

# Machine Learning and Cognitive Technology for Intelligent Wireless Networks

Xiangwei Zhou, Mingxuan Sun, Geoffrey Ye Li, and Biing-Hwang (Fred) Juang

## Abstract

The ability to dynamically and efficiently allocate resources to meet the need of growing diversity in services and user behavior marks the future of wireless networks, giving rise to intelligent processing, which aims at enabling the system to perceive and assess the available resources, to autonomously learn to adapt to the perceived wireless environment, and to reconfigure its operating mode to maximize the utility of the available resources. The perception capability and reconfigurability are the essential features of cognitive technology while modern machine learning techniques project effectiveness in system adaptation. In this paper, we discuss the development of the cognitive technology and machine learning techniques and emphasize their roles in improving both spectrum and energy efficiency of the future wireless networks. We describe in detail the state-of-the-art of cognitive technology, covering spectrum sensing and access approaches that may enhance spectrum utilization and curtail energy consumption. We discuss powerful machine learning algorithms that enable spectrum- and energy-efficient communications in dynamic wireless environments. We also present practical applications of these techniques to the existing and future wireless communication systems, such as heterogeneous networks and device-to-device communications, and identify some research opportunities and challenges in cognitive technology and machine learning as applied to future wireless networks.

## Index Terms

Cognitive radio, energy efficiency, machine learning, reconfiguration, spectrum efficiency.

X. Zhou is with the Division of Electrical and Computer Engineering, Louisiana State University, Baton Rouge, LA 70803.  
Email: xwzhou@lsu.edu.

M. Sun is with the Division of Computer Science and Engineering, Louisiana State University, Baton Rouge, LA 70803.  
Email: msun@csc.lsu.edu.

G. Y. Li and B.-H. Juang are with the School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA 30332. Email: {liye, juang}@ece.gatech.edu.

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## I. INTRODUCTION

Global mobile data traffic has grown 18-fold over the past 5 years. In terms of monthly volume, it grew from 400 petabytes/mo in 2011 to 7.2 exabytes/mo at the end of 2016, and is predicted to reach 49 exabytes/mo by 2021 [1]. In addition, by 2020, the smartphone traffic will exceed the PC traffic and mobile devices will account for two-thirds of the total IP traffic [2]. Along with the remarkable growth in data traffic, new applications of wireless communications, such as wearable devices and *Internet of Things* (IoT) [3], continue to emerge and generate even more data traffic. With the exploding wireless traffic, applications, and device diversity, the future wireless networks must embrace intelligent processing [4], [5] to address the universal scarcity in spectrum and energy resources. This has led to research on cognitive technology [6], [7] and machine learning [8], [9], both of which form the pillars to support the intelligent processing requirements of wireless networks.

Intelligent processing or system intelligence in a communication network encompasses at least the following: 1) the perception capability, 2) reconfigurability, and 3) the learning capability.

The perception capability enables wireless environment awareness and is one of the most important features in intelligent wireless networks. As a key component of cognitive radio [6], [7], it allows the wireless operation of a device to adapt to its environment and maximize the utility of the available spectrum resources. The perception capability is afforded by spectrum sensing [10], [11], which in a narrow sense determines the spectrum availability. Many basic spectrum sensing techniques have been proposed, including matched filter detection, energy detection, feature detection, and covariance-based detection [10], [12]. Advanced spectrum sensing techniques to cope with various scenarios, such as cooperative spectrum sensing [13]–[16], wideband spectrum sensing [17], and sequential spectrum sensing [18], have also been studied over the last decade. In a broad sense, spectrum sensing can be regarded as a paradigm for wireless environment perception. From this perspective, spatial-temporal spectrum sensing [19], real-time spectrum measurements [20], and interference sensing [21] have been considered in the recent literature. Since spectrum sensing requires resources at the sensing nodes, efficient scheduling of spectrum sensing [22], [23] has been discussed to balance the time, bandwidth, and power spent in between sensing and transmission.

To adapt to the surrounding environments, intelligent wireless devices need to be reconfigurable

in addition to being able to perceive the environment. Reconfigurability is achieved by dynamic spectrum access and optimization of operational parameters [24]. Based on the available information on the wireless environments and particular regulatory constraints, dynamic spectrum access techniques can be classified as interweave, underlay, overlay, and hybrid schemes [25]. The main reconfigurable parameters of these schemes in the physical layer include waveform, modulation, time slot, frequency band, and power allocation. Given different levels of perception capability, various designs of spectrum access have been proposed [26]. To achieve high performance, such as the throughput, and to satisfy certain constraints, such as the quality-of-service requirements, different optimization algorithms [27]–[30], including graph-based and market-based approaches, have been developed. The main challenges on the issue, including imperfect information, real-time requirements, and complexity limitations, have been considered. With the exploding number of wireless devices consuming a large amount of energy, energy efficiency is also important for dynamic spectrum access and resource optimization. Therefore, it has received increased attention recently [31].

Resources in the wireless environments recognized by the perception capability and reconfigurability design are characterized in a slew of factors, such as frequency band, access method, power, interference level, and regulatory constraints, to name a few. Interactions among these factors in terms of how they impact on the overall system utility are not always clearly known. As we try to maximize the utility of the available resources, the system complexity may thus be already daunting and can be further compounded by the diverse user behaviors, thereby calling for a proper decision scheme that would help realize the potential of utility enhancement. Modern machine learning techniques [8], [9], [32], [33] would find ample opportunities in this particular application [34]–[37]. The learning capability enables wireless devices to autonomously learn to optimally adapt to the wireless environments. In addition to the traditional machine learning approaches that use offline data, i.e., data collected in the past, to train models, efficient and scalable online learning algorithms that can train and update models continuously using real-time data are of great interest and have been successfully applied in various domains, including web search [38], [39] and cognitive radio networks [40], [41].

Machine learning algorithms are being developed at a fast pace. Both supervised and unsupervised learning algorithms have been used to address various problems in wireless networks.

Different from the standard supervised learning, reinforcement learning has been found useful to maximize the long-term system performance and to strike a balance between exploration and exploitation [42]–[44]. In addition, deep learning has emerged as a powerful approach to achieve superior and robust performance directly from vast amounts of data, and therefore has great potential in wireless networks [45].

Different from the scope of existing surveys in this area, we provide in this article a comprehensive overview of the development of cognitive technology and machine learning; in particular, we elaborate on their relationships and interactions in their roles towards achieving intelligent wireless networks. Moreover, we consider spectrum and energy efficiency, both of which are important characteristics of intelligent wireless networks, rather than only focusing on improving spectrum efficiency as most other overview papers on cognitive radio.

The rest of this paper is organized as follows. We describe in detail the state-of-the-art of cognitive technology, covering spectrum sensing and access approaches that perceive and adapt to the wireless environments in Sections II and III, respectively. In Section IV, we present powerful machine learning algorithms that enhance the perception capability and reconfigurability in wireless networks. We discuss practical applications of these techniques to the existing and future wireless networks, such as heterogeneous networks and *device-to-device* (D2D) communications, with performance evaluation in Section V. In Section VI, we further elaborate some open research challenges in cognitive technology and machine learning and suggest likely improvements in the future wireless networks. Finally, we conclude the paper in Section VII.

## II. SPECTRUM SENSING AND ENVIRONMENT PERCEPTION

The perception capability is the system’s ability to detect and assess the parameters that exist in the wireless environment, ranging from the spectrum availability to the power consumption level and reserve during operation. It is one of the most important features in intelligent wireless networks. As a key component of cognitive radio [6], [7], it is a prerequisite for the wireless operation of a device to adapt to its environment and maximize the utility of the available spectrum resources. In this section, we focus on the scope and techniques associated with the perception capability that have been proposed. We start with an introduction to spectrum sensing, including its basics and techniques for determining the spectrum availability. We re-

view various categories of spectrum sensing methods, such as local and cooperative spectrum sensing, narrowband and wideband spectrum sensing, block and sequential spectrum sensing, to cope with various scenarios in wireless communications. We then extend our discussion to environment perception, including multi-dimensional spectrum sensing, spectrum measurements and statistical modeling, and interference sensing and modeling, to enhance the intelligence in future wireless networks. We further include spectrum and energy efficiency considerations in wireless environment awareness, such as scheduling of spectrum sensing.

### A. Spectrum sensing

The perception capability is mainly afforded by spectrum sensing [10], [11], [46], which in a narrow sense determines the spectrum availability at a particular time and geographical location. For a particular frequency band, the goal of spectrum sensing is to decide between two hypotheses,  $\mathcal{H}_0$  and  $\mathcal{H}_1$ , corresponding to the absence and the presence of the licensed user signal, respectively. Specifically, spectrum sensing can be formulated as the following binary hypothesis testing problem

$$y(t) = \begin{cases} w(t), & \mathcal{H}_0, \\ s(t) + w(t), & \mathcal{H}_1, \end{cases} \quad (1)$$

where  $y(t)$  is the received signal,  $s(t)$  is the licensed user signal, and  $w(t)$  includes interference and noise.

With the spectrum sensing capability, an unlicensed cognitive radio user, also called a secondary user, can utilize the spectrum resources when a licensed user, also called a primary user, is absent or inactive. The spectrum sensing performance is usually characterized by the probabilities of detection and false alarm. The probability of detection is the probability that the decision is  $\mathcal{H}_1$  while  $\mathcal{H}_1$  is true; the probability of false alarm is the probability that the decision is  $\mathcal{H}_1$  while  $\mathcal{H}_0$  is true in (1).

It is desirable to achieve a large probability of detection to enable efficient spectrum exploitation and a small probability of false alarm to limit or avoid undue interference to the licensed operation. In practice, spectrum sensing needs to strike a balance between the probabilities of detection and false alarm, as in typical hypothesis testing tasks where a proper operating point must be chosen.

1) *Basic approaches*: Many basic spectrum sensing approaches have been proposed, including matched filter detection, energy detection, feature detection, and covariance-based detection [7], [10], [12], [47]–[55]. The matched filter detector [10] correlates the received signal with a known copy of the licensed user signal and maximizes the received *signal-to-noise ratio* (SNR). For a known signal under *additive white Gaussian noise* (AWGN), it is optimal. However, it can only be applied when the patterns of the licensed user signal, such as preambles, pilots, and spreading sequences, are known to the secondary cognitive radio user. Energy detection [47] is, in contrast, the simplest spectrum sensing approach, which decides on the presence or the absence of the licensed user signal by comparing the energy of the observed signal with a threshold. It does not require a priori knowledge of the licensed user signal but is susceptible to the uncertainty of noise power level [56], [57]. Feature detection [48]–[52] analyzes cyclic autocorrelation of the received signal. It is capable of differentiating the licensed user signal from the interference and noise and even works in very low SNR regimes. Covariance-based detection [12], [53], [54] utilizes the property that the licensed user signal received at the cognitive radio user is usually correlated because of the dispersive channels, the use of multiple receive antennas, or oversampling, thus providing differentiation from the noise. It can be used without the knowledge of signal, noise power, and detailed channel properties.

2) *Local and cooperative spectrum sensing*: Spectrum sensing may be performed at a local cognitive radio user with the above basic spectrum sensing approaches. However, local spectrum sensing techniques do not always guarantee a satisfactory performance due to noise uncertainty and channel fading [58]–[60]. For example, a cognitive radio user cannot detect the signal from a licensed transmitter shadowed by a high building as shown in Figure 1, which is known as the hidden node problem. If multiple cognitive radio users collaborate in spectrum sensing, the possibilities of detection error can be reduced with the introduced spatial diversity [61]–[64]. It has been shown in recent studies [61] that cooperative spectrum sensing can improve the probability of detection in fading channels. The required detection time at an individual cognitive radio user may also decrease [13], [14].

In cooperative spectrum sensing, cognitive radio users first independently perform local spectrum sensing. Then each user sends either a binary decision or its sensing data to a fusion node as shown in Figure 1. Finally, the fusion node makes a decision on the presence or

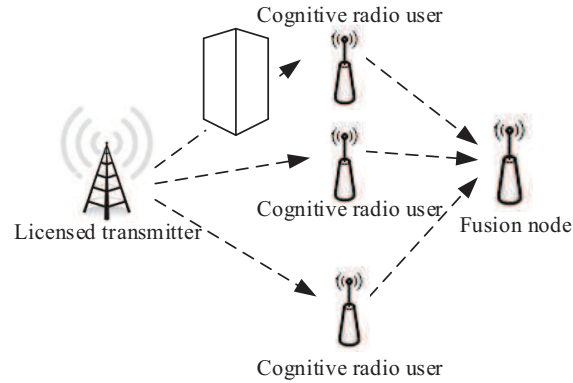


Fig. 1. Hidden node problem and cooperative spectrum sensing.

absence of the licensed user signal based on its received information. A straightforward form of cooperative spectrum sensing is to transmit and combine the signal samples received by all the cognitive radio users in the local spectrum sensing phase. In [65], a fusion scheme is proposed to process all samples using tools from random matrix theory. Combining schemes using all samples nevertheless require significant bandwidth to report the data from the individual users to the fusion node. When implemented over a wired high-speed backbone, the bandwidth concern with these schemes is not prohibitive, but not the case with the strict communication constraints over wireless channels. To reduce the required bandwidth, each user may instead report summary statistics, such as the observed energy acquired during energy detection. In [15], different cooperative energy detection schemes with low complexity are investigated, where the final testing decision is based on a weighted summation. In the case that the communication constraints are more strict, hard combination schemes are proposed in [61] and [15]. In these schemes, each user transmits quantized sensing information to the fusion node. The simplest form is the counting scheme, in which each cognitive radio user makes a binary decision based on its observation (e.g., the threshold test in energy detection), and forwards the one-bit decision to the fusion node [66]. If there are at least  $K_0$  out of  $K$  users inferring the presence of a licensed user signal, the licensed user will be declared present [16], [67]–[70]. Although  $K_0$  is generally a design parameter, it is shown in [71] that 1-out-of- $K$  rule results in the best detection performance under most practical cases. In [15], one-bit combination is also extended to two-bit combination, in which three thresholds are used to divide the observed energy into four regions.

Each user reports two-bit information to indicate the region of its observed energy. Then the fusion node calculates a weighted summation of the numbers of users falling in different regions. The optimal partition of the regions and weight allocation are given in [15] and the performance is shown to be comparable with that of equal-gain combination of the observed energies. In [72], the correlation among individual sensing results is considered and a linear-quadratic fusion strategy is proposed and compared with the counting rule.

3) *Narrowband and wideband spectrum sensing*: While many existing spectrum sensing methods focus on exploiting spectral opportunities over narrow frequency ranges, spectral opportunities over a wide frequency range are of great importance for wireless environment awareness and intelligent wireless networks. Different from narrowband spectrum sensing that makes a single decision for the entire frequency band of interest, wideband spectrum sensing identifies the availabilities of multiple frequency bands within the wideband spectrum. Wideband spectrum sensing can be categorized into Nyquist and sub-Nyquist approaches.

Nyquist wideband sensing uses a standard *analog-to-digital converter* (ADC) with a high sampling rate to acquire the wideband signal and then digital signal processing to detect signals over subbands [73]. In [17], a wavelet-based method is developed to identify and locate the spectral opportunities by analyzing the irregularities in the estimated *power spectral density* (PSD) with wavelet transform. It can be used to estimate the number of subbands and the corresponding frequency boundaries. In Nyquist sensing, the sampling rate needs to be at least twice the highest frequency of the signal, i.e., the Nyquist rate, and therefore the real-time processing can be very expensive and challenging in hardware design. To alleviate the high sampling rate requirement, filter bank spectrum sensing [74] is proposed to process the wideband signal with lower sampling rates and instead requires a large number of *radio frequency* (RF) components.

To reduce the implementation complexity, sub-Nyquist wideband sensing is introduced based on the compressive sensing technique. It allows the use of a sampling rate much lower than the Nyquist rate and thus fewer observations in comparison with its Nyquist counterpart. In [75], a cyclic feature detection algorithm is proposed to extract the second-order statistics of wideband signals with compressive sensing and to detect spectral opportunities. In [76] and [77], wideband sensing for cooperative cognitive radio networks is developed to achieve a satisfactory detection



performance with a smaller number of observations and low overhead.

4) *Block and sequential spectrum sensing*: Most spectrum sensing algorithms require a prescribed number of samples of the received signal for the testing task of (1), which is referred to as block spectrum sensing. In this case, a given time slot is provided for spectrum sensing. In some applications, the decision on the presence or absence of a licensed user signal needs to be made as quickly as possible using a variable number of samples in spectrum sensing, targeting a given probability of detection. Based on the sequential testing methodology introduced in [78], sequential spectrum sensing [18], [79] can be applied in such a case, where received signal samples are taken sequentially and the decision can be made as soon as the required detection reliability is satisfied. Sequential spectrum sensing is also employed for cooperative spectrum sensing [80], [81] and wideband spectrum sensing [82].

### B. *Environment perception*

Spectrum sensing is an important component in wireless environment perception. Conventional spectrum sensing focuses on the spectral opportunities in frequency bands not being used at a particular time and geographical location. The broad sense of spectral opportunities nonetheless can be further expanded beyond the conventional concept of unused spectrum to other possibilities such as shared spectrum as long as no harmful interference is introduced by the augmented spectral use. Therefore, multi-dimensional spectrum sensing that creates more spectral opportunities has become a subject of great interest lately. Furthermore, effective utilization of the spectrum resources is often enhanced by proper prediction of the spectral availability and thus it is advantageous and necessary to keep track of the past spectrum usage pattern over larger time and geographical scales. For this purpose, spectrum measurements and statistical modeling can be used [20]. To fully explore the expanded paradigm of spectral opportunities, interference sensing [21] has also been considered in the recent literature to address the interference factor that limits the potential spectrum reuse.

1) *Multi-dimensional spectrum sensing*: To allow wireless systems to operate in the same frequency band, it is desirable to avoid interference at the particular time and geographical location. Conventional spectrum sensing schemes intend to achieve this goal by identifying either temporal or spatial spectral opportunities. However, joint spatial-temporal opportunities

can be exploited to further enhance spectrum efficiency. In [19], a joint spatial-temporal spectrum sensing scheme is proposed and the performance benefit over spatial-only or temporal-only spectrum sensing is analyzed. Furthermore, a geolocation database is used in [83] together with spectrum sensing to better capture the joint spatial-temporal spectral opportunities.

Note that other information beyond spectrum occupancies, such as the SNRs, channels, and modulation and coding schemes, can be acquired with parameter estimation algorithms to better exploit the spectral opportunities. For example, SNR and channel estimation methods for the cognitive technology are presented in [84] and [85] while modulation and coding scheme identification methods are proposed in [86] and [87].

2) *Spectrum measurements and statistical modeling*: A fundamental key to environment perception is the understanding of the historical and statistical properties of the spectrum occupancy. The spectral opportunities in Chicago are studied in [88], which demonstrates the potential use of cognitive technology for improved spectrum efficiency. In [89], a framework for collecting and analyzing spectrum measurements is provided and evaluated. A statistical spectrum occupancy model in time and frequency domains is designed in [90], where the first- and second-order parameters are determined from actual RF measurements. In [91], a spectrum measurement setup is presented with lessons learned during the measurement activities. A new model for the duty cycle distribution of spectrum occupancy is introduced and the impact of duty cycle correlation in the frequency band is discussed. The drawback of Poisson modeling of licensed user activities is considered in [92], in which a new model is introduced to account for the correlation in the licensed user statistics. In addition, the radio environment map is investigated in [20] to act as an integrated database consisting of multi-domain information.

3) *Interference sensing and modeling*: Interference temperature was proposed by the *Federal Communications Commission* (FCC) as an indicator to guarantee minimal interference to the licensed users [93], [94]. While this concept is no longer popular nowadays, interference sensing and modeling are still an important aspect of environment perception for efficient and intelligent wireless networks. In [95], the distribution of aggregated interference from cognitive radio users to a licensed user is characterized in terms of the sensitivity, transmitted power, and density of the cognitive radio users as well as the propagation environment. This statistical model can help to design system-level parameters based on the interference constraint. The statistical behavior

of interference in cognitive radio networks is also studied in [96] using the theory of truncated stable distributions. The effect of power control is included in the discussion.

### *C. Spectrum and energy efficiency considerations*

Since spectrum sensing requires resources at the sensing nodes, efficient scheduling of spectrum sensing is very important to balance the time, bandwidth, and power spent in between sensing and transmission. Note that periodic spectrum sensing is commonly used to avoid interference with licensed users that may appear in the middle of cognitive communications. As a result, the efficiency of opportunistic spectrum utilization relies not only on the spectrum sensing technique itself but also on the scheduling of spectrum sensing activities. On the one hand, cognitive radio users may spend too much time on sensing activities rather than data transmission if sensing activities are scheduled too often. On the other hand, available spectrum opportunities may not be quickly discovered if sensing activities are scheduled too sporadically. As a result, the overall efficiency of opportunistic spectrum utilization relies not only on the spectrum sensing technique itself but also on the scheduling of spectrum sensing activities.

In a typical periodic spectrum sensing framework, each frame consists of a sensing block and an inter-sensing block [97], the ratio of the sensing block length to the inter-sensing block length represents how frequently sensing activities are scheduled, and therefore is a key parameter for spectrum sensing scheduling. Recently, optimization of spectrum sensing scheduling has been intensively studied for reliability-efficiency tradeoff [98]–[101]. Sensing block length optimization is investigated in [98] and [99] to improve the spectrum efficiency of a cognitive radio user utilizing a single licensed channel and multiple licensed channels, respectively. The optimal sensing block length is determined to maximize the achievable throughput for the cognitive radio user under the constraint that the licensed users are sufficiently protected. Similarly, the optimal inter-sensing block length is considered in [23], [100], [102]. In [22], [101], the optimization of both sensing and inter-sensing block lengths is studied. For better energy efficiency rather than spectrum efficiency, the optimization of inter-sensing block with data transmission is addressed in [103].

Moreover, the channel sensing order also affects the efficiency when there are multiple channels of interest. In [104], a dynamic programming-based solution is provided for optimal channel

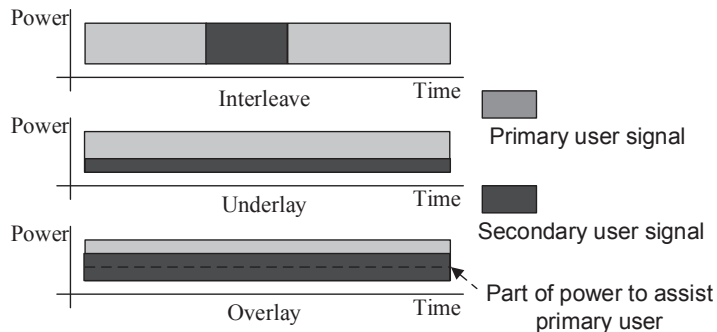


Fig. 2. Dynamic spectrum access with temporal spectrum sharing.

sensing order with adaptive modulation, where both the independent and correlated channel occupancy models are considered.

### III. RECONFIGURATION: SPECTRUM ACCESS AND RESOURCE OPTIMIZATION

To adapt to the surrounding environments, an intelligent wireless device needs to be reconfigurable in addition to being able to perceive the environment. Reconfigurability is achieved by dynamic spectrum access and optimization of operational parameters [24].

In this section, we focus on reconfigurability for intelligent wireless networks. We start with different types of dynamic spectrum access techniques, including interweave, underlay, overlay, and hybrid, as ways of coexistence in wireless networks with different levels of intelligence. Then we review resource optimization methods, including waveform and modulation design, resource allocation and power control, and graph- and market-based approaches. We will address uncertainties, imperfections, and errors, as well as other requirements and limitations. We further consider spectrum and energy efficiency tradeoff in intelligent reconfiguration, such as interference-aware spectrum access and resource optimization.

#### A. Dynamic spectrum access techniques

Based on the available information of the wireless environments and particular regulatory constraints, dynamic spectrum access techniques can be classified as interweave, underlay, overlay, and hybrid schemes [25], as illustrated in Figure 2.

Interweave<sup>1</sup>: As the original motivation for cognitive radio, secondary users exploit gaps in time, frequency, space, and/or other domains that are not occupied by primary users in this paradigm. Obviously, wireless environment awareness is very important to identify such gaps, called spectrum holes, for the secondary users to communicate in an opportunistic manner. The aforementioned perception techniques, such as spectrum sensing, are therefore essential to interweave communications. Ideally, since no user activities are found in spectrum holes, interference is avoided in this paradigm. In practice, there may still be minor interference to the primary users with reliable spectrum sensing.

Underlay: Secondary users are allowed to transmit together with primary users over the same frequency band at the same time if the interference generated by the secondary transmitters at the primary receivers is within some acceptable level. In this paradigm, the tolerable interference level at a primary receiver can be modeled by the interference temperature concept defined by the FCC [105]. To ensure the reliable operation of the primary users, the interference constraint is very restrictive and thus the secondary transmitters are typically very conservative in their transmit powers.

Overlay: In this paradigm, secondary users are also allowed to transmit simultaneously with the primary users over the same frequency band at the same time. Different from the underlay communications, the interference generated by a secondary transmitter at a primary receiver in overlay communications can be offset by using part of the power of the secondary user to assist the transmission of the primary user. The overlay paradigm requires cooperation between the primary and secondary users so that the secondary system has certain knowledge about the primary system and uses it to design advanced coding and transmission schemes.

Hybrid: The hybrid paradigm [106], [107] combines some of the above paradigms to overcome their drawbacks. For example, the interweave paradigm does not consider the tolerable interference level at a primary receiver while the underlay paradigm does not allow secondary transmission at a full power level. In contrast, a hybrid scheme may enable a secondary user to access an occupied frequency band with a controlled power and an idle frequency band with a full power. This paradigm has received great attention in the recent literature even though the term “hybrid” is not always explicitly used.

<sup>1</sup>Interweave is referred to as overlay in some literature.

## B. Resource optimization

The main reconfigurable physical-layer parameters include waveform, modulation, time slot, frequency band, and power allocation. Given different levels of perception capability, various designs of spectrum access have been investigated [26]. To achieve high performance, such as the throughput, and satisfy certain constraints, such as the quality-of-service requirements, different optimization algorithms, including graph- and market-based approaches, have been developed [27]–[30]. The main challenges on the issue, including imperfect information, real-time requirements, and complexity limitations, have been considered in the recent literature.

1) *Waveform and modulation design*: To enhance the spectrum usage and minimize interference to the primary users, the design of waveform and modulation for the secondary users can be optimized. In the underlay spectrum access, the secondary users can apply *ultra wideband* (UWB) waveforms and optimize the pulse width and position [108], [109]. In the overlay spectrum access, *orthogonal frequency-division multiplexing* (OFDM) is an attractive transmission technique [110] that flexibly turns on or off tones to adapt to the radio environments. Meanwhile, with *orthogonal frequency-division multiple access* (OFDMA) as a multiple access technique, non-adjacent sub-bands can be utilized with dynamic spectrum aggregation [111]. Due to the *out-of-band* (OOB) leakage of the OFDM signal, spectrum shaping that suppresses the OOB radiation and reduces the interference in the adjacent bands becomes necessary [112].

Existing spectrum shaping approaches can be divided into time- and frequency-domain approaches. It is well known that a raised cosine window can be applied to the time-domain signal to suppress the OOB radiation [112]. But system throughput is reduced in the windowing method because extension of symbol duration is needed to prevent *inter-symbol interference* (ISI). Another time-domain method at the cost of throughput reduction is adaptive symbol transition that inserts extensions between OFDM symbols [113]. In the frequency domain, a simple tone-nulling scheme [110] deactivates OFDM subcarriers at the edges of the utilized frequency band with the most significant impact on the OOB emission in the adjacent bands. Moreover, active interference cancellation [114] inserts cancelling tones adaptively at the edges, which enables deep spectrum notches but is computational intensive at the transmitter. Similarly, subcarrier weighting [115], multiple-choice sequence [116], and selected mapping [117] can suppress the OOB radiation based on the transmitted data. Recently, spectral precoding is proposed

[118]–[120] and capable of reducing the OOB emission significantly. The precoding matrix is constructed from delicately designed basis sets [118] or to render time continuity of adjacent OFDM symbols or spectrum nulls at notched frequencies [119], [120].

2) *Resource allocation and power control*: Resource allocation and power control have always been effective approaches for wireless networks. With the development of intelligent and cognitive wireless systems, various types of users may coexist in the same area and share the available spectrum resources through advanced dynamic spectrum access techniques. As a result, dynamic resource allocation and adaptive power control have been paid more and more attention recently. In the following, we discuss recent development of dynamic resource allocation and adaptive power control from different aspects, including information availability, allocation manners, requirements, and metrics.

*Information availability*: In resource allocation and power control, the available information, such as *channel state information* (CSI), is crucial. For intelligent wireless networks, such information plays a more important role in dynamic resource allocation and adaptive power control. To explore the benchmark performance and facilitate analysis, the availability of CSI is usually assumed. In [121], with the perfect CSI at the transmitter, the optimal power allocation strategies for cognitive radio users with fading channels is proposed and the corresponding ergodic capacity and outage capacity are analyzed. With the assumption of perfect CSI, spectrum and energy efficient resource allocation for cognitive radio networks is considered in [122] and [123], respectively.

In the dynamic wireless environments, obtaining the perfect information is not realistic, especially for intelligent communications where a large number of parameters are taken into consideration for performance improvement. In addition, precise information exchange also introduces unacceptable overhead. Therefore, more recent work considers dynamic resource allocation with partial CSI, imperfect spectrum sensing, and channel uncertainty. In [124], with the use of the estimated CSI, a resource allocation framework is proposed in cognitive radio networks. In [125], a robust power allocation scheme is proposed to limit the interference to the primary user in cognitive radio networks with partial CSI. In [28], resource allocation based on probabilistic information from spectrum sensing is derived for opportunistic spectrum access. With imperfect spectrum sensing and channel uncertainty, resource allocation in femtocell net-

works is addressed in [126], where the overall throughput of femtocell users is maximized under probabilistic constraints. In [127], chance-constrained uplink resource allocation is considered in downlink OFDMA cognitive radio networks with imperfect CSI. Moreover, optimal resource allocation with average bit-error-rate constraint is proposed in [128].

*Allocation manners:* With different structures and scales of wireless networks, resource allocation may be in a centralized or distributed manner. In the centralized manner, a central controller has sufficient information to render globally optimal allocation and hence to achieve good performance. In [129], through correlations of sensor data and energy adaptive mechanisms, a centralized spectrum and power allocation scheme achieves maximum information capacity in a multi-hop cognitive radio network. To reduce spectrum sensing overhead and errors, centralized dynamic resource allocation for cooperative cognitive radio networks is proposed to improve the spectrum efficiency in [130]. However, in the centralized manner, resource allocation encounters some practical issues, including huge overhead for information exchanging, signal transmission delay, high computational complexity, and the scalability of the proposed algorithms.

In distributed resource allocation, the aforementioned issues can be effectively alleviated. As a result, distributed resource allocation becomes the subject of recent research endeavor. In [131], joint subcarrier assignment and power allocation distributively optimizes the performance of an OFDMA ad hoc cognitive radio network. The proposed distributed algorithms are with affordable computational complexity and reasonable performance. In [132], a two-stage heuristic resource allocation scheme through a learning-based algorithm is designed. The dynamic spectrum allocation and adaptive power control are accomplished through individual user observations in two separated stages. To balance the performance and practical issues, a four-phase partially distributed downlink resource allocation scheme is developed for a large-scale small-cell network in [133].

*Requirements:* To satisfy various demands and application requirements, optimal resource allocation and power control can be designed in different ways. Fairness and outage probability of joint rate and power allocation for cognitive radio networks are studied in a dynamic spectrum access environment in [134]. Furthermore, resource allocation schemes with max-min and proportional fairness are proposed in cognitive radio networks in [124]. With spectrum sharing, the optimal solutions to the admission control problem for the primary users and the joint rate



and power allocation for the secondary users are obtained through the proposed algorithms. To better manage interference, a three-loop power control architecture is presented in [135]. Based on the feedback information, the proposed architecture determines the optimal maximum transmit power, the target *signal-to-interference-plus-noise ratio* (SINR), and the instantaneous transmit powers of femtocell users. In [136], a link adaption-based power control scheme is derived in two-tier femtocell networks. The optimal power allocation is obtained through solving the formulated reward-penalty link SINR problem. Meanwhile, to alleviate the cross-tier interference to the cellular users, a cellular link protection algorithm is proposed. To accommodate the *quality-of-service* (QoS) requirement, QoS provisioning spectrum resource allocation is proposed for cognitive heterogeneous networks and cooperative cognitive radio networks in [137] and [138], respectively. Moreover, delay-aware resource allocation is developed based on a Lagrangian dual problem in [139]. With the fast development of intelligent wireless networks, dynamic resource allocation problems with different requirements need to be further explored.

*Metrics:* With the explosive growth of wireless communications, the spectrum scarcity and energy consumption have been paid more and more attention. The most recent resource allocation and power control research has been focusing on spectrum efficiency and energy efficiency metrics. In the IoT, thousands of devices and sensors are connected to the Internet wirelessly, resulting in more and more scarce spectrum resources. Therefore, the study on resource allocation for high spectrum efficiency, especially in dynamic spectrum sharing scenario, has drawn a lot of attention. In [140], an adaptive time and power allocation policy over cognitive broadcast channels is studied. A sensing-based optimal resource allocation scheme and a low-complexity suboptimal solution are proposed to maximize the spectrum efficiency. From the throughput perspective, a three-dimensional resource allocation optimization problem is solved through the proposed heuristic algorithms in [141]. The tradeoffs between performance and computational complexity of the proposed learning and optimization algorithms are analyzed in dynamic spectrum access networks. Due to increasing energy consumption in wireless applications and services, the concept of green communications has been emphasized recently. Therefore, energy efficiency, as an important metric, has been extensively explored in resource allocation and power control. More details will be provided in the following subsection.

3) *Graph-based and market-based approaches*: Graph theory is a useful tool to model pairwise relationships between nodes. Most common application of graph theory to resource optimization is conflict graph, or interference graph, which describes co-channel interference using nodes and edges. With the help of independent sets, groups of users allowed to use the same channel simultaneously without unacceptable interference can be identified. This feature benefits spatial spectrum reuse that significantly enhances spectrum efficiency. In [142] and [143], a spatial channel selection game is proposed to increase spectrum efficiency with the help of conflict graph. In [144], spatial spectrum reuse is modeled as a price competition game among primary users, which is solvable and has a unique symmetric *Nash Equilibrium* (NE) if the conflict graph of secondary users admits specific topologies defined as mean valid. In [145], a peer-to-peer content sharing approach is proposed in vehicular ad hoc networks, in which a coalitional graph game is introduced to model the cooperation among vehicles and a dynamic algorithm is developed to find the best response network graph. In [146], a graphical game that describes channel selections for opportunistic spectrum access systems is proved to be a potential game and an NE, which minimizes *media access control* (MAC) layer interference. In addition, two uncoupled learning algorithms are proposed to approach the NE.

Market-based approaches of resource optimization treat spectrum resources as tradable items. These approaches give primary and secondary users motivations, usually opportunities of maximizing their own utilities, to participate in a predesigned spectrum sharing mechanism. The measure of utility varies in different scenarios. Common measures of utility are channel capacity and price of unit spectrum resource. The design of a spectrum sharing mechanism expresses the will of authority and the relationships among users are often involved in a game. Spectrum efficiency maximization is a common goal of a spectrum sharing mechanism using market-based approaches. In [147], an auction process is introduced to implement dynamic spectrum access for secondary users when there are multiple channel holders. Assuming the existence of price competition among auctioneers systematically, the proposed multi-auctioneer progressive auction maximizes spectrum efficiency. In [148], a truthful spectrum auction mechanism is proposed to allocate spectrum according to both QoS demands and spectrum utilization. In [149], dynamic spectrum access of SUs is implemented by cooperative spectrum sharing under incomplete information. In the cooperative game, the secondary users work as relays of the primary user

to exchange spectrum access time. By applying contract theory, two optimal contract designs are proposed for weakly and strongly incomplete information scenarios. In [150], a two-layer game is proposed between a *primary network operator* (PNO) and a *secondary network operator* (SNO). In the top layer, the revenue sharing game is modeled as a Nash bargaining game, and both the PNO and SNO are benefited if they choose to cooperate. In the bottom layer, the resource allocation game is modeled as a Stackelberg game to determine the optimal spectrum allocation. These two layers improve iteratively and an equilibrium state exists. In [151], an agent-based spectrum trading game in consideration of the flexible demand of secondary users is introduced. In the case of a single agent, it is proved that there exists an optimal solution. In the case of multiple agents, the equilibrium of strategies of the agents can be obtained.

In some cases, utility maximization of users conflicts with spectrum efficiency maximization of spectrum sharing systems. In [152], an evolutionary game is applied to modeling the pricing competitions among the primary users when the demands of the secondary users are adaptive according to channel prices. An evolutionary stable strategy is proved to exist when the primary users sell all their channels. However, the primary users have the opportunities to increase their payoffs by selling a portion of their channels. In [153], an adaptive spectrum sharing market between multiple primary and secondary users is introduced, in which the primary users adjust their prices and spectrum supplies and the secondary users change their channel valuations accordingly. By modeling the behavior of the secondary users as an evolutionary game and the competition of the primary users as a non-cooperative game, optimal strategies of both types of the users are provided accordingly.

### *C. Spectrum- and energy-efficient designs*

With the exploding number of wireless devices consuming a large amount of energy, energy efficiency is also important for dynamic spectrum access and resource optimization. Therefore, it has received increased attention recently, especially for battery-powered mobile devices. In [154], reliable power and subcarrier allocation in OFDM-based cognitive radio networks is studied from the energy efficiency perspective, where an energy-aware convex optimization problem is formulated and the corresponding optimal solution is obtained through a risk-return model. In [155], user selection and power allocation schemes are proposed to reduce the energy

consumption for a multi-user multi-relay cooperative system. A weighted power summation optimization for base and relay stations is formulated and solved. Furthermore, a multi-objective scheme that jointly considers the energy and throughput performance is proposed to strike a balance between spectrum and energy efficiency.

As two important metrics for resource optimization, spectrum- and energy-efficient resource allocation schemes have been studied and proposed in different scenarios. However, simultaneously optimizing spectrum and energy efficiency is not possible in most cases [103], [156]. Therefore, the tradeoff between spectrum and energy efficiency plays an important role in resource allocation with different network structures and requirements. For example, in an interference-free environment, the increasing transmit power always improves spectrum efficiency but may reduce the energy efficiency. But in an interference-limited environment, the increasing transmit power may decrease spectrum and energy efficiency at the same time. Moreover, the tradeoffs between spectrum and energy efficiency in downlink and uplink are not equivalent. The subcarrier allocation, power allocation, and rate adaptation need to be jointly considered in the downlink while it is hard to perform joint optimization in the uplink. In addition to the energy consumption for data transmission, the energy consumption for spectrum sensing, information exchange, and the training of learning algorithms needs to be taken into account and the corresponding tradeoff between spectrum and energy efficiency needs to be reconsidered.

Market-based spectrum sharing approach can also help improve energy efficiency when the measure of utilities of secondary users is related to transmit power. In [157], a decentralized Stackelberg pricing game is developed to find the optimal power allocation in the scenario of spatial spectrum reuse, such that utilities of the primary and secondary users are maximized. Two methods are proposed to solve the Stackelberg game in two different cases, i.e., active and inactive power constraints. In [158], two auction mechanisms corresponding to two different pricing schemes are proposed for spatial spectrum reuse. When prices are set according to the received SINR, the auction mechanism leads to a weighted max-min fair allocation in terms of SINR. When prices are set according to the transmit power of users, the auction mechanism maximizes the total channel utility.

#### IV. MACHINE LEARNING FOR INTELLIGENT WIRELESS NETWORKS

In this section, we focus on machine learning for intelligent wireless networks. Machine learning aims at providing a mechanism to guide the system reconfiguration, given the environment perception results and the device reconfigurability, to maximize the utility of the available resources. Basic machine learning algorithms can be categorized into supervised and unsupervised learning. Reinforcement learning is emerging as a new category. Under each category, we will introduce specific learning models and discuss their applications in achieving intelligent wireless networks. We further introduce the most recent development in machine learning, i.e., neural networks and deep learning, and discuss their potential for enhancing intelligent communications.

In our discussion, we consider different subcategories of machine learning algorithms based on their functionalities, such as support vector machines, Bayesian learning, k-means clustering, principal component analysis, and Q-learning. We will review the roles of different learning techniques in enhancing perception capability and reconfigurability, in which we specify the inputs, i.e., what to use, and the outputs, i.e., what to learn. For example, the required detection probability, observable wireless environment information, and available time or energy resource can be used to learn the selection of spectrum sensing methods and parameters while the available frequency bands, transmit power limit, and interference level can be used to learn the choice of channel assignment and power allocation. We evaluate and compare the strengths and limitations of different machine learning algorithms, to enable the choice of learning techniques and address various accuracy, complexity, and efficiency requirements of individual and cooperative tasks in centralized and decentralized wireless networks.

##### *A. Broad categories of machine learning algorithms*

Machine learning algorithms [159] learn to accomplish a task  $T$  based on a particular experience  $E$ , the goal of which is to improve the performance of the task measured by a specific performance metric  $P$  by exploiting the experience  $E$ . Depending on how to specify  $T$ ,  $E$  and  $P$ , machine learning algorithms are typically divided into three broad categories. Supervised learning accomplishes tasks by learning from examples provided by some external supervisor. Each training example consists of a pair of an input and an expected output/label, and the goal

is to learn a function that predicts correctly the output for any input. In contrast to supervised learning, unsupervised learning algorithms generally assume that there are no labeled examples and the goal is to discover the hidden structure in the input. Typical algorithms include clustering algorithms that group inputs into a set of clusters and dimension reduction algorithms that reduce the dimensionality of the inputs. Furthermore, reinforcement learning emerges as a popular category, where an agent learns to perform a certain task such as driving a car with minimal collisions by interacting with a dynamic environment. In contrast to supervised learning, the agent obtains the feedbacks in terms of rewards only by interacting with the environment and learns on its own, which makes the reinforcement learning very useful for cases of decision making under uncertainty.

### *B. Supervised learning*

Assume that there are  $n$  training examples  $\{(x_1, y_1), \dots, (x_n, y_n)\}$  available, where  $x_i \in \mathcal{X} \subseteq \mathbb{R}^d$  is an input of dimension  $d$  and  $y_i \in \mathcal{Y} \subseteq \mathbb{R}$  is the corresponding output label. The goal of supervised learning is to find some function  $f : \mathcal{X} \rightarrow \mathcal{Y}$  from a set of possible functions, such that  $f$  not only approximates the relationship between input  $\mathcal{X}$  and output  $\mathcal{Y}$  encoded by the training examples but also generalizes well on unseen data. The learning task can be further divided into a regression task if the output is continuous or a classification task if the output is discrete. Taking classification as an example, an input  $x_i$  can consist of the measurements from energy detection mentioned in Section II with  $d$ -dimension attributes, and the output is a binary variable indicating spectrum availability.

The set of possible functions that we are looking for, i.e., hypothesis class, should be specified, which can be *k-nearest neighbors* ( $k$ -NN or KNN), *support vector machine* (SVM), *artificial neural network* (ANN), or many other types of models. As a simple technique,  $k$ -NN predicts the output corresponding to a new input based on the labels of its nearest neighbors, where  $k$  is the number of neighbors to be considered. For the classification tasks, a sample input is classified into a specific class by taking the majority vote of the labels from its  $k$ -nearest neighbors. For the regression tasks, the output corresponding to a sample input is the average value of the labels of its neighbors. As one of the most popular classification techniques and illustrated in Figure 3, SVM with a linear kernel behaves in a similar way to logistic regression, which aims to find a

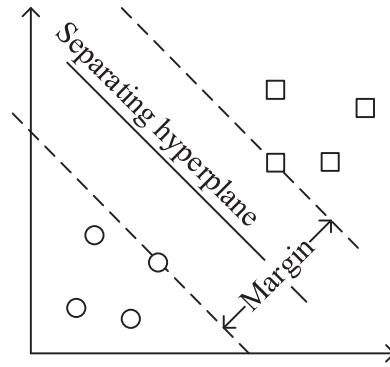


Fig. 3. Illustration of SVM. The SVM classifier searches for the optimal separation hyperplane that separates two classes and maximizes the margin between them.

linear separating hyperplane to separate the inputs into two classes. If the inputs are not linearly separable in the original space, SVM with a non-linear kernel can map the original inputs into a higher-dimension feature space in which they become separable, search for a hyperplane to separate the two classes, and maximize the margin between them. Binary classifiers can be extended to multi-class classification by treating a  $k$ -class classification problem as  $k$  binary classification problems.

Probabilistic graphical models, such as Bayesian networks, aim to compute the a posteriori probability distribution of the output variables conditioned on its observed input variables given the set of training examples. Those models go beyond the aforementioned ones in that they can predict interdependent outputs  $y_i \in \mathcal{Y}$ , e.g., sequences. In particular, *hidden Markov model* (HMM) is designed to model the probability distributions of sequences of observations, e.g., measurements of time series. In particular, each observation at time  $t$ , such as a vector of power features in successive time frames, is associated with a hidden variable, such as a binary variable indicating spectrum availability. HMM assumes that the hidden variables are related to each other through a Markov process. However, due to the complexity of graphical models, the training process and even the prediction process given a trained model are often computationally intractable. In such cases, approximate inference and learning methods are used.

Inspired by psychology and biology, the ANN models have been developed to mimic human learning behaviors. As shown in Figure 4, an artificial neural network learns complicated tasks through the interactions of a number of interconnected processing nodes (neurons) in a network

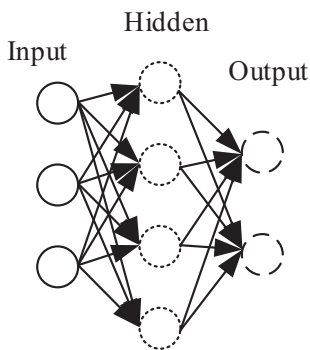


Fig. 4. Illustration of ANN. Each circular node represents a neuron and an arrow connects the output of one neuron to the input of another. Signals travel from the input layer to the output layer by traversing multiple hidden layers.

of multiple layers. The most beneficial property of a neural network is that it can model any function regardless of its linearity between inputs and outputs given sufficient hidden layers and nodes in the network. However, one of the disadvantages is that the model parameters, such as the weights between pairs of nodes, become increasingly large as the number of hidden layers increases, and thus the model is often hard to train due to hardware limitations and lack of effective training algorithms. Traditional ANNs usually construct networks with fewer than 5 layers and the performance sometimes is not so good as other simpler models. As the accelerated *graphics processing unit* (GPU) computing becomes more and more popular, larger volumes of training data become available, and more and more effective training algorithms are developed, deep learning [160], [161], with constructions of deeper layers of a neural network, has been enjoying a major resurgence very recently, which we will discuss in detail later.

Since each specific model encodes different assumptions about the learning problem, they are different in terms of accuracy, computational efficiency, and types of applications. SVM with a linear kernel and logistic regression are both well-behaved classification algorithms and easy to train as long as the inputs are roughly linearly separable. SVM with non-linear kernel performs better for problems where the inputs might not be linearly separable. However, the models can be painfully inefficient to train especially when the number of training examples,  $n$ , becomes increasingly large. Moreover, the neural network models are likely to perform well for most cases but are slower and harder to train. In contrast to all of the previous “eager” learners, “lazy” learners, such as KNN, do not learn a discriminative function from the training



examples but simply “memorize” all of them. However, the simplicity of KNN comes with a huge computational cost in prediction given new input, which involves searching for its nearest neighbors in the whole training set.

KNN and SVM can be used in intelligent wireless networks for cooperative spectrum sensing [34], where the input is the energy level estimation from a set of cognitive radio users and the output is the label for one of the two classes/hypotheses, corresponding to the absence and presence of the licensed user signal, respectively. The proposed cooperative spectrum sensing techniques based on KNN and SVM are shown to be more adaptive to the changing environments than the traditional methods. In addition, a computational efficient architecture is proposed for cooperative spectrum sensing using SVM, where the training process and online prediction can be operated independently. Specifically, the training process, regardless of its computational cost, can be performed in the background and the SVM model will be only updated when the radio environment changes. Whenever the cognitive radio network needs to identify the channel availability, energy features will be collected as input to the model and the model will generate output about the prediction of channel availability without too much delay.

SVM is also useful to perform classifications [162]–[168] in wireless networks. Variations of SVM are adopted in [167], [169] to classify MAC protocols, which is helpful for users to change their transmission parameters in heterogeneous networks. In [167], SVM is used to classify contention based or control based MAC given the input features, the mean and variance of the received power at a cognitive radio terminal. From [167], the model deployed by the cognitive radio terminals can classify *time-division multiple access* (TDMA) and slotted ALOHA MAC protocols effectively. As the features related to the instantaneous received power are more distinctive between the two protocols when the new packet generating/arriving probability of the primary network increases, the classification accuracy improves. Similarly, SVM with different types of kernels is used in [169] to identify one of the four types of MAC protocols, including TDMA, *carrier sense multiple access with collision detection* (CSMA/CA), pure ALOHA, and slotted ALOHA, according to the power features. Multi-class SVM models are proposed in [168] to classify seven distinct modulation schemes based on their spectral and statistical features, where the spectral features include the maximum of the spectral power density of the normalized centered instantaneous amplitude and the standard deviation of the absolute non-linear centered

instantaneous phase and the statistical features include higher-order statistics of the real part of the complex envelope.

A hierarchical SVM model is proposed in [170] to identify wireless network parameters, including the physical location in an indoor wireless network and channel noise level in a *multiple-input multiple-output* (MIMO) wireless network. When there are a large number of transmit and receive antennas, the parameter identification may lead to search problems in a high-dimensional space. The proposed SVM based model is able to determine these parameters according to simple network information, such as the hop counts. Five different models, including KNN and SVN, are used to predict a mobile user's specific usage pattern of wireless data and location services [171], which can further help optimize energy consumptions of mobile devices. Specifically, the input consists of spatial temporal context and device features, such as time, location, battery, and the number of running processes. The output of the classification is the on/off status of data and location services. Among the five strategies, the SVM achieves higher prediction accuracy and more energy savings with a minimal number of active users.

In [172], the multi-channel sensing and access problem is modeled as an Indian Buffet game, where the secondary users are customers and the primary channels are represented as a number of dishes in the restaurant. The proposed algorithm finds the perfect Nash equilibria of the subgames for the secondary users. To address the multi-channel sensing problem, a cooperative approach is used to estimate the channel state using Bayesian learning. To maximize the spectrum utilization in cognitive radio networks [173], a Bayesian detector for multi-phase shift keying modulated primary user signals is proposed based on Bayesian decision rule. From [173], the Bayesian detector performs better than the traditional energy detector in terms of both spectrum utilization and secondary user throughput, especially in the high SNR regime.

The Bayesian learning techniques can also address the pilot contamination problem in massive MIMO systems [174]. The proposed approach outperforms the conventional estimators in both channel estimation accuracy and achievable rates when pilot contamination occurs.

An HMM model is constructed in [175] to estimate the sojourn times of a primary user in both active and inactive states as well as the primary user signal strength, based on the sequence of the sensing results. The HMM is based on a two-state hidden Markov process, where the two states are whether the primary user is absent or not at each observation time in successive

time frames. The parameters are estimated by extending the standard *expectation-maximization* (EM) algorithm. The proposed algorithm can estimate the channel parameters well under certain conditions.

Variations of ANN models are used for spectrum sensing [176]–[178]. An ANN model is proposed in [176] to predict binary channel status according to the features extracted from energy detection and cyclostationarity feature detection. The proposed method can detect the signals well even if the SNR is low. By representing the channel status at every time slot as a time series [177], a *multilayer feedforward neural networks* (MFNN) model is used to predict if the channel is busy or idle in the next slot based on the states in the previous  $n$  slots. Compared with the HMM based approaches [175], the proposed approach can model the correlation between the current status and a large number of past observations more effectively. Instead of directly modeling the channel status, by exploring the cyclostationary signal features at every time slot, the model in [178] constructs a multivariate time series and predicts the evolution of RF time series data using a *recursive neural network* (RNN).

There are also some applications of the ANN in the context of signal classification. An ANN model is used in [179] to classify the signal into one of 12 classes of analog and digital modulation schemes. The ANN models are also used for performance prediction and resource optimization. For example, the model in [180], [181] predicts the application-layer throughput of the mobile user, based on both environmental measurements, such as packet rate, idle time, day of the week, and hour of the day, and parameter settings, such as the routing protocol being used via an MFNN. The proposed method for dynamic channel selection is implemented in IEEE 802.11 wireless networks, which demonstrates that the model can effectively predict the network performance with respect to the changes in the environment and dynamically select the best channels.

### C. Unsupervised learning

As illustrated in Figure 5, clustering, a typical unsupervised learning approach, groups  $n$  observations  $\{x_1, \dots, x_n\}$  to  $k$  clusters, where  $x_i \in \mathcal{X} \subseteq \mathbb{R}^d$  is an observation of dimension  $d$ , so that the observations in the same cluster are more similar to each other and those in different clusters are less similar. Clustering has various applications in intelligent wireless networks. For

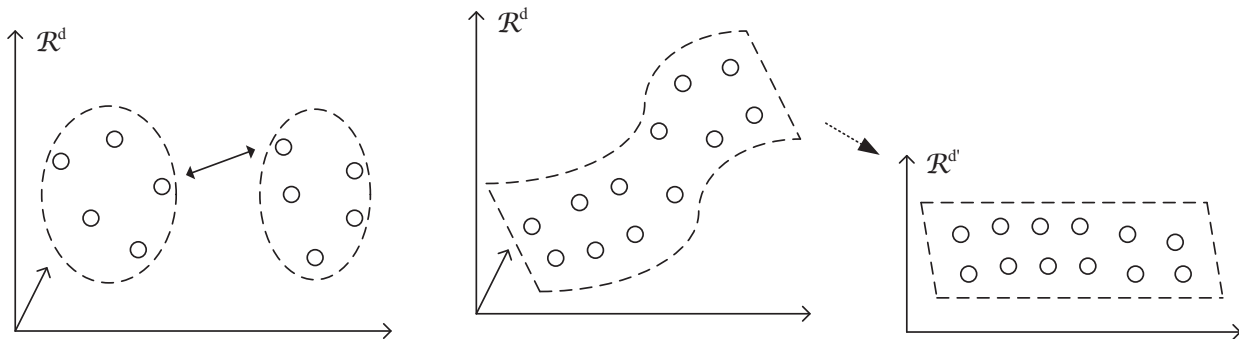


Fig. 5. Illustration of clustering (left) and dimensionality reduction (right).

example, small cells in heterogeneous networks can be clustered to avoid interference, the mobile users can be clustered to satisfy an optimal offloading policy and the devices can be clustered to achieve high energy efficiency.

As one of the most popular clustering algorithms, centroid-based clustering, such as k-means, assumes that there are  $k$  clusters and each is associated with a centroid that is the average of all observations in the cluster. The goal is to find the clusters such that the sum of distances of the observations in the clusters to the centroids is minimized. The algorithm iteratively assigns each observation to its nearest centroid based on Euclidean distance and recomputes the centroid in each cluster based on the current assignments. The algorithm converges when the current assignments are the same as those in the previous iteration. The k-means approach is computational efficient and works well for most types of data in practice. However, it cannot handle clusters with non-spherical shapes or of different sizes and densities.

A cluster-based approach, “HEED”, is proposed in [182] to group ad hoc sensor networks when channel allocation is fixed. As the radio spectrum usage paradigm tends to be open, the topology management algorithm in [183] solves the network formation problem in the cognitive radio context. The algorithm optimizes the cluster configurations to adapt to network and radio environment changes. To aggregate efficient source information under energy constraints, a distributed spectrum-aware clustering technique is developed in [184] to identify energy-efficient clusters and restrict interference to the primary users in cognitive radio sensor networks. The goal is to identify a set of clusters to minimize communication power, which is proved to be equivalent to minimizing the sum of squared distances between each node and its cluster center. A group-

wise constrained clustering approach similar to k-means is proposed to minimize intra-cluster distances with an additional spectrum-aware constraint. The proposed clustering technique is proved to be scalable and stable due to quick convergence under dynamic primary user activities.

In contrast to the k-means algorithm that assumes a fixed number of clusters, a *Dirichlet Process Mixture Model* (DPMM) is a non-parametric Bayesian approach applied to clustering without predefining the number of clusters. Note that “non-parametric” here implies a model whose parameters may change with observations, rather than a parameter-less model. In particular, the DPMM assumes an infinite number of clusters and assigns an observation to a cluster probabilistically. The model parameters are estimated to best fit the observations using Gibbs sampling. The flexibility offered by non-parametric approaches, such as the DPMM, leads to a wide range of clustering applications that take account of the dynamic RF environments.

The DPMM can identify different types of wireless systems coexisting in the same frequency band [185], where the number of wireless systems may change over time. The observation here consists of features extracted from the received signal, including the center frequency and frequency spread after sensing. Since systems transmitting at different carrier frequencies will result in different observations, the DPMM only needs to group observed data to different clusters, each representing a primary system that exists in a certain frequency band at a certain time. Similarly, the DPMM can be used to infer different types of signals, such as WiFi and Bluetooth signals, given their spectral and cyclic properties [186].

Dimensionality reduction, as shown in Figure 5, aims to transform observations of high-dimensional variables into meaningful lower-dimensional representations without losing too much information. Specifically, dimensionality reduction techniques map observations  $\{x_1, \dots, x_n\}$  into new representations  $\{z_1, \dots, z_n\}$ , where  $x_i \in \mathcal{X} \subseteq \mathbb{R}^d$ ,  $z_i \in \mathcal{Z} \subseteq \mathbb{R}^{d'}$ , and  $d' \leq d$ . *Principle component analysis* (PCA) projects the observations into a set of  $k$  linearly uncorrelated variables also known as the principle components, where the first principal component has the largest variance, and the subsequent principle components maximize the variance among all directions orthogonal to the previous  $k-1$  components. *Independent component analysis* (ICA) assumes that the observations are linear combinations of variables that are statistically independent and non-Gaussian, such as different mixtures of signals from multiple independent sources. In contrast to PCA that projects observations to components that maximize the variance, the components

of ICA have maximum statistical independence. Dimensionality reduction, including PCA and ICA, can be applied to various areas, such as signal denoising and separation.

Robust PCA is applied to recovering the low-rank covariance matrix of a signal in cognitive radio networks, which is corrupted by a sparse covariance matrix with arbitrarily large magnitude non-zero entries of a noise [187]. In particular, assume that the received signal can be divided into two segments, including the signal and noise, as the covariance matrix of the white noise is diagonal, which can be regarded as sparse, and the covariance matrix of the signal is usually low-rank. After the low-rank matrix from the sample covariance matrices of both segments is extracted with robust PCA, the primary user signal can be found present if the difference between the recovered low-rank matrix and the original one is smaller than a predefined threshold, which is verified with both the simulated and captured digital television signals. The robust PCA can also be regarded as a denoising process for the sample covariance matrix in a similar way [188]. In [188], ICA is used in a smart grid scenario to separate wireless signals of smart utility meters from independent sources. The proposed model can be used to avoid channel estimation in each time frame and thus enhance the transmission efficiency. In addition, data security is preserved by avoiding wideband interference and eliminating jamming signals. Another example of ICA [189] is to decompose the observations of the secondary users to mixtures of hidden binary primary user sources in cognitive radio networks. From [189], the activities of up to  $2m - 1$  distinct primary users can be inferred given  $m$  monitors or secondary users.

#### *D. Reinforcement learning*

Reinforcement learning is very useful when little knowledge about an environment is known and a decision maker, i.e., an agent, needs to learn and adapt to its environment with significant uncertainty, such as the case of a wireless radio learning and adapting to the RF environment. As illustrated in Figure 6, a stochastic finite state machine is usually used to model the environment with inputs, such as an action sent from the agent, and outputs, such as observations and rewards sent to the agent. The agent's objective is to maximize rewards by exploring and exploiting the environment. Reinforcement learning can be applied to energy harvesting [190], spectrum sensing [191], and spectrum access in cognitive radio networks [44], [192].

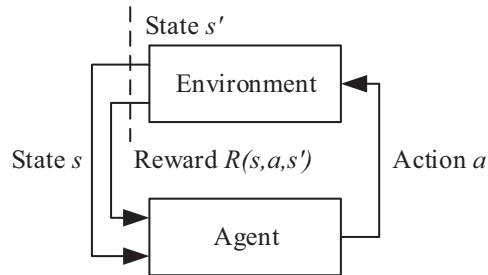


Fig. 6. Illustration of reinforcement learning. An agent interacts with its environment and receives the feedback in the form of rewards. The agent's objective is to learn to take actions to maximize the expected rewards.

*Markov decision process* (MDP) is a widely used mathematical framework to model decision-making under uncertainty, where the outcomes are partially random and partially controllable by an agent. An MDP can be characterized by a tuple of four components  $(S, A, T, R)$ , where  $S$  is the state space,  $A$  is the action space,  $T(s, a, s')$  is the probability of reaching state  $s' \in S$  if action  $a \in A$  is taken in state  $s \in S$ , and  $R(s, a, s')$  is the reward of transition  $(s, a, s')$ . At each time step  $t$ , the process is in some state  $s \in S$ , and an agent needs to choose a legitimate action  $a \in A$ . The process then moves to a new state  $s' \in S$  at time  $t+1$  probabilistically and the agent receives a reward correspondingly. The probability that the process moves into a new state  $s' \in S$  is determined by both the current state  $s \in S$  and chosen action  $a \in A$ , formally described by state transition probability  $T(s, a, s')$ . Given  $s \in S$  and  $a \in A$ , the probability is conditionally independent of all previous states and actions, which indicates that the state transitions satisfy the Markov property. To model a problem using MDP, the four components,  $(S, A, T, R)$ , need to be specified. Several iterative algorithms, such as the value-iteration algorithm based on the Bellman's principle of optimality, can be used to identify the optimal action in each state. A *partially observable Markov decision process* (POMDP) can be used to model the decision process in the situations where an agent does not directly observe the underlying states.

MDP is used to formulate the dynamic spectrum access problem [193], where the state space  $S$  denotes all legitimate frequency bands that a secondary user can use. The set of available actions in each state  $s \in S$  contains three types: performing a cycle of detection and transmission in the current frequency band  $s \in S$ , performing out-of-band detection in other frequency bands, and switching to another frequency band. Furthermore, a state transition occurs only if the action

of switching to another band is selected. In addition, the reward function  $R(s, a, s')$  is defined as follows: the first type of rewards is the bits that have been transmitted while staying in the current frequency band  $s \in S$ , the second is the reward of performing a detection in a different frequency band, and the third is the reward of switching to another frequency band, which may be negative due to transmission delay.

Going beyond traditional MDP, reinforcement learning does not require any prior knowledge of the transition probabilities  $T$  or the reward functions  $R$  and is capable of addressing complicated tasks when the traditional approaches are intractable. This makes reinforcement learning a desired approach for many real-world applications. Specifically, Q-learning is an efficient model-free reinforcement learning technique, which can be used to identify an optimal policy for any finite MDP. Q-learning also consists of state space  $S$  and actions in  $A$  for each state. The reward of executing an action  $a \in A$  in a specific state  $s \in S$  is characterized by a Q-function, where the Q-value,  $Q(s, a)$ , of the joint state-action pair is updated iteratively after the agent takes an action and observes the corresponding reward at a new state at each time step.

Q-learning can be applied to spectrum access in cognitive radio networks. Specifically, Q-learning is used to control the interference in a cognitive radio network [44], where the aggregated interference caused by the secondary users to the primary user is below a certain threshold. In particular, each secondary user needs to determine how much power it can transmit to avoid interference. The state of the secondary user consists of three components, a binary indicator specifying whether the secondary user interferes with the primary user, the estimated distance between the interference contour and the secondary user, and the power at which the secondary user is currently transmitting. The action set includes power levels of the secondary user and the reward due to action  $a \in A$  in state  $s \in S$  is quantified as the improvement in SINR. It is demonstrated that the strategy can alleviate interference to the primary user regardless of the partial state observability. In [191], a reinforcement learning framework is proposed based on Q-learning to identify the presence of the licensed user signals and to access the licensed channels whenever they are idle. In [194], reinforcement learning based on Q-learning is used for routing in multi-hop cognitive radio networks, which allows learning the good routes more efficiently.

A channel selection strategy based on multi-agent reinforcement learning is proposed in multi-



user and multi-channel cognitive radio systems for secondary users to avoid the negotiation overhead [195]. In contrast to single-agent reinforcement learning, there are more challenges associated with multi-agent reinforcement learning, such as the nonstationary and coordination. In [192], reinforcement learning is used to improve opportunistic spectrum access in cognitive radio networks by interacting with the environment.

In [196], reinforcement learning is employed in a dynamic spectrum leasing framework, which allows the proposed auction game to reach an equilibrium with both centralized and distributed network architectures. A stochastic game framework based on reinforcement learning is proposed in [197] for anti-jamming defense. In particular, minimax Q-learning is used to learn the optimal policy, which results in maximizing the expected sum of discounted payoffs defined as the spectrum-efficient throughput. Simulation results demonstrate that the optimal policy obtained from minimax Q-learning can achieve much higher throughput, in comparison with the myopic learning policy that maximizes the payoff at each step ignoring the dynamics of the environment.

A key component in reinforcement learning for cognitive radio networks is the tradeoff between exploration and exploitation. Specifically, novel exploration schemes, such as re-partitioning and weight-driven exploration proposed in [198], significantly outperform the traditional uniform random exploration scheme. A distributed multi-agent multi-band reinforcement learning framework is developed in [199] for spectrum sensing in ad hoc cognitive radio networks. The goal is to maximize spectrum utilization for secondary use given a desired diversity order, where a desired number of secondary users can coexist in each frequency band. It is proved that the proposed model of spectrum sensing in a multi-agent scenario is computational efficient and can be deployed in networks with a large number of secondary users and a set of different frequency bands. In [200], a MAC protocol is proposed for autonomous cognitive radio users. The protocol is based on Q-learning and allows learning an efficient sensing policy in a multi-agent decentralized POMDP environment.

In contrast to full MDP where the environment has many states and new states depend on previous states and actions, *multi-arm bandit* (MAB) can be regarded as a simple version of MDP where the environment has only one state. In this stateless situation, the reward depends only on the action, i.e., arm, and the agent simply needs to learn to choose the best action, i.e., pull the arm, iteratively to maximize the sum of the cumulative rewards. MAB can be

extended to a *multi-player multi-armed bandit game* (MP-MAB), where the reward collected by any player depends on other players' decisions. MAB based models require the balance between choosing the actions to maximize rewards based on the acquired knowledge and attempting new actions to explore unknown knowledge, which is known as the aforementioned exploitation versus exploration tradeoff in reinforcement learning.

The MAB and MP-MAB models are capable of addressing channel selection problems in wireless networks, where some of the wireless environment parameters, such as the channel conditions, have to be “explored” while the information of the known channels needs to be “exploited”. For example, a semi-dynamic parameter tuning scheme to update the multi-armed bandit parameters is proposed in [201] to balance exploring the external environment and exploiting the acquired knowledge to decide which channel to access in dynamic environments. The above machine learning models are summarized in Table I.

#### *E. Emerging machine learning techniques*

Traditionally, the training process of a machine learning algorithm occurs in a centralized processor that contains all training examples. As more and more data are available, e.g., reaching petabyte or exabyte magnitude, distributed frameworks with parallel computing become a promising direction to scale up machine learning algorithms. Distributed computing platforms, such as Hadoop MapReduce and Spark, are developed to enable parallel computations on large clusters of machines. A general approach of implementing machine learning algorithms on top of MapReduce is investigated in [205]. Another impressive progress is made in cloud-computing-assisted learning [206], [207].

In cognitive technology applications, most of the learning tasks, such as spectrum sensing, need to be finished within a certain period of time since observations change over time. In these time-sensitive cases, a learning algorithm needs to incorporate fresh input data and make predictions/decisions in a real-time manner. In contrast to the traditional offline or batch learning, which needs to collect the full training examples, the online learning [208]–[211], a well-established learning paradigm, is capable of learning one instance at a time. In addition, several streaming processing architectures, including Borealis [212], S4 [213], and Kafka [214], are proposed recently to support real-time data analytics [215], [216].

TABLE I  
COMPARISON OF MACHINE LEARNING MODELS FOR INTELLIGENT WIRELESS NETWORKS

Category	Learning Algorithms	Characteristics	Applications
Supervised Learning	KNN	majority votes of neighbors lazy learner	spectrum sensing [34]
	Logistic/SVM-linear	linear separable input easy to train	spectrum sensing [34] MAC protocols [167], [169]
	SVM-nonlinear	non-linear input to high dimension expensive to train	spectrum sensing [34] MAC protocols [167], [169]
	Bayesian Net/HMM	statistical models, interdependent outputs such as Markov time series	spectrum sensing [172], [173] channel estimation [174], [175]
	ANN	model any complicated function hard to train	spectrum sensing [176]–[178] signal classification [179]
Unsupervised Learning	k-means	parametric, need to specify $k$ centroid based clustering, iteratively update	network formation [183] power optimization [184]
	DPMM	nonparametric, clusters adapt to data fully Bayesian, approximate inference	network clustering [185], [186]
	PCA	orthogonal axes to maximize variance reduce dimension	denoising [187], [188]
	ICA	independent components reduce dimension, signal separation	source separation in smart grid [188] signal source decomposition [189]
Reinforcement Learning	MDP/POMDP	decision-making under uncertainty specify full model ( $S, A, T, R$ )	energy harvesting [190] dynamic spectrum access [193]
	Q-learning	unknown state transition and rewards address complicated tasks efficiently	self-configuration in femtocells [202] power control in small cells [203] spectrum access [191], [192], [203]
	Multi-arm bandit	learning in stateless environment exploitation and exploration	channel selection [201], [204]

Deep learning [160], [161], as one of the most popular research fields inspired by a large ANN, can capture complicated and potentially hierarchically organized statistical features of inputs and outperform state-of-the-art methods with carefully drafted hand-made features. Deep learning with either supervised or unsupervised strategies has shown great success in computer vision [217]–[219], speech recognition [220], and natural language processing [221]–[223]. Traditional neural networks with very few layers have been widely utilized in cognitive radio networks

[35], [177], [224]. As the accelerated GPU computing becomes more and more popular, larger volumes of training data become available, and more and more effective training algorithms are developed, deep learning will play a pivotal role in supporting predictive analytics, which also makes it a promising research direction in supporting intelligent wireless networks.

## V. APPLICATIONS IN FUTURE WIRELESS NETWORKS

In this section, we focus on applications of cognitive technology and machine learning to the future wireless networks. The compelling applications include small cells and heterogeneous networks, device-to-device communications, and energy harvesting. For each of these applications, we discuss why intelligence is important, review how perception, reconfiguration, and machine learning techniques can be applied, and evaluate the corresponding performance to show the power of intelligence in wireless systems.

### A. *Small cells and heterogeneous networks*

The deployment of small cells, such as femtocells, has emerged as a promising technology to extend service coverage and increase network throughput [225]. In such a heterogeneous network, both small cells and macrocells face the cross-tier interference and co-tier interference from the network elements belonging to different and the same tiers, respectively. Intelligence is therefore important to improve the network performance for the coexistence of small cells and macrocells. First of all, the aforementioned spectrum sensing techniques can be used in small cells to identify if a macrocell is transmitting over a specific channel or not to facilitate interference management.

Meanwhile, spectrum-aware resource optimization can be designed in heterogeneous multicell networks [226]. With consideration of proportional fairness and traffic demands, the overall network spectrum efficiency can be maximized through the proposed channel allocation scheme. In [227], resource allocation with imperfect spectrum sensing for heterogeneous OFDM-based networks is investigated. A two-step scheme decomposes the resource allocation problem into subchannel allocation and power allocation subproblems. The optimal sum rate through a polynomial complexity and near optimal sum rate through a constant complexity are analyzed and illustrated. From the energy efficiency perspective, centralized power allocation in heterogeneous

architecture is studied in [228]. The energy efficiency performance with exclusive spectrum use and spectrum sharing is optimized through Newton method based power allocation algorithms. The convergence of the proposed algorithms and significant energy efficiency gain are illustrated via numerical results. Applying graph-based and market-based approaches to the heterogeneous network users often involves an intermediary agent as a secondary service provider. In this way, small cells can purchase channels without spectrum sensing capabilities. This market structure is also designed for small cells with limited capability in computation and communications. In [229], an auction-based secondary spectrum market is proposed to share spectrum with small cell users in a two-tier heterogeneous network. In [230], a virtual network operator is involved in a two-tier spectrum sharing market, in which users have heterogeneous demand requirements and channel valuations. By making the trading process a five-stage Stackelberg game, optimal decisions are proved to exist and an algorithm is proposed to find the optimal decisions. In [231], the cellular operator provides both femtocell and macrocell services with limited spectrum resources. The spectrum allocation and pricing are modeled as a Stackelberg game and optimal decisions under different assumptions are discussed.

Machine learning has been extensively applied to heterogeneous networks. For example, a distributed strategy based on reinforcement learning is formulated as dynamic learning games in [202] for the optimization and self-configuration of femtocells in heterogeneous networks, where closed-access *Long-Term Evolution* (LTE) femtocells overlay an LTE network. Specifically, the learning strategy enables opportunistic spectrum sensing of the radio environment and parameter tuning, to avoid interference in heterogeneous networks and satisfy QoS requirements. Another example of Q-learning in dense small cell networks is to manage cell outage and compensation [203]. The state space of the problem consists of the allocations of resources to users. The actions are downlink power control and the rewards are quantified as SINR improvement. It has been shown that the reinforcement learning based compensation strategy achieves better performance.

### *B. Device-to-device communications*

To further alleviate the huge infrastructure investment of operators, D2D communications have been considered as another promising technique in the future wireless networks [232]. Similar to the case of heterogeneous networks, intelligence is important for the coexistence of D2D

and cellular links. The aforementioned spectrum sensing techniques can also be used in D2D communications to facilitate interference management.

Furthermore, to achieve better performance in relay-aided D2D communications, a message passing-based resource allocation scheme is designed in [233] to maximize the network throughput in a distributed manner. The spectrum efficiency of multi-user multi-relay networks is improved through the proposed resource allocation with low computational complexity. Meanwhile, the interference introduced by the coexistence of D2D and cellular users is effectively mitigated through the proposed interference and QoS constraints. Considering the channel uncertainties, the work in [233] is extended in [234] to be more practical. A new distributed resource allocation scheme based on a stable matching approach is developed in the same framework. The achievable rate under channel uncertainties is improved in the D2D network. Moreover, since D2D communications introduce an alternative mode for users, resource allocation jointly optimized with mode selection is proposed to maximize the system throughput in [235]. With consideration of different spectrum sharing patterns in different modes, the properties of different modes are explored through the proposed power control and channel assignment schemes. The spectrum efficiency is therefore significantly improved. An example of applying machine learning lies in distributed D2D communications [204], where each individual D2D user aims to optimize its own performance over the vacant cellular channels with unknown statistics to the user. The distributed channel selection problem is modeled as an MP-MAB game. Specifically, each D2D user is modeled as a player of the MP-MAB game while arms represent channels and pulling an arm corresponds to selecting a channel. A channel selection strategy, consisting of the calibrated forecasting and no-regret bandit learning strategies, is proposed.

### *C. Energy harvesting*

Energy harvesting converts ambient energy to electrical energy and has been emerging as an alternative to power wireless nodes. To exploit recharging opportunities and balance lifetime and performance, intelligence becomes an important characteristic for energy harvesting systems. In [236], the analytically tractable models given the complex time varying nature of such sources are provided and distributed methods to efficiently use the harvested energy are proposed. To maximize the throughput with the harvested energy over a finite horizon, dynamic programming

and convex optimization techniques are used in [237] to obtain the optimal energy allocation with causal and full CSI, respectively. MDP and POMDP are adopted in [190] to model the power control problem in energy harvesting, where the state space consists of the combination of the battery state, the channel state, and the packet transmission and reception states, and the action space of a node is defined as sending a packet at different power levels. The implicit feedback from the energy harvesting system contains partial CSI, which corresponds to the observations in a POMDP formulation. Due to the complexity in finding exact solutions to the POMDP, computationally efficient suboptimal solutions, such as the maximum-likelihood heuristic policy and the voting heuristic policy, are explored.

## VI. CHALLENGES AND FUTURE DIRECTIONS

In this section, we discuss challenges and future directions of cognitive technology and machine learning for intelligent wireless networks. To improve the level of intelligence and enable more applications, we suggest further development in the domains of wideband and higher frequencies, full-duplex radios, and massive MIMO. For each domain, we present technical challenges and point out the possible use of perception, reconfiguration, and machine learning techniques to address these challenges.

### A. Wideband and higher frequencies

To keep up with the growing wireless traffic and applications, the future wireless networks will require not only higher spectrum efficiency but also more bandwidth resources. Wideband communications in the higher frequency band are therefore receiving more and more attention [238]. As the number of users and channels can be significantly more than that in the current wireless systems, the scalability becomes extremely important. Besides the aforementioned wideband spectrum sensing algorithms, spectrum access and resource optimization also need to be more efficient and adapt to the higher signal attenuation. For such a purpose, novel machine learning algorithms need to be designed together with the use of perception capability and reconfigurability of wireless networks to achieve the best performance.

### B. Full-duplex radios

The existing work mostly considers *half-duplex* (HD) communications without exploring the potential of *full-duplex* (FD) communications [239]. With FD communications, a user can transmit and receive signals over the same spectrum band simultaneously, which potentially improves the spectrum efficiency and provides more access flexibility. Compared with traditional HD communications, FD communications require perfect coordination of resource optimization in uplink and downlink to control the self-interference, which also increases the complexity of resource allocation and needs further study. Intelligence is therefore essential for FD communications. Novel perception and reconfiguration techniques need to be studied to enable the coexistence of uplink and downlink while new machine learning algorithms need to address the added complexity in interference management.

### C. Massive MIMO

Massive MIMO uses a large number of antennas, usually at base stations, and can potentially bring huge improvements in throughput and energy efficiency [240], [241]. To enable the exploitation of extra degrees of freedom provided by the excess of antennas, intelligence is especially important and can enhance both the performance and efficiency in the new scenario. As in the case of wideband communications, machine learning needs to be exploited to transform the big data from the extra degrees of freedom into the right data with improved perception capability and reconfigurability of wireless networks.

## VII. CONCLUSIONS

The intelligence of cognitive technology and machine learning offers the potential to learn and adapt to the wireless environments. As the use of machine learning techniques in wireless networks is usually combined with cognitive technology, we have focused on both cognitive technology and machine learning to provide a comprehensive overview of their roles and relationship in achieving intelligent wireless networks. We have considered spectrum efficiency and energy efficiency, both of which are important characteristics of intelligent wireless networks. We have also presented some practical applications of these techniques to the existing and future wireless networks, such as heterogeneous networks and D2D communications. In addition, we



have elaborated open research challenges in cognitive technology and machine learning and suggested likely improvements in future wireless networks.

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