Spectrum Inference in Cognitive Radio Networks: Algorithms and Applications

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***Abstract*—Spectrum inference, also known as spectrum prediction in the literature, is a promising technique of inferring the occupied/free state of radio spectrum from already known/measured spectrum occupancy statistics by effectively exploiting the inherent correlations among them. In the past few years, spectrum inference has gained increasing attention owing to its wide applications in cognitive radio networks (CRNs), ranging from adaptive spectrum sensing, and predictive spectrum mobility, to dynamic spectrum access and smart topology control, to name just a few. In this paper, we provide a comprehensive survey and tutorial on the recent advances in spectrum inference. Specifically, we first present the preliminaries of spectrum inference, including the sources of spectrum occupancy statistics, the models of spectrum usage, and characterize the predictability of spectrum state evolution. By introducing the taxonomy of spectrum inference from a time-frequency-space perspective, we offer an in-depth tutorial on the existing algorithms. Furthermore, we provide a comparative analysis of various spectrum inference algorithms and discuss the metrics of evaluating the efficiency of spectrum inference. We also portray the various potential applications of spectrum inference in CRNs and beyond, with an outlook to the 5th generation mobile communications (5G) and next generation high frequency (HF) communications systems. Last but not least, we highlight the critical research challenges and open issues ahead.**

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***Index Terms*—Spectrum inference, spectrum prediction, cognitive radio, 5G, HF communications**

I. Introduction

A. Background and Motivation

The contradiction between spectrum shortage and spectrum under-utilization has motivated the emergence of dynamic spectrum access (DSA) or opportunistic spectrum access (OS-A) [1]. Cognitive radio (CR) [2] has been well recognized as one of the crucial techniques of realizing the DSA/OSA concept. Since its conception, CR has been designed for autonomous reconfiguration by learning from and ultimately adapting to the continuously changing radio environment [3].

The first step of implementing a CR is to capture the relevant information about the spectral evolution. In the spectrum management framework relying on spectrum sensing, spectrum allocation decisions, spectrum sharing, and spectrum mobility proposed in [4], spectrum sensing has the task of sensing its occupancy and capturing the characteristics of the primary user (PU). However, in the practical sensing process, some inevitable problems arise concerning the sensing speed, the potentially excessive energy consumption and the limited sensing scope, all of which hinder the efficient operation of the CR. The main reason for these problems is that each CR can only sense the current radio environment at its operating location without any awareness of the unsensed bands or locations and of the future trends of the spectral domain activities [5]. This inevitably wastes precious information about the evolution of spectral states between time slots, frequency bands, geographical locations, etc.

Spectrum inference/prediction is known as an effective technique complementary to spectrum sensing for capturing the relevant information about the spectral evolution and identifying spectrum holes. Briefly, spectrum sensing determines the spectrum state in a passive manner using various signal detection methods. By contrast, spectrum inference/prediction is a promising technique of inferring the occupied/free state of radio spectrum from already known/measured spectrum occupancy statistics by effectively exploiting the inherent correlations among them, in a proactive manner. Fortunately, some other fields of application, such as the atmosphere [6], finance [7], network traffic [8] and human mobility [9], inference/prediction techniques (including the popular big data technique [10]) have provided potential techniques of discovering the usage patterns hidden in the data and have

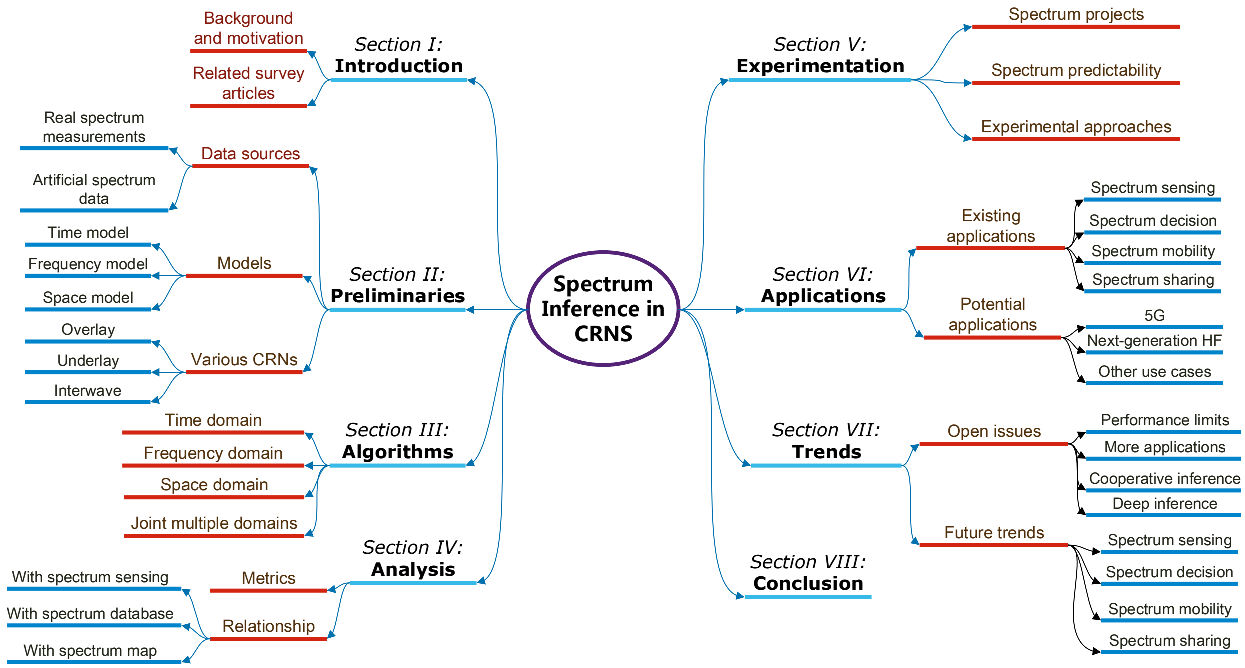

Fig. 1: The structure of this paper.

succeeded in maintaining the stability of the economy, forecasting the weather conditions and so on. Similarly, spectrum inference/prediction is a promising technique that can be utilized for acquiring precious unknown spectrum occupancy information in advance and for enhancing the performance of the CRs by accelerating the process of choosing the best channel and expanding the sensing scope in the time-frequency-spatial-domain [11]–[13]. Therefore, an increasing number of researchers have been focusing on using or developing effective inference/prediction techniques for CRs. Preliminary results (see, e.g., [14]–[20]) demonstrate that spectrum inference/prediction algorithms operating across the time-frequency-spatial dimensions may equip CRs with an accurate forecasting capability. Consequently, there is an urgent need for a survey of the specific algorithms, since the inference/prediction function is at the heart of the CR architecture and operates in a realm, where communications techniques meet artificial intelligence.

B. Comparison with Related Survey Articles

Historically speaking, there is only a brief survey relying on 15 citations [21] on spectrum prediction in CRNs, which is focused on a temporal scope. By contrast, the goal of this paper is twofold. The first is to present an all-encompassing systematic survey of the recent advances in spectrum inference/prediction algorithms from a time-frequency-spatial domain perspective. The second is to discuss the potential applications and prospects in order to emphasize the significance of inference/predicton techniques in the context of the CR technology and to provide guidelines for researchers focusing on making CR more intelligent and efficient.

Notably, spectrum inference is also related to the subject of spectrum occupancy measurements [23], [24] and primary user activity modeling [22]. Briefly, primary user activity models use mathematical or theoretical expressions to mimic the underlying PU activities, while spectrum inference algorithms use machine learning or data mining methods to predict or infer the future or unknown PU activities based on the available historic data. Refs. [22]–[24] are excellent survey and tutorial papers on spectrum occupancy measurements and/or theoretical modeling relying on statistical analysis, while our paper focuses on presenting various data mining algorithms conceived for spectrum inference/prediction. Indeed, the spectrum models in Refs. [22]–[24] are very useful for theoretical performance analysis or simulated data generation. However, they cannot be directly used for prediction.

Moreover, the work of this survey paper is also related to the survey papers on various aspects of CRNs, such as spectrum sensing [25]–[30], spectrum decision [31]–[35], resource allocation [36]–[41], security and privacy [42]–[48], MAC protocols [49], [50], routing [51], network coding [52], various applications [53]–[56], to just mention a few. A list of the related survey papers is provided in Table I for further references. On one hand, the studies on spectrum inference can find their applications in these aspects, which will be discussed in detail in the following sections. On the other hand, spectrum inference to some extent is a parallel or complementary technique to those in Table I. This paper fills the gap between them by providing a comprehensive survey of spectrum inference in CRNs.

C. Organization and Notation

This paper is organized as illustrated in Fig. 1. We introduce the necessary preliminary knowledge on spectrum inference in **Section II**. Specific inference algorithms operating in the time-frequency-spatial domain are detailed in **Section III**, while

TABLE I: A List of Related Survey Articles

Topic	Year	Reference	Contribution
Spectrum prediction	2013	[21]	A brief survey of spectrum prediction in CRNs relying on only 15 citations, which focused on spectrum prediction in time domain.
Spectrum measurements	2014	[22]	A survey of primary radio user activity models for CRNs with spectrum measurements.
	2016	[23]	A survey of spectrum occupancy measurements and the use of interference maps.
	2016	[24]	A survey on measurement-based spectrum occupancy modeling for cognitive radios.
Spectrum sensing	2009	[25]	A survey of spectrum sensing algorithms for cognitive radio applications.
	2010	[26]	A review on the challenges and solutions of spectrum sensing for cognitive radio.
	2011	[27]	A survey of cooperative spectrum sensing in cognitive radio networks.
	2012	[28]	A tutorial on spectrum sensing for cognitive radio.
	2013	[29]	A tutorial on kernel-based learning for spectrum sensing in CRNs.
	2017	[30]	A survey of the applications of spectrum sensing in CR interweave communications.
Spectrum decision	2013	[31]	A survey of spectrum decision in CRNs and issues of spectrum characterization, spectrum selection and CR reconfiguration.
	2013	[32]	An overview of Artificial Intelligence techniques, i.e, learning and reasoning for optimzing spectrum usage and management in CRNs.
	2013	[33]	A survey of the approaches and techniques used to solve the spectrum assignment problem in CRNs, including centralized, cluster-based, and distributed.
	2016	[34]	A comprehensive survey on the state-of-the-art channel assignment algorithms in CRNs.
	2017	[35]	A survey of the overlay spectrum access scheme in cooperative CRNs.
Resource allocation	2014	[36]	A survey of resource allocation in cooperative CRNs.
	2015	[37]	An overview on robust design for power control and beamforming in CRNs.
	2015	[38]	A survey of the recent advances in radio resource allocation in CR sensor networks.
	2016	[39]	A survey of recent advances in resource allocation techniques and the CR networks architectural design.
	2016	[40]	A survey of channel bonding schemes for traditional wireless networks and a detailed discussion on the channel bonding schemes proposed for CRNs.
	2017	[41]	A survey for resource allocation in underlay CRNs.
Security and privacy	2012	[42]	A survey of security aspects in software defined radio and CRNs.
	2012	[43]	A survey of security challenges in cognitive radio networks: Solutions and future research directions.
	2012	[44]	A review of robust cooperative spectrum sesnsing techniques for CRNs.
	2013	[45]	An overview of the security threats and challenges that CRs and CRNs face, along with the current state-of-the-art techniques to detect the corresponding attacks.
	2015	[46]	A survey and tutorial on the Byzantine attack and defense for cooperative spectrum sensing in CRNs.
	2015	[47]	A survery of the recent advances on security threats/attacks and countermeasures in CRNs focusing more on the physical layer.
	2017	[48]	A survey that investigates the various location privacy risks and threats that may arise from the different components of this CRN technology, and explores the different privacy attacks and countermeasure solutions.
MAC protocols	2012	[49]	A survey on MAC strategies for CRNs.
	2014	[50]	Develops generic, modular and easily extensible layout for classification and systematization of Cognitive MAC protocols, offers extensive overview on the state-of-the-art advances, and highlights the role of regulative and standardization activities.
Routing	2014	[51]	A survey of the state-of-the-art routing metrics for multi-hop CRNs.
Network coding	2017	[52]	A survey of network coding schemes in CRNs.
Cooperative communications	2014	[53]	A tutorial on various cooperative techniques in CRNs.
Green-energy-powered CR	2015	[54]	A survey of the energy-efficient CR techniques and the optimization of green-energy-powered wireless networks.
Cognitive capacity harvesting networks	2017	[55]	A tutorial that systematically summarizes the principles for CRN architecture design and presents a novel flexible network architecture, termed cognitive capacity harvesting network.
CR for smart grids	2016	[56]	A survey on the CRN communication paradigm in smart grids.

Section IV proposes a macroscopic view of various inference methods. The current and potential future applications are introduced in **Section V**. Finally, a range of challenges and future trends are presented in **Section VI** along with our conclusions. The acronyms used in this article can be found in the Table VII for convenience.

II. Preliminaries for spectrum inference in CRNs

A. Sources of Spectrum Data

Empirical real world spectrum measurements constitute the very important source of spectrum data and play a fundamental role in supporting the research and development of spectrum inference techniques. Numerous spectrum occupancy measurement campaigns have been conducted all over the world (see, e.g., [23], [24], [59]–[87]). Excellent surveys and tutorials on the latest advances of worldwide spectrum occupancy measurements can be found in [23] and [24]. Briefly, here we highlight some common features of the spectrum measurement campaigns as follows.

Firstly, the campaigns have covered various frequency ranges. For example, the probably earliest measurement campaigns conducted by the Institute of Telecommunication Science in the USA around 1995 [59] measured very broad frequency bands spanning from 108 MHz to 19.3 GHz. One the other hand, the very recent ones carried out in Beijing [86]

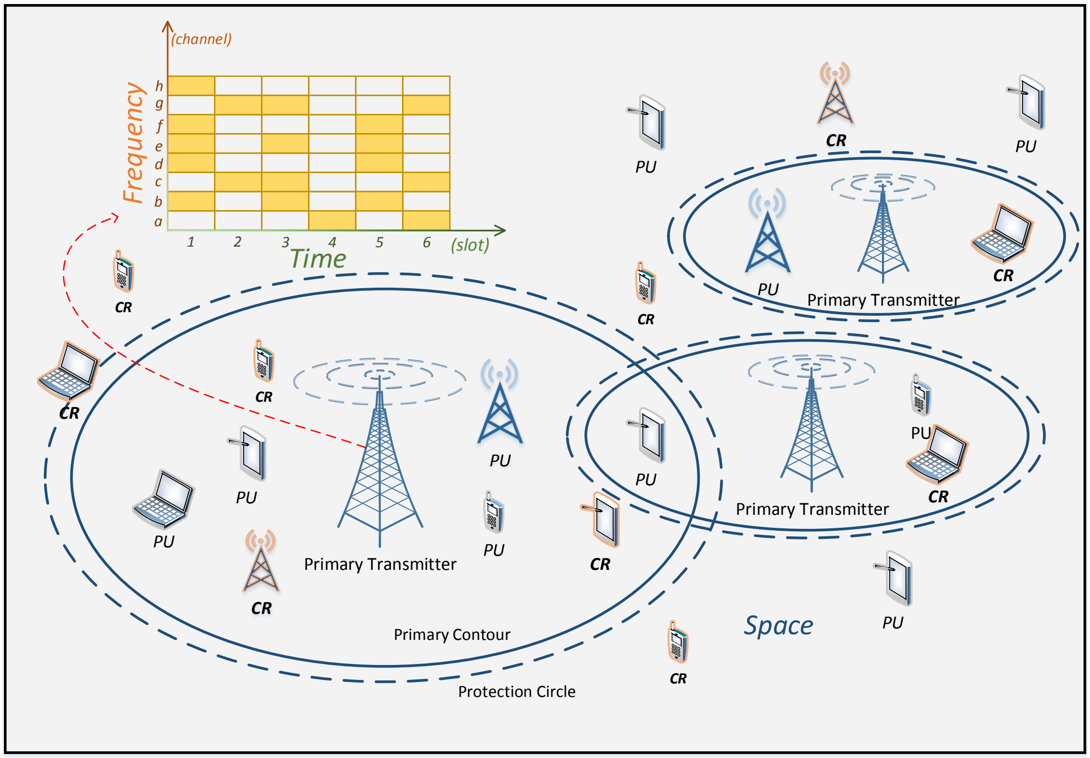

Fig. 2: An illustrative scenario in the time-frequency-spatial dimension.

and London [87] focused on TV bands (e.g., 470 MHz∼790 MHz) to identify TV white spaces. Moreover, there are many other campaigns that measured specific licensed bands (like WiFi bands, TV bands, radar bands and cellular bands) relying on diverse lengths of measurement periods (from a few hours to several years) as well as different places (e.g., Denver, Dublin, Aachen, and Singapore, etc) and scenarios (including rural, suburban and urban areas, indoor and outdoor cases) [23], [24], [59]–[87].

Second, the campaigns have had various measurement setups. In terms of hardware devices, the spectrum measurement systems generally consist of the antenna, the filter, the amplifier and the spectrum analyser to collect the spectrum data. Most of the spectrum measurement campaigns specify several common setups. For example, both the sampling rate and the measurement period, as well as the frequency span and frequency points, the measurement location, antenna polarization and direction have to be chosen according to the particular applications considered. Moreover, since the various settings may lead to different levels of measurement complexity and accuracy, the tradeoffs among of these potentially conflicting factors have been carefully taken into consideration.

Third, the campaigns have a tendency to bridge real world spectrum measurements and the public/private spectrum databases [247]–[250]. On one hand, the collection, storage and evaluation of massive amounts of spectrum measurements requires advanced databases. On the other hand, spectrum measurements ensures a data-driven approach, complementarily to the traditional propagation model-based approach [242], when aiming for improving the accuracy and the update speed of the spectrum availability provided by the geolocation spectrum databases [5], [88], [246]. Moreover, spectrum measurements are also coupled with the building of radio environment maps (REM) [255]–[257].

B. Models of Spectrum Usage

Exploiting the statistics of spectrum use or the deterministic status of PUs have been one of the critical issues for secondary use of the licensed spectrum. The research on the PU's behavior gleans lessons from the spectrum measurement campaigns. A brief conclusion is that the obtained spectrum occupancy results, e.g., in terms of the duty cycle, from spectrum measurement campaigns run by different groups are not always the same at different measurement time, locations, frequency bands with various measurement hardware and softwares. However, the primary user occupancy models (e.g., DTMC and CTMC) discussed in the following are widely used by different measurement campaigns associated with various parameter setups for specific bands, locations, and time.

Specifically, in CRNs, spectrum usage models of the primary system usually determine both the action and the performance of a secondary network and thus they play a significant role in spectrum inference, since the exploration and evaluation of inference algorithms as well as techniques is often based on them [90]. Spectrum usage models can be utilized to discover patterns of the PU's activities by analyzing the spectrum data and by reconstructing the statistical properties of the spectrum usage in real radio communication systems. By taking advantage of these models, we can generate simulated data for validating the inference algorithms. In order to prepare a solid basis for our discussions in the next section, we will

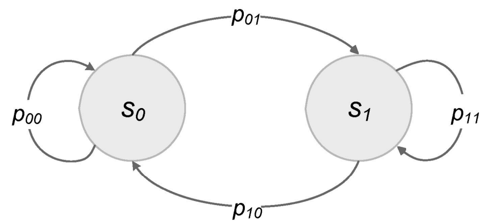

Fig. 3: DTMC model.

briefly present the most common approaches of modelling spectrum usage across the three orthogonal dimensions of time, frequency and space, as illustrated in Fig. 2 [19], [22], [89], [91]–[93]. Explicitly, in Fig. 2, there are several primary transmitters having their own primary coverage area, which are carefully coordinated for mitigating the interference arising from the others. A number of PUs and CRs are roaming either within or outside the coverage area of these primary transmitters. Furthermore, every primary transmitter has its spectrum for licensed or unlicensed use.

1) Time Domain Model: In the time domain, the spectrum usage may simply be modeled by a Markov chain having two states, one representing that the channel is busy and the other one representing that it is idle. In terms of temporal continuity, these models can be classified either into the discrete-time Markov chain (DTMC) model or into the continuous-time Markov chain (CTMC) model.

a) DTMC Model: Since the PU's states can be described as being either busy or idle and most measured data are usually represented in the form of binary sequences, the spectrum usage patterns are reflected by bits of zero value indicating having no traffic and logical ones indicating that the spectrum is being used by the PU at a particular time instant [94], [95]. The state space of a primary radio channel obeying the DTMC is denoted by $S = \{0, 1\}$. The time index set is discrete, $t = t_k = kT_s$, where k is a non-negative integer representing the step index and T_s is the time period between consecutive transitions or state changes.

The most important parameter of the DTMC model is the transition probability $p_{ij}(t_m, t_n) \in \{0, 1\}$, which represents the probability that channel state moves from state i in the m-th slot to state j in slot n. In this particular case, the transition matrix is given by:

$$P = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix}. \tag{1}$$

The overall DTMC model describing the activity of a PU's channel is illustrated in Fig. 3. We can use the above-mentioned concept of DC, denoted by Ψ, as a metric of describing the ratio of time during which the channel is declared busy as well as idle [89], [91].

In terms of stationarity, the DTMC models fall into two categories: stationary and non-stationary DTMC models. In the stationary DTMC model, the transition matrix can be formulated as,

$$P = \begin{bmatrix} 1-\Psi & \Psi \\ 1-\Psi & \Psi \end{bmatrix}, \tag{2}$$

where Ψ is a constant parameter and it can be selected as $\Psi = p_{01} = p_{11}$, especially in the long term $\Psi = P(s = 1)$. In this way, the DTMC model becomes capable of reproducing the mean DC of a real channel. However, the stationary DTMC may only be valid for a limited time period, if the system exhibits only an approximately stationary behavior during this period, where the reproduced average DC approximately matches the instantaneous DC at all times [89].

If the modeled system does not appear to exhibit strictly stationary characteristics, a non-stationary DTMC model should be considered. In this case, the transition matrix should be defined as,

$$P(t) = \begin{bmatrix} 1-\Psi(t) & \Psi(t) \\ 1-\Psi(t) & \Psi(t) \end{bmatrix}, \tag{3}$$

where $\Psi(t)$ is a variable, which is a function of the discrete time t. Based on different patterns of the channel's load, DC models can be developed using both deterministic and stochastic modelling approaches [89]. On one hand, in many particular services, like GSM and TETRA, common human habits and social behaviors impose a significant impact on the load patterns, which deterministically shape the characteristics of $\Psi(t)$. On the other hand, the stochastic DC modelling approaches are presented to describe the random variable $\Psi(t)$ as a function of numerous random factors contributing to the PU's behavior in real scenarios. It was found that the empirical PDFs of $\Psi(t)$ can be modelled by the Beta distribution [96] and the Kumaraswamy distribution [97].

Furthermore, extensive empirical measurement results have shown that the DTMCs associated with the deterministic and stochastic DC models mentioned above are capable of reproducing the average DC value and the statistical properties of the PU's idle or busy duration in real-world channels. The DTMCs have also been widely used in the literature to analyze the system throughput, the average packet delay and the end-to-end packet delay (see, e.g. [98], [99]).

b) CTMC Model: In contrast to the DTMC model, the CTMC model pays closer attention to modeling the length of a state's holding time. Note that the traditional exponential distribution used for characterizing the state holding time in CTMC is not necessarily accurate enough, according to a range of realistic measurements and analysis conducted across the globe [91], [100]–[106]. In view of this, many researchers considered the Continuous-Time Semi-Markov Chain (CTSMC) models, where the sojourn time may obey arbitrary distributions. In [104], [105], [107], [108], the idle duration was assumed to obey either a generalized Pareto distribution [108], or a mixture of uniform distribution and the generalized Pareto distribution, or alternatively, obey a hyper-Erlang distribution [104], [105] and so on. In [89], the Lopez *et al.* employ goodness-of-fit metrics to evaluate several common distributions and to demonstrate that in real-world systems CTSMC models have a better performance in terms of reproducing the statistical properties of the busy and idle durations. Additionally, the correlation between the busy and idle durations, which the CTSMC fails to reproduce has been analyzed in [91], [109].

2) Frequency Domain Model: In this paper, the frequency-domain model can also be termed as the time-frequency model, since we do analyze the properties of spectrum data over the allocated frequency band based on the channel's DC which is a temporal parameter. Although the channels are considered to be mutually independent within a spectrum band [90], [110], this may not be the case for adjacent frequency-domain channels [92]. Hence, when modeling the spectrum usage in the frequency domain, the dependency among neighboring channels should be taken into consideration. With respect to the statistical correlation across the frequency band, two aspects can be investigated through the analysis of real-world spectrum data. The first one is the DC distribution within an allocated band, while the second is the cumulative distribution function (CDF) of the DC distribution, which are closely matched by the Beta distribution, by the Kumaraswamy distribution and so on [89].

Another aspect to consider is the DC clustering across the frequency bands. In [111], the similar DC values of the adjacent channels were classified into the same group, and the distribution of the size of the cluster group was described by an appropriately shifted version of the geometric distribution [96].

3) Spatial Domain Model: In recent years, numerous studies considered the relationships among the channel states observed by CRs in different scenarios [112]–[114]. Making use of the location information beneficially supports the CR's initial awareness of the environment and its ability of taking actions efficiently [115], [116]. Based on the above-mentioned DC models in the time- and frequency- domains, the spatial DC models and the modelling of simultaneous observations are briefly introduced below. Reference [89] discussed the spatial DC models under different conditions, namely when concerning either time-varying or constant power and continuous or discontinuous transmitters.

The DC values, Ψ , are calculated after the process of energy detection. The authors in [89] also discussed the conditional and the joint probabilities of the state observed at an arbitrary location and the simultaneously observed state at the reference location. Given these two probabilities, we will be able to model the spectrum usage at another location based on the model at the reference location. Therefore, the spatial modelling procedure attaches importance to the correlation of the spectrum usage at various locations for supporting spectrum inference/prediction. However, it should be noted that generally spectrum measurement campaigns are conducted by measuring the received signals and then estimating the status of the PUs using various spectrum sensing techniques, such as energy detection [117], matched filtering, and waveform based sensing. Due to the inevitable noise, incomplete observations, and the ambiguity of parameters like the energy decision threshold and the undiscovered spectrum features, such formulations are unable to accurately infer the PUs' true status and to capture the real characteristics of the PU's activity [117]–[119]. In this sense, all the models, including those introduced above may be imperfect, which necessitates further research.

C. *Spectrum Inference in Various CRNs*

Depending on the type of available side information and on the regulatory constraints, there are three main CRNs paradigms: underlay, overlay, and interweave [120]. Briefly, the underlay CRN allows CRs to operate if the interference they cause is below a given threshold. In overlay CRNs, the CRs overhear the transmissions of the PUs, and then use this information along with sophisticated signal processing techniques to improve the performance of PUs, while also obtaining some additional bandwidth for the CRs' own transmission. In interweave CRNs, the CRs sense the absence of a PU signal in the time, frequency, and/or spatial domains, and opportunistically communicate during the PUs' absence. Generally, underlay, overlay, and interweave can be used in different bands (e.g., TV white space, radar bands and cellular bands) according to the specific regulations in a separate or hybrid manner [121], [122].

Most of the existing studies on spectrum inference focus their attention on interweave CRNs, i.e., on predicting the spectrum occupancy state in terms of being idle (i.e. the absence of a PU signal) or occupied (i.e. the presence of a PU signal), by licensed users. There are relatively few studies on spectrum inference in other types of CRNs such as underlay, overlay and hybrid CRNs. It is an interesting and fruitful research direction to extend the research from interweave CRNs to other types of CRNs. Technically, a key difference is that the inference of binary spectrum state (i.e. idle or busy) in interweave CRNs should be extended to the inference of multi-level or even continuous spectrum state values in underlay and overlay CRNs, relying on the knowledge of the channel state information between PU transmitters and PU receivers.

III. Spectrum Inference Algorithms in CRNs

Numerous prediction algorithms have been proposed for forecasting the channel state, the spectrum occupancy, the potential interference imposed, the PU's coverage area and so on. In this section, the common spectrum inference/prediction algorithms found in the literature will be surveyed in the time, frequency and spatial domains by adopting a multi-dimensional approach. The taxonomy of these spectrum inference algorithms is illustrated in Fig. 4.

A. *Temporal Spectrum Inference Algorithms*

The three main branches of Fig. 4 will be surveyed in Subsections A, B and C respectively, commencing with the temporal techniques. In the time domain, spectrum prediction infers the status of spectrum according to the historical information on the evolution of the spectral occupancy [128]. The information gleaned is represented by a series of numbers extracted from the original data, with the aid of linear prediction, Markov modelling, neural networks, pattern mining, etc. After acquiring the regular patterns of the PU, we can sense the spectrum in less time than usual, conserve precious energy and make collisions among PUs and CRs more infrequent.

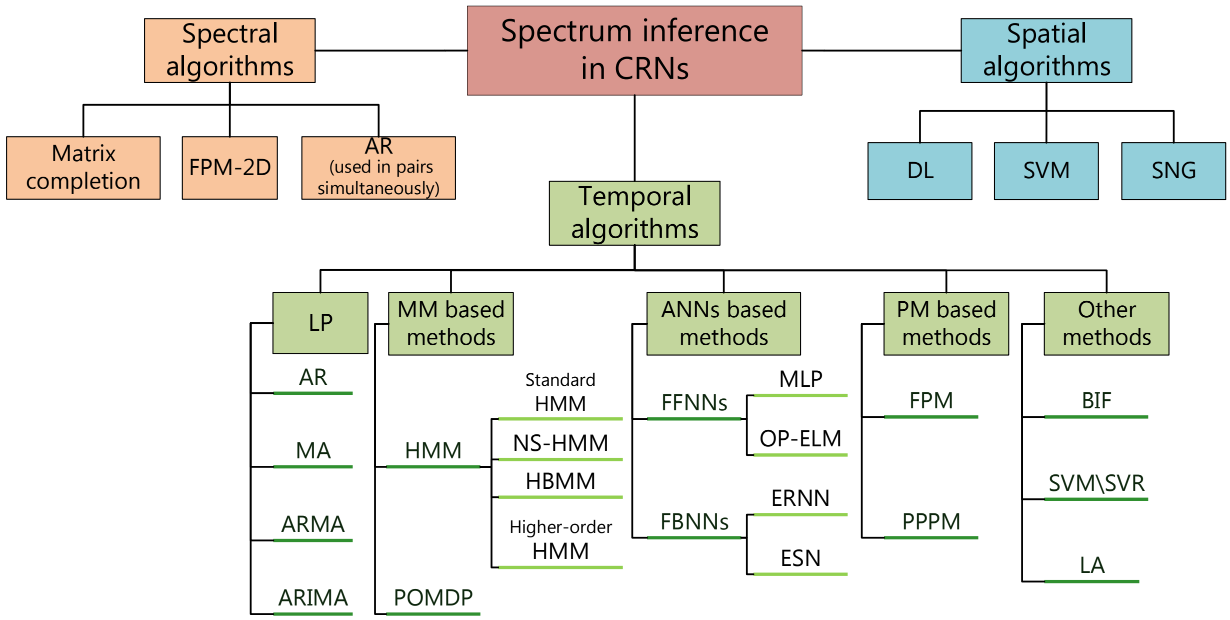

Fig. 4: Taxonomy of spectrum inference algorithms in the literature (See Table VII for the acronyms).

1) Linear Prediction (LP): Let us commence with LP algorithms seen at the top of the temporal branch. Linear prediction is an important branch of mathematical statistics, where future values are predicted as a linear function of previous samples. The LP based approach is widely used in digital signal processing for predicting the signal power as a benefit because of its remarkable simplicity, and it has also been invoked for implementing temporal-domain spectrum prediction [15], [93], [128]–[130]. Other applications include speech- and audio-compression [131] as well as video compression [132].The most commonly used linear prediction models include the autoregressive (AR) model, the moving average (MA) model, the autoregressive moving average (ARMA) model and the autoregressive integrated moving average (ARIMA) model.

a) AR Model: With reference to the left column of the middle branch in Fig. 4, the AR model of order m, $AR(m)$, can be formulated as [133],

$$X(t) = \sum_{i=1}^{m} \alpha_j X(t-i) + e(t). \tag{4}$$

In the spectrum prediction context, $X(t-i)$ represents the past observation before the t-th slot, while $X(t)$ and $e(t)$ represent the observation and error terms of the t-th slot. The expression $\sum_{i=1}^{m} \alpha_j X(t-i)$ aims for weighting the historical observations, where m is the length of the prediction memory window and α_j is the weighting parameter of the AR model. Reference [15] used a second-order autoregressive model, i.e. AR(2), for performing spectrum prediction in the time domain, where the coefficient α_j has been obtained as the solution of the Yule-Walker equations. Then a Kalman filter has been used for predicting the state of a spectrum hole. In [130], the channel occupancy status is converted into a binary form and the AR model is used for spectrum occupancy characterization as well as for prediction. Finally, artificial signals complying with the Global System of Mobile (GSM) communication standard were generated for testing the performance of prediction. Furthermore, AR models have also been applied for predicting both the channel state transitions in fading channels [134], [135] and the channel occupancy [93].

b) MA Model: The MA model is similar to the autoregressive model, except that the predicted value for the observation in the t-th slot depends on the error values observed in the past [136], rather than on the current values.

The MA model of order n, namely $MA(n)$, can be formulated as [133],

$$X(t) = \sum_{i=0}^{n} \beta_i e(t-i), \tag{5}$$

where, the notations $X(t)$ and $e(t)$ are the same as in the AR model, while β_j is the parameter of the MA model and $\beta_0 = 1$.

In [137], when analysing the Chinese TV-band channels spanning from 603.25 MHz to 843.25 MHz, the results indicate that the MA model is more suitable for predicting the strength of television signals than the 'experience based' method. Additionally, in [129], a non-linear exponential moving average (EMA) model is proposed, whose weighting factor decreases exponentially for each older data point, in order to put more emphasis on the recent observations, while giving some cognizance to former observations.

c) ARMA Model: Still referring to the left column of the middle branch in Fig. 4, the MA model is combined with the AR model to form an autoregressive moving average model $ARMA(m, n)$ [16] as follows:

$$X(t) + \sum_{i=1}^{m} \alpha_j X(t-i) = \sum_{i=0}^{n} \beta_i e(t-i), \tag{6}$$

where the notations of $X(t)$ and $e(t)$ are the same as in the AR and MA models. Furthermore, α_j and β_j are the parameters

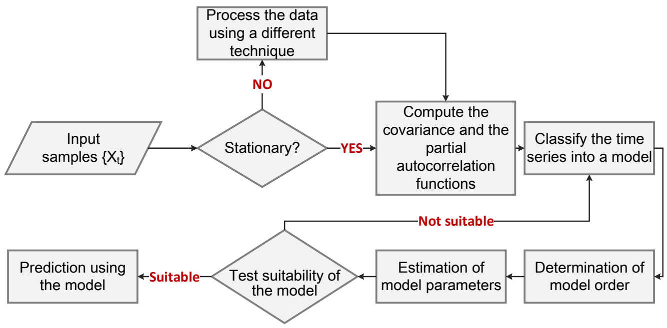

Fig. 5: Linear prediction (LP) structure.

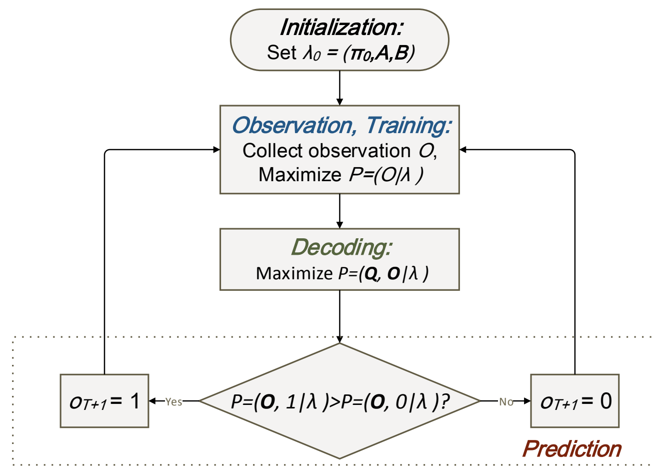

Fig. 6: HMM prediction process.

of the ARMA model, $\beta_0 = 1$. In [138], the ARMA model shows a better prediction performance in channels which have cyclic behaviors compared to the performance in forecasting the Bluetooth and WiFi channels that have more random behaviors.

d) ARIMA Modeling: The most important feature of the more flexible ARIMA model is that it is capable of handling non-stationary time series as well as rapidly decaying autocorrelation functions [139], etc. The general $ARIMA(m, n, d)$ model is formulated as [136],

$$W(t) = \sum_{i=1}^{m} \alpha_j W(t-i) + \sum_{i=0}^{n} \beta_i e(t-i), \tag{7}$$

where we have $W(t) = X(t) - X(t-d)$, while α_j and β_i are the parameters of the ARMA model of order m, $e(t)$ represents random errors, and d is the degree of non-stationary homogeneity.

The overall process of using these models is illustrated in Fig. 5 adopted from [128]. The samples $\boldsymbol{X}$ of the time series constitute the input of this procedure. As seen in Fig. 5, we first judge the degree of stationarity for the input data, and if the samples are not deemed to be stationary, they will have to be processed by different techniques. Following this step, we calculate both the covariance function as well as the partial autocorrelation function, and then classify $\boldsymbol{X}$ into a specific model. Finally, we compute m and n. As seen in Fig. 5, we also have to estimate the parameters α_j and β_i. Finally, we use the selected model to forecast the prospective values.

2) Markov Model (MM) Based Methods: Let us now consider the second column of the middle branch in Fig. 4. The Markov chain based modelling of sub-band PUs was validated by analyzing real-world measurements in the paging spectrum band in [140]. The Markov model has an appealingly simple structure characterized by its state-transition matrix. In this subsection, we will discuss a pair of temporal prediction methods, namely the Hidden Markov models (HMM) and the partially observable Markov decision processes (POMDP), also featuring in Fig. 4.

a) HMM: According to [141], an HMM is usually formulated as $\lambda = (\boldsymbol{\pi}, \boldsymbol{A}, \boldsymbol{B})$, where $\boldsymbol{\pi}$ represents the initial state probability vector, defined as:

$$\boldsymbol{\pi} = [\boldsymbol{\pi}_i] = P(q_t = s_i), 1 \le i \le N, \tag{8}$$

where $S = \{s_1, s_2, , s_N\}$ denotes N different states in a Markov chain and $q_t \in \boldsymbol{S}$ represents the state at time instant t, where π_i satisfies the conditions $0 \le \pi_i \le 1$, $\sum_{i=1}^{N} \pi_i = 1$. Furthermore, $\boldsymbol{A} = [a_{ij}]$ is the state transition matrix, which defines the probability of traversing from one state to another, formulated as:

$$a_{ij} = P(q_t = s_j | q_{t-1} = s_i), 1 \le i, j \le N. \tag{9}$$

Furthermore, $\boldsymbol{B} = [b_{ik}]$ is the observation probability matrix that offers the option of producing different observed values, while being in a particular state, which is encapsulated in:

$$b_{jk} = P(o_t = v_k | q_t = s_j), 1 \le j \le N, 1 \le k \le M, \tag{10}$$

where $\boldsymbol{V} = \{v_1, v_2, ..., v_M\}$ represents the space containing M observed symbols and o_t is the value observed at time instant t, $o_t \in \boldsymbol{V}$. Note that we have $0 \le a_{ij}, b_{jk} \le 1$, $\sum_{j=1}^{N} a_{ij} = 1$ and $\sum_{k=1}^{M} a_{jk} = 1$.

Traditionally, a standard HMM predictor is based on the discrete-time model introduced in **Section II**, where the time is slotted and the state space is binary, with the spectrum slot being either in state $s_i = 1$ or $s_i = 0$. The set $\boldsymbol{O} = \{o_1, o_2, ..., o_T\}$ may be used for representing the past observation sequence in T consecutive slots. In order to predict the state in the $(T+1)$-st slot, a HMM predictor of the standard form may be designed by obeying the following four steps [20], [111], which are illustrated in Fig. 6 and detailed as follows:

Step 1: Initialization. Set the initial parameters of the HMM $\lambda_0 = (\boldsymbol{\pi}_0, \boldsymbol{A}_0, \boldsymbol{B}_0)$.

Step 2: Observation. The CR senses the sub-band spectrum and collects the observed data $\boldsymbol{O} = \{o_1, o_2, ..., o_T\}$.

Step 3: Training. Given the observed sequence, the parameters of the HMM will be adapted by invoking an appropriate training approach, such as the Monte-Carlo method, and the Baum-Welch algorithm [141], for maximizing the likelihood associated with the model and defined as $P(\boldsymbol{O}|\lambda)$.

Step 4: Prediction. The state observed at slot $(T+1)$, o_{T+1}, can be predicted by the following rule:

$$o_{T+1} = \begin{cases} 1, & \text{if } P(\boldsymbol{O}, 1|\lambda) \ge P(\boldsymbol{O}, 0|\lambda), \\ 0, & \text{if } P(\boldsymbol{O}, 1|\lambda) < P(\boldsymbol{O}, 0|\lambda). \end{cases} \tag{11}$$

This standard HMM approach has been investigated in [14], [20], [95], [111], [140], [142], [143] for the sake of predicting the future states and the idle/busy durations of the channel. In [95], the HMM is used for predicting the spectrum usage patterns, which are assumed to be deterministic Poisson distributed. Given a sequence of predicted states, the CR will dynamically choose these surmised frequencies for its use, even though the spectrum occupancy should generally be modeled by stochastic distributions, as previously mentioned in **Section II**. This algorithm was also advocated in [142], matching its output to the data collected from the 450-470 MHz band in Australia, but the specific implementation of the algorithm was not detailed in [142]. Meanwhile, the authors of [14] considered a realistic propagation environment that took into account the time delay incurred both by the hardware and software. It should be mentioned that in [14] the parameters of the HMM used are obtained statistically, without employing any training for the model. Instead, the authors verify the proposed method using measured WiFi data instead of artificial data. Both the model complexity and the computational complexity have been studied in order to provide a qualitative characterization of the HMM performance, which were complemented by a range of implementation issues arising during the design [118]. As the number of states N increases, the number of model parameters to be estimated also increases. The computational complexity of the HMM based predictor is directly related both to the number of states N and to the size of the observation sequence T.

Moreover, MM or HMM-based methods work well under the assumption of having memoryless or Markovian spectrum state evolution, where the future state depends only on the relevant information about the current, not on information from distant the past. The Markovian property has been validated by analyzing real-world measurements in the paging spectrum band in [140], which motivates the research of HMM-based spectrum inference methods. Most of the related studies have focused on first-order and stationary HMM. However, in practical systems, the spectrum state of the future may depend on a relatively long historical information (see the tide effects in the GSM bands [209]). The state distribution of PUs may also dynamically change. In order to improve the performance of the standard HMM, in recent years researchers have developed several sophisticated HMMs by carefully considering the stationarity and the high-order Markovian nature of the spectral slot occupancy pattern. Some representative advances are summarized below as follows:

- **Non-stationary Hidden Markov model (NS-HMM)**. Here we are still considering the Markov-modeling belonging to the second branch of the temporal algorithms seen in Fig. 4. As mentioned above, the PU's spectral slot occupancy pattern is assumed to be deterministically distributed, when the standard HMM model is used. However, in reality the PU's behaviors obey time-varying non-stationary DTMC [89]. Under these circumstance, conventional HMMs may fail to adequately characterize the PU's dwelling time distributions [17]. For this reason, the NS-HMM was employed for modeling the channel's status in [17] in order to characterize the idle/busy duration of the PU's channel. The NS-HMM can be described as $\lambda_{NS} = [\boldsymbol{\pi}, \boldsymbol{A}(t), \boldsymbol{B}]$, which replaces the static transition probabilities of the conventional HMMs with dynamic ones. In [17], the parameters of the NS-HMM are inferred through Bayesian inference with the aid of Gibbs sampling, and the impact of different model parameters on the model's accuracy has been investigated. It was found that as expected the channel quality experienced by the CR is an increasing function of the sensing accuracy and of the estimated idle duration. In [118], the so-called expectation maximization based algorithm was developed for calculating the parameters of a NS-HMM. Numerical experiments relying on real spectrum measurement data have been carried out for demonstrating that the NS-HMM outperforms the traditional HMM-based approaches.
- **Hidden Bivariate Markov Model (HBMM)**. As an extension of the standard HMM, HBMMs have been proposed for more accurately characterizing the transmission pattern of a PU [144]. In contrast to the standard univariate HMM, the HBMM incorporates a number of additional variables by introducing a state duration distribution for modeling the channel usage in CR, rather than using the geometric duration distribution of a standard HMM. In [144], the HBMM was described in form of the function $\lambda_B = (\boldsymbol{\pi}, \boldsymbol{G}, \boldsymbol{\mu}, \boldsymbol{R})$, where $\boldsymbol{\pi}$ is the initial state probability vector reminiscent of that in the standard HMMs, $\boldsymbol{G}$ is the state transition matrix, while $\boldsymbol{\mu}$ and $\boldsymbol{R}$ represent the vector of observed receive signal strength average and variance. Repeatedly using the definitions of the standard HMM parameters, let $\boldsymbol{Z} = \boldsymbol{O} \times \boldsymbol{S} = [Z_t] = (o_t, q_t)$ denote the specific value returned by the bivariate Markov chain. The state transition matrix can be defined as:
$$\boldsymbol{G} = [g_{ab}(ij)] = [P(Z_{t+1} = (b, j)|Z_t = (a, i))]. \quad (12)$$
The parameter λ_B may be estimated by extending the Baum algorithm [145], which is simpler than an explicit duration estimating algorithm. When determining the model parameters, the authors of [144] apply forward-backward recursions for predicting the spectral slot state at a future time instant. The performance of the HBMM in spectrum sensing and prediction was characterized by numerical results in [144], demonstrating that the HBMM is capable of more accurate state predictions than a standard HMM.
- **Higher-order HMM**. Still referring to Fig. 4, we note that although the first-order standard HMM has been broadly adopted for predicting the channel's state, this model does not make full use of the historical information, since a state only depends on the immediate preceding state. To alleviate this problem, a higher-order HMM was also proposed for predicting the next channel state [146]. A higher-order HMM can be formulated as $\lambda_{HO} = (\boldsymbol{\pi}, \boldsymbol{A}_{HO}, \boldsymbol{B})$. In contrast to the standard HMMs, $\boldsymbol{A}_{HO} = [a_{ij}^{HO}]$ is the state transition matrix representing the transition from the states in the previous D slots to

the current state, which can be defined as [146]:

$$\boldsymbol{A}_{HO} = [a_{ij}^{HO}] = P(q_{t+1} = s_{i_{D+1}} | q_t = s_{i_D}, ..., q_{t-D+1} = s_{i_1}), i_1, i_2, ..., i_D, i_{D+1} = 1, ..., N.$$

When considering the computational complexity versus model accuracy trade-offs, there are several variants of the higher-order HMMs [146]–[149]. By relying on real-world WiFi signals recorded, it was shown that the performance of the proposed approach is significantly better than that of the nearest neighbor prediction relying on first-order HMMs, especially when the order of the HMM increases [146].

b) POMDP: The last member of the MM-based temporal methods seen in Fig. 4 is constituted by the POMDP family, which is a generalization of a Markov decision process that tolerates uncertainty about the state of a Markov process and allows the acquisition of environmental information [150]. Based on DTMC model of **Section II** [89], a POMDP applied in CRNs is defined by the six-tuple $(\boldsymbol{S}, \boldsymbol{A}, \boldsymbol{T}, \boldsymbol{R}, \boldsymbol{Z}, \boldsymbol{O})$ [151]–[154], where

$\boldsymbol{S}$ is the channel state space $\{0(\text{idle}), 1(\text{busy})\}$;

$\boldsymbol{A}$ is a discrete and finite set denoting the CR actions, i.e. as $\{a_1(\text{access}), \text{a}_2(\text{no access})\}$;

$\boldsymbol{T} : \boldsymbol{S} \times \boldsymbol{A} \rightarrow \boldsymbol{\Pi}(\boldsymbol{S})$ is the state-transition function. If s is the current channel state and action a is chosen by the decision maker, the process will move to a new state s with the probability of $\boldsymbol{T}(s'|s, a)$.

$\boldsymbol{R} : \boldsymbol{S} \times \boldsymbol{A} \rightarrow \mathbb{R}$ is the reward function that defines the expected immediate reward $\boldsymbol{R}(s, a)$ received, when the process is in state s and action a is taken;

$\boldsymbol{Z}$ is a finite set of observations the CR infers from the radio environment;

$\boldsymbol{O} : \boldsymbol{S} \times \boldsymbol{A} \rightarrow \boldsymbol{\Pi}(\boldsymbol{Z})$ is the observation function and for each action and resultant state, $O(s'|a, o)$ denotes the probability of observing o and moving to state s' after taking action a;

The POMDP based CR engine [155] is depicted in the Fig. 7, with the state predictor being the core component in the process [151], [153]. In this procedure, b is the 'belief state', which describes the probability that the channel's state is idle, summarizing all the past information necessary for formulating the allocation decision π [154]. The channel state predictor computes the probability b based on a combination of the most recent value, on the current observation and on the previous action. More specifically, the authors of [153] proposed an approach for channel state prediction based on POMDP by finding the optimal policy that maximizes some aspect of the reward. In this approach, the probability $b'(s')$ that the future state s' is idle can be calculated by the Bayesian formula as follows

$$b'(s') = P(s'|a, b, o) = \frac{\sum_S O(o_{t+1}|s', a) T(s'|s, a) b(s)}{P(o_{t+1}|b, a)}. \tag{13}$$

The numerical results provided in [152], [156] have shown that the performance of the spectrum access approach using the POMDP based CR improves over time upon gleaning increasingly more accurate information concerning the channel's state inferred from the accumulated observations. As a benefit,

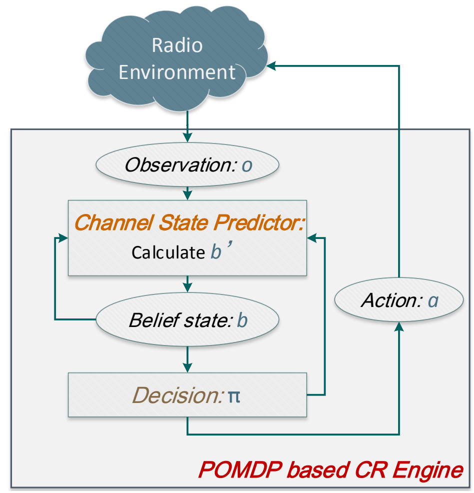

Fig. 7: POMDP based prediction.

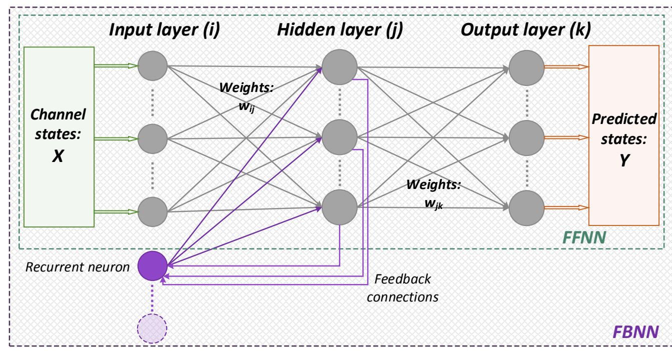

Fig. 8: Artificial neural network (ANN) based prediction.

the collisions of CRs with PUs were substantially reduced. However, a problem concerning the POMDP based approach is its potentially excessive complexity, especially when the number of channels is high. To tackle this problem, more research is required for developing efficient algorithms for solving POMDP problems.

3) Artificial Neural Network (ANN) Based Methods: Let us now move on to the third family of the temporal methods portrayed in Fig. 4. As a key technique in machine learning, the ANNs have been extensively applied to communications, signal processing, intelligent control, etc. They represent a class of flexible nonlinear models based on parallel computation, which consist of both input and output layers as well as intermediate layers composed of artificial neurons [157]. In CRNs, an ANN allows for learning the PU's behavioral patterns by invoking a training set of spectrum data, learn these patterns, and then capitalize on it for classifying new patterns and for making forecasts. Because of its high prediction accuracy and capability of learning, ANNs constitute a popular approach of predicting the spectrum state's evolution. Generally, depending on their architecture, we can categorize ANNs into two classes: feedforward and feedback neural networks [158]. The architecture of ANNs invoked for predicting channel states is depicted in Fig. 8.

a) Feedforward Neural Networks (FFNNs): Feedforward neural networks enter the spectrum data strictly into the input layer and give the states predicted by the output layer without any feedback. Referring to the rich literature concerning FFNN based algorithms invoked for spectrum prediction [20], [157], [159]–[168], we will first provide a brief overview of typical multilayer feedforward neural networks (MFNNs), also known as the multilayer perceptron (MLP). Then we will describe the overall spectrum prediction procedure of neural networks.

Based on the PU's activity modeled by DTMC, where the input and output data are represented by binary sequences, MFNNs rely on neurons as their basic computing unit for calculating a weighted sum of the inputs and perform a nonlinear transformation of the sum [20], [160], [168], which can be expressed as follows [20], [168]:

$$y_j^l = f\left(a_j^l\right), \tag{14}$$

$$a_j^l = \sum_i y_i^{l-1} w_{ji}^l, \tag{15}$$

where y_j^l is the output of a neuron j in the l_{th} layer; w_{ji}^l represents the adaptive weights connecting the neuron j in the l_{th} layer and neuron i in the $(l-1)_{st}$ layer; a_j^l is the weighted sum of the inputs yielding the outputs of the former layer, and $f(a_j^l)$ is the activation function, often represented by the tangent sigmoid function [160]:

$$y_j^l = \frac{2}{1+e^{-2a_j^l}} - 1. \tag{16}$$

Before performing spectrum prediction, there should be a training process for MFNNs. First, the observed spectrum data vectors $\boldsymbol{X}(t-\tau+1,t) = \{x_t, x_{t-1}, ..., x_{t-\tau+2}, x_{t-\tau+1}\}$ are imported into the input layer and the estimated output data y_{t+1}^o is calculated using the activation function. Then, the difference between the desired value x_{t+1} and its estimation y_{t+1}^o is denoted as the error e_t, which can be expressed as follows [20], [160]:

$$e_t = x_{t+1} - y_{t+1}^o. \tag{17}$$

Finally, in order to minimize the prediction error e_t, the adaptive weight w_{ji}^l will be updated by repeatedly using the back propagation algorithm [169] until the prediction error reaches its minimum. In [160], the prediction error is measured by the mean squared error (MSE), denoted as $E(w)$, which can be computed as follows [160]:

$$E\left(w\right) = \frac{1}{2}\sum_t e_t^2 = \frac{1}{2}\sum_t \left(x_{t+1} - y_{t+1}^o\right)^2. \tag{18}$$

Once the training process is completed, the future spectrum state can be predicted by capitalizing on the observations with the aid of the MFNNs. In [20], the predicted value y_{t+1}^o is decided by invoking a threshold at the output layer, which can be expressed as follows:

$$y_{t+1}^o = \begin{cases} 0, & \text{if } y_{t+1}^o \geq 0, \\ 1, & \text{if } y_{t+1}^o \leq 1. \end{cases} \tag{19}$$

It is noteworthy that the learning speed of the traditional FFNNs, like MFNNs, is generally slower than desired, which would naturally evolve the attainable prediction efficiency. This problem was solved by the extreme learning machine (ELM) of [177]. Furthermore, the authors of [159] optimized the original ELM, while in [158] the optimally pruned extreme learning machine (OP-ELM) was used for spectrum prediction. OP-ELM based spectrum prediction also relies on the structure of single hidden layer neural networks (SLFNs), just like the original ELM, where the input weights are randomly assigned, but the output weights are calculated using a different procedure. According to the experiments conducted in [158], [159], the OP-ELM algorithm is more robust and flexible than the original ELM, showing a higher learning speed and a higher accuracy compared to other FFNNs.

b) Feedback Neural Networks (FBNNs): The only difference between FBNNs and FFNNs is the presence or absence of feedback links that span from the outputs of neurons to the inputs of neurons in the previous layer [178], [179], as depicted in Fig. 8. The FBNN requires the data to be passed both forward as well as backward, hence imposing a high complexity and often making the FBNNs 'confused' or unstable. In this sense, the forecasting performance of FBNNs may become less attractive than that of FFNNs [180]. FBNNs gleam information from the sequence or time dependence of the inputs and the inputs themselves, which means that the features detected in previous patterns form a part of each new pattern.

Therefore, when we want to take the previous spectrum observations into consideration in order to sense or predict the spectrum, the FFNNs discussed above are less pragmatic for us. In [178], Elman recurrent neural networks (ERNN) is used for radio frequency (RF) multivariate time series modelling in order to predict the spectral evolution. This feedback method leads to more intelligent CR decisions for exploiting the expected spectrum opportunities, thereby leading to optimized spectrum usage and interference avoidance [178]. Although ERNN is powerful in predicting the time domain sequences, it has slow convergence and does not excel in terms of determining the network structure [181]. The Echo State Network (ESN) concept is proposed as a new technique of overcoming these problems in [182]. Taking this as a basis, the authors of [183] further proposed a method based on an improved form of ESN for spectrum prediction. The proposed ESN structure is also visualized in [183]. In contrast to the ERNN, the intermediate hidden layers are replaced by a cycle reservoir associated with fixed feedback connections and randomly connected neurons [183]. The parameters of the improved ESN are calculated using particle swarm optimization (PSO). It should be noted that the PSO is known to outperform the traditional back propagation algorithms in training ANNs, as a benefit of their faster convergence and lower complexity [165], [184]. Experiments have been conducted in [183] to demonstrate that the performance of the optimal ESN is better than that of the ERNN in predicting both the specific state and the state duration of the primary spectrum, since it reduces the training time required for obtaining a higher prediction accuracy.

4) Pattern Mining (PM) Based Methods: PM is a classic data mining technique conceived for discovering underlying patterns in large amounts of data. In CRNs, the patterns usually reflect the rules hidden in the spectrum occupancy of a channel. The motivation of finding the rules arises from the desire to analyze historical spectrum data for predicting the future channel states, so as to improve the attainable spectral efficiency and hence to reduce the collision rate. In previous research, the spectrum usage prediction has relied on frequent pattern mining (FPM) [119] and partial periodic pattern mining (PPPM) [16]. Both methods are based on a binary channel state model.

- **FPM**. In the context of CRNs, the channel state values observed are delivered in a sequence and serve as the spectrum occupancy history database. The mission of FPM is to find the specific sequences that appear in the data set with a frequency above a threshold, which are referred to as a frequent sequential patterns [185]. Thus, it becomes possible to predict the next state or next sequence. Although the FPM of [119] is two-dimensional, its ability to predict the future spectral states is only known in the time domain.
- **PPPM**. In contrast to FPM, the partial periodic patterns observe the PU's features during certain time periods instead of the entire time span [186]. Since the propagation environment is stochastic and the PU's behaviors may not show an obvious regularity. The patