deep reinforcement learning," in *IEEE ICASSP*, 2017.
- [18] N. A. E. Kuadey, G. T. Maale, T. Kwantwi, G. Sun, and G. Liu, "Deepsecure: Detection of Distributed Denial of Service attacks on 5G network slicing—deep learning approach," *IEEE COMMML*, 2021.
- [19] S. Chinchali, P. Hu, T. Chu, M. Sharma, M. Bansal, R. Misra, M. Pavone, and S. Katti, "Cellular network traffic scheduling with deep reinforcement learning," in *AAAI Conference on AI*, 2018.
- [20] H. A. Shah and L. Zhao, "Multiagent deep-reinforcement-learning-based virtual resource allocation through network function virtualization in Internet of Things," *IEEE IoTJ*, 2020.
- [21] B. Mahesh, "Machine learning algorithms-a review," *IJSR*, 2020.
- [22] H. Zhang and T. Yu, *Deep Reinforcement Learning: Fundamentals, Research and Applications*. Springer, 2020.
- [23] C. C. Aggarwal *et al.*, "Neural networks and deep learning," *Springer*, 2018.
- [24] F. A. Aoudia and J. Hoydis, "Model-free training of end-to-end communication systems," *IEEE JSAC*, 2019.
- [25] S. Dörner, S. Cammerer, J. Hoydis, and S. Ten Brink, "Deep learning based communication over the air," *IEEE JSTSP*, 2017.
- [26] V. Raj and S. Kalyani, "Design of communication systems using deep learning: A variational inference perspective," *IEEE TCCN*, 2020.
- [27] M. Goutay, F. A. Aoudia, and J. Hoydis, "Deep hypernetwork-based MIMO detection," in *IEEE SPAWC*, 2020.
- [28] H. He, C.-K. Wen, S. Jin, and G. Y. Li, "Model-driven deep learning for MIMO detection," *IEEE TSP*, 2020.
- [29] X. Tan, Z. Zhong, Z. Zhang, X. You, and C. Zhang, "Low-complexity message passing MIMO detection algorithm with deep neural network," in *IEEE GlobalSIP*, 2018.
- [30] S. Chaudhari, H. Kwon, and K.-B. Song, "Reliable and low-complexity MIMO detector selection using neural network," in *IEEE ICNC*, 2020.
- [31] E. Balevi, A. Doshi, and J. G. Andrews, "Massive MIMO channel estimation with an untrained deep neural network," *IEEE TWC*, 2020.
- [32] Z. Lu, J. Wang, and J. Song, "Multi-resolution CSI feedback with deep learning in massive MIMO system," in *IEEE ICC*, 2020.
- [33] Y. Yang, Z. Gao, Y. Ma, B. Cao, and D. He, "Machine learning enabling analog beam selection for concurrent transmissions in millimeter-wave V2V communications," *IEEE TVT*, 2020.
- [34] L. Senigagliaesi, M. Baldi, and E. Gambi, "Comparison of statistical and machine learning techniques for physical layer authentication," *IEEE TIFS*, 2020.
- [35] H. Fang, X. Wang, and L. Hanzo, "Learning-aided physical layer authentication as an intelligent process," *IEEE TCOM*, 2018.
- [36] L. Xiao, Y. Li, G. Han, G. Liu, and W. Zhuang, "PHY-layer spoofing detection with reinforcement learning in wireless networks," *IEEE TVT*, 2016.

- [37] L. Xiao, X. Wan, and Z. Han, "PHY-layer authentication with multiple landmarks with reduced overhead," *IEEE TWC*, 2017.
- [38] L. Senigagliales, M. Baldi, and E. Gambi, "Statistical and machine learning-based decision techniques for physical layer authentication," in *IEEE GLOBECOM*, 2019.
- [39] P. Jiang, H. Wu, C. Wang, and C. Xin, "Virtual MAC spoofing detection through deep learning," in *IEEE ICC*, 2018.
- [40] C. Benzaïd, A. Boulgheraïf, F. Z. Dahmane, A. Al-Nemrat, and K. Zeraoulia, "Intelligent detection of MAC spoofing attack in 802.11 network," in *ACM ICDN*, 2016.
- [41] S. Zhao, Z. Qu, Z. Luo, Z. Lu, and Y. Liu, "Comb decoding towards collision-free WiFi," in *USENIX NSDI*, 2020.
- [42] E. Nachmani, Y. Be'ery, and D. Burshtein, "Learning to decode linear codes using deep learning," in *IEEE Allerton*, 2016.
- [43] Y. Huang, Y. T. Hou, and W. Lou, "A deep-learning-based link adaptation design for eMBB/URLLC multiplexing in 5G NR," in *IEEE INFOCOM*, 2021.
- [44] V. Saxena, H. Tullberg, and J. Jaldén, "Reinforcement learning for efficient and tuning-free link adaptation," *IEEE TWC*, 2021.
- [45] H. He, C.-K. Wen, S. Jin, and G. Y. Li, "A model-driven deep learning network for MIMO detection," in *IEEE GlobalSIP*, 2018.
- [46] M. Khani, M. Alizadeh, J. Hoydis, and P. Fleming, "Adaptive neural signal detection for massive MIMO," *IEEE TWC*, 2020.
- [47] H. He, C.-K. Wen, S. Jin, and G. Y. Li, "Deep learning-based channel estimation for beamspace mmWave massive MIMO systems," *IEEE COMML*, 2018.
- [48] S. Liu, Z. Gao, J. Zhang, M. Di Renzo, and M.-S. Alouini, "Deep denoising neural network assisted compressive channel estimation for mmWave intelligent reflecting surfaces," *IEEE TVT*, 2020.
- [49] T. Wang, C.-K. Wen, S. Jin, and G. Y. Li, "Deep learning-based CSI feedback approach for time-varying massive MIMO channels," *IEEE COMML*, 2018.
- [50] C.-K. Wen, W.-T. Shih, and S. Jin, "Deep learning for massive MIMO CSI feedback," *IEEE WCL*, 2018.
- [51] Y. Lin, Y. Tu, Z. Dou, L. Chen, and S. Mao, "Contour stella image and deep learning for signal recognition in the physical layer," *IEEE TCCN*, 2020.
- [52] M. W. Aslam, Z. Zhu, and A. K. Nandi, "Automatic modulation classification using combination of genetic programming and knn," *IEEE TWC*, 2012.
- [53] H. Ahn, I. Orikumhi, J. Kang, H. Park, H. Jwa, J. Na, and S. Kim, "Machine learning-based vision-aided beam selection for mmWave multiuser MISO system," *IEEE COMML*, 2022.
- [54] A. Klautau, P. Batista, N. González-Prelcic, Y. Wang, and R. W. Heath, "5G MIMO data for machine learning: Application to beam-selection using deep learning," in *IEEE ITA*, 2018.
- [55] H.-L. Chiang, K.-C. Chen, W. Rave, M. K. Marandi, and G. Fettweis, "Machine-learning beam tracking and weight optimization for mmWave multi-UAV links," *IEEE TWC*, 2021.
- [56] S. H. Lim, S. Kim, B. Shim, and J. W. Choi, "Deep learning-based beam tracking for millimeter-wave communications under mobility," *IEEE TCOT*, 2021.
- [57] S. Sarkar, M. Krunch, I. Aykin, and D. Manzi, "Machine learning for robust beam tracking in mobile millimeter-wave systems," in *IEEE GLOBECOM*, 2021.
- [58] Y. Heng and J. G. Andrews, "Machine learning-assisted beam alignment for mmWave systems," *IEEE TCCN*, 2021.
- [59] W. Ma, C. Qi, and G. Y. Li, "Machine learning for beam alignment in millimeter wave massive MIMO," *IEEE COMML*, 2020.
- [60] B. W. Domae, R. Li, and D. Cabric, "Machine learning assisted phaseless millimeter-wave beam alignment in multipath channels," in *IEEE GLOBECOM*, 2021.
- [61] X. Meng, H. Inaltekin, and B. Krongold, "Deep reinforcement learning-based power control in full-duplex cognitive radio networks," in *IEEE GLOBECOM*, 2018.
- [62] F. B. Mismar, J. Choi, and B. L. Evans, "A framework for automated cellular network tuning with reinforcement learning," *IEEE TCOT*, 2019.
- [63] H.-S. Lee, J.-Y. Kim, and J.-W. Lee, "Resource allocation in wireless networks with deep reinforcement learning: A circumstance-independent approach," *IEEE Systems Journal*, 2019.
- [64] H. Zhang, N. Yang, W. Huangfu, K. Long, and V. C. Leung, "Power control based on deep reinforcement learning for spectrum sharing," *IEEE TWC*, 2020.
- [65] Y. S. Nasir and D. Guo, "Multi-agent deep reinforcement learning for dynamic power allocation in wireless networks," *IEEE JSAC*, 2019.
- [66] L. Xiao, H. Zhang, Y. Xiao, X. Wan, S. Liu, L.-C. Wang, and H. V. Poor, "Reinforcement learning-based downlink interference control for ultra-dense small cells," *IEEE TWC*, 2019.
- [67] J. Liu, B. Krishnamachari, S. Zhou, and Z. Niu, "DeepNap: Data-driven base station sleeping operations through deep reinforcement learning," *IEEE IoT*, 2018.
- [68] S. Wang, H. Liu, P. H. Gomes, and B. Krishnamachari, "Deep reinforcement learning for dynamic multichannel access in wireless networks," *IEEE TCCN*, 2018.
- [69] O. Naparstek and K. Cohen, "Deep multi-user reinforcement learning for distributed dynamic spectrum access," *IEEE TWC*, 2018.
- [70] U. Challita, L. Dong, and W. Saad, "Proactive resource management for LTE in unlicensed spectrum: A deep learning perspective," *IEEE TWC*, 2018.
- [71] Z. Li and C. Guo, "Multi-agent deep reinforcement learning based spectrum allocation for D2D underlay communications," *IEEE TVT*, 2019.
- [72] A. Koushik, F. Hu, and S. Kumar, "Intelligent spectrum management based on transfer actor-critic learning for rateless transmissions in cognitive radio networks," *IEEE TMC*, 2017.
- [73] Y. Li, W. Zhang, C.-X. Wang, J. Sun, and Y. Liu, "Deep reinforcement learning for dynamic spectrum sensing and aggregation in multi-channel wireless networks," *IEEE TCCN*, 2020.
- [74] N. Ye, X. Li, H. Yu, L. Zhao, W. Liu, and X. Hou, "DeepNOMA: A unified framework for NOMA using deep multi-task learning," *IEEE TWC*, 2020.
- [75] R. Zhong, Y. Liu, X. Mu, Y. Chen, and L. Song, "AI empowered RIS-assisted NOMA networks: Deep learning or reinforcement learning?" *IEEE JSAC*, 2021.
- [76] S. Wang, T. Lv, W. Ni, N. C. Beaulieu, and Y. J. Guo, "Joint resource management for MC-NOMA: A deep reinforcement learning approach," *IEEE TWC*, 2021.
- [77] N. Rupasinghe and İ. Güvenç, "Reinforcement learning for licensed-assisted access of LTE in the unlicensed spectrum," in *IEEE WCNC*, 2015.
- [78] E. Nisioti and N. Thomos, "Robust coordinated reinforcement learning for MAC design in sensor networks," *IEEE JSAC*, 2019.
- [79] —, "Fast Q-learning for improved finite length performance of irregular repetition slotted ALOHA," *IEEE TCCN*, 2019.
- [80] M. Sana, A. De Domenico, and E. C. Strinati, "Multi-agent deep reinforcement learning based user association for dense mmWave networks," in *IEEE GLOBECOM*, 2019.
- [81] N. Zhao, Y.-C. Liang, D. Niyato, Y. Pei, and Y. Jiang, "Deep reinforcement learning for user association and resource allocation in heterogeneous networks," in *IEEE GLOBECOM*, 2018.
- [82] N. Zhao, Y.-C. Liang, D. Niyato, Y. Pei, M. Wu, and Y. Jiang, "Deep reinforcement learning for user association and resource allocation in heterogeneous cellular networks," *IEEE TWC*, 2019.
- [83] C. Hu, Y. Liu, Z. Lu, S. Zhao, X. Han, and J. Xiong, "Smartphone location spoofing attack in wireless networks," in *SecureComm*, 2021.
- [84] Y. Shi, K. Davaslioglu, and Y. E. Sagduyu, "Generative adversarial network in the air: Deep adversarial learning for wireless signal spoofing," *IEEE TCCN*, 2020.
- [85] L. Xiao, Y. Li, G. Liu, Q. Li, and W. Zhuang, "Spoofing detection with reinforcement learning in wireless networks," in *IEEE GLOBECOM*, 2015.
- [86] A. Alagil, M. Alotaibi, and Y. Liu, "Randomized positioning DSSS for anti-jamming wireless communications," in *IEEE ICNC*, 2016.
- [87] Y. Wu, B. Wang, K. R. Liu, and T. C. Clancy, "Anti-jamming games in multi-channel cognitive radio networks," *IEEE JSAC*, 2011.
- [88] M. Labib, S. Ha, W. Saad, and J. H. Reed, "A colonel blotto game for anti-jamming in the Internet of things," in *IEEE GLOBECOM*, 2015.
- [89] L. Xiao, J. Liu, Q. Li, N. B. Mandayam, and H. V. Poor, "User-centric view of jamming games in cognitive radio networks," *IEEE TIFS*, 2015.
- [90] T. Erpek, Y. E. Sagduyu, and Y. Shi, "Deep learning for launching and mitigating wireless jamming attacks," *IEEE TCCN*, 2018.
- [91] Y. Gwon, S. Dastangoo, C. Fossa, and H. Kung, "Competing mobile network game: Embracing anti-jamming and jamming strategies with reinforcement learning," in *IEEE CNS*, 2013.
- [92] M. A. Aref, S. K. Jayaweera, and S. Machuzak, "Multi-agent reinforcement learning based cognitive anti-jamming," in *IEEE WCNC*, 2017.

- [93] M. Letafati, H. Behroozi, B. H. Khalaj, and E. A. Jorswieck, "Deep learning for hardware-impaired wireless secret key generation with man-in-the-middle attacks," in *IEEE GLOBECOM*, 2021.
- [94] S. Fang, Y. Liu, and P. Ning, "Mimicry attacks against wireless link signature and new defense using time-synched link signature," *IEEE TIFS*, vol. 11, 2016.
- [95] M. Agarwal, S. Biswas, and S. Nandi, "Detection of de-authentication DoS attacks in Wi-Fi networks: A machine learning approach," in *IEEE SMC*, 2015.
- [96] Z. Luo, S. Zhao, Z. Lu, Y. E. Sagduyu, and J. Xu, "Adversarial machine learning based partial-model attack in IoT," in *ACM WiseML*, 2020.
- [97] Z. Luo, S. Zhao, Z. Lu, J. Xu, and Y. E. Sagduyu, "When attackers meet AI: Learning-empowered attacks in cooperative spectrum sensing," *IEEE TMC*, 2020.
- [98] Z. Luo, S. Zhao, R. Duan, Z. Lu, Y. E. Sagduyu, and J. Xu, "Low-cost influence-limiting defense against adversarial machine learning attacks in cooperative spectrum sensing," in *ACM WiseML*, 2021.
- [99] A. Kavousi-Fard, W. Su, and T. Jin, "A machine-learning-based cyber attack detection model for wireless sensor networks in microgrids," *IEEE TH*, 2020.
- [100] G. Han, J. Tu, L. Liu, M. Martinez-Garcia, and Y. Peng, "Anomaly detection based on multidimensional data processing for protecting vital devices in 6G-enabled massive IIoT," *IEEE IoT*, 2021.
- [101] P. Satam and S. Hariri, "WIDS: An anomaly based intrusion detection system for Wi-Fi (IEEE 802.11) protocol," *IEEE TNSM*, 2020.
- [102] Y. Meng, J. Li, H. Zhu, X. Liang, Y. Liu, and N. Ruan, "Revealing your mobile password via WiFi signals: Attacks and countermeasures," *IEEE TMC*, 2019.
- [103] S. Fang, I. Markwood, Y. Liu, S. Zhao, Z. Lu, and H. Zhu, "No training hurdles: Fast training-agnostic attacks to infer your typing," in *ACM CCS*, 2018.
- [104] D. He, C. Liu, H. Wang, and T. Q. Quek, "Learning-based wireless powered secure transmission," *IEEE COMML*, 2018.
- [105] A. Vashist, A. Keats, S. M. P. Dinakarrao, and A. Ganguly, "Securing a wireless network-on-chip against jamming-based Denial-of-Service and eavesdropping attacks," *IEEE TVLSI Systems*, 2019.
- [106] E. Testi, E. Favarelli, and A. Giorgetti, "Machine learning for user traffic classification in wireless systems," in *IEEE EUSIPCO*, 2018.
- [107] Z. Ye, A. A. Abouzeid, and J. Ai, "Optimal stochastic policies for distributed data aggregation in wireless sensor networks," *IEEE/ACM TON*, 2009.
- [108] B. Yu, C.-Z. Xu, and M. Guo, "Adaptive forwarding delay control for VANET data aggregation," *IEEE TPDS*, 2011.
- [109] N. Taherkhani and S. Pierre, "Centralized and localized data congestion control strategy for vehicular ad hoc networks using a machine learning clustering algorithm," *IEEE T-ITS*, 2016.
- [110] M. Gholipour, A. T. Haghighat, and M. R. Meybodi, "Hop-by-hop congestion avoidance in wireless sensor networks based on genetic support vector machine," *Neurocomputing*, 2017.
- [111] A. A. Al Islam and V. Raghunathan, "End-to-end congestion control in wireless mesh networks using a neural network," in *2011 IEEE WCNC*, 2011.
- [112] W. Li, F. Zhou, K. R. Chowdhury, and W. Meleis, "QTCP: Adaptive congestion control with reinforcement learning," *IEEE TNSE*, 2018.
- [113] P. K. Donta, T. Amgoth, and C. S. R. Annavarapu, "Congestion-aware data acquisition with Q-learning for wireless sensor networks," in *IEEE IEMTRONICS*, 2020.
- [114] L. Cui, Z. Yuan, Z. Ming, and S. Yang, "Improving the congestion control performance for mobile networks in high-speed railway via deep reinforcement learning," *IEEE TVT*, 2020.
- [115] B. He, J. Wang, Q. Qi, H. Sun, J. Liao, C. Du, X. Yang, and Z. Han, "DeepCC: Multi-agent deep reinforcement learning congestion control for multi-path TCP based on self-attention," *IEEE TNSM*, 2021.
- [116] R. Xie, X. Jia, and K. Wu, "Adaptive online decision method for initial congestion window in 5G mobile edge computing using deep reinforcement learning," *IEEE JSAC*, 2019.
- [117] S. Yao, S. Hu, Y. Zhao, A. Zhang, and T. Abdelzaher, "Deepsense: A unified deep learning framework for time-series mobile sensing data processing," in *ACM WWW*, 2017.
- [118] L. Li, X. Guo, and N. Ansari, "SmartLoc: Smart wireless indoor localization empowered by machine learning," *IEEE TIE*, 2019.
- [119] J. Wang, X. Zhang, Q. Gao, H. Yue, and H. Wang, "Device-free wireless localization and activity recognition: A deep learning approach," *IEEE TVT*, 2016.
- [120] A. Vashist, D. R. Bhanushali, R. Relyea, C. Hochgraf, A. Ganguly, P. S. Manoj, R. Ptucha, A. Kwasinski, and M. E. Kuhl, "Indoor wireless localization using consumer-grade 60 GHz equipment with machine learning for intelligent material handling," in *IEEE ICCE*, 2020.
- [121] P. Lin, Q. Song, J. Song, A. Jamalipour, and F. R. Yu, "Cooperative caching and transmission in CoMP-integrated cellular networks using reinforcement learning," *IEEE TVT*, 2020.
- [122] Z. Zhang, H. Chen, M. Hua, C. Li, Y. Huang, and L. Yang, "Double coded caching in ultra dense networks: Caching and multicast scheduling via deep reinforcement learning," *IEEE TCOM*, 2019.
- [123] Z. A. Qazi, J. Lee, T. Jin, G. Bellala, M. Arndt, and G. Noubir, "Application-awareness in SDN," in *ACM SIGCOMM*, 2013.
- [124] T. Subramanya and R. Riggio, "Machine learning-driven scaling and placement of virtual network functions at the network edges," in *IEEE NetSoft*, 2019.
- [125] J. Luo, F. R. Yu, Q. Chen, and L. Tang, "Adaptive video streaming with edge caching and video transcoding over software-defined mobile networks: A deep reinforcement learning approach," *IEEE TWC*, 2019.
- [126] H. Zhang, W. Wu, C. Wang, M. Li, and R. Yang, "Deep reinforcement learning-based offloading decision optimization in mobile edge computing," in *IEEE WCNC*, 2019.
- [127] Q. Tang, R. Xie, F. R. Yu, T. Huang, and Y. Liu, "Decentralized computation offloading in IoT fog computing system with energy harvesting: A Dec-POMDP approach," *IEEE IoT*, 2020.
- [128] Y. Zhan, S. Guo, P. Li, and J. Zhang, "A deep reinforcement learning based offloading game in edge computing," *IEEE TC*, 2020.
- [129] D. Zeng, L. Gu, S. Pan, J. Cai, and S. Guo, "Resource management at the network edge: A deep reinforcement learning approach," *IEEE Network*, 2019.
- [130] M. Almiani, A. AbuGhazleh, Y. Jararweh, and A. Razaque, "DDoS detection in 5G-enabled IoT networks using deep Kalman backpropagation neural network," *Springer IJMLC*, 2021.
- [131] S. Shamshirband, A. Patel, N. B. Anuar, M. L. M. Kiah, and A. Abraham, "Cooperative game theoretic approach using fuzzy Q-learning for detecting and preventing intrusions in wireless sensor networks," *Elsevier Engineering Applications of Artificial Intelligence*, 2014.
- [132] M. Chowdhury, B. Ray, S. Chowdhury, and S. Rajasegarar, "A novel insider attack and machine learning based detection for the Internet of Things," *ACM TIOT*, 2021.
- [133] J. Liu, B. Kantarci, and C. Adams, "Machine learning-driven intrusion detection for Contiki-NG-based IoT networks exposed to NSL-KDD dataset," in *ACM WiseML*, 2020.
- [134] C. Pham, L. A. Nguyen, N. H. Tran, E.-N. Huh, and C. S. Hong, "Phishing-aware: A neuro-fuzzy approach for anti-phishing on fog networks," *IEEE TNSM*, 2018.
- [135] N. Guizani and A. Ghafoor, "A network function virtualization system for detecting malware in large IoT based networks," *IEEE JSAC*, 2020.
- [136] B. Amos, H. Turner, and J. White, "Applying machine learning classifiers to dynamic android malware detection at scale," in *IEEE IWCMC*, 2013.
- [137] L. Xiao, Y. Li, X. Huang, and X. Du, "Cloud-based malware detection game for mobile devices with offloading," *IEEE TMC*, 2017.
- [138] S. Fang, Y. Liu, W. Shen, H. Zhu, and T. Wang, "Virtual multipath attack and defense for location distinction in wireless networks," *IEEE TMC*, 2016.
- [139] T. Wang, Y. Liu, Q. Pei, and T. Hou, "Location-restricted services access control leveraging pinpoint waveforming," in *ACM CCS*, 2015.
- [140] X. Han, J. Xiong, W. Shen, Z. Lu, and Y. Liu, "Location heartbleeding: The rise of Wi-Fi spoofing attack via geolocation API," in *ACM CCS*, 2022.
- [141] Y. Wang, Z. Tian, Y. Sun, X. Du, and N. Guizani, "LocJury: an IBN-based location privacy preserving scheme for IoCV," *IEEE TITS*, 2020.
- [142] S. Shaham, M. Ding, B. Liu, S. Dang, Z. Lin, and J. Li, "Privacy preserving location data publishing: A machine learning approach," *IEEE T-ITS*, 2020.
- [143] F. Papst, N. Stricker, R. Entezari, and O. Saukh, "To share or not to share: On location privacy in IoT sensor data," in *IEEE/ACM IoTDI*, 2022.
- [144] B. Hussain, Q. Du, B. Sun, and Z. Han, "Deep learning-based DDoS-attack detection for cyber-physical system over 5G network," *IEEE TH*, 2020.
- [145] B. S. Rawal, S. Patel, and M. Sathiyarayanan, "Identifying DDoS attack using split-machine learning system in 5G and beyond networks," in *IEEE INFOCOM WKSHPs*, 2022.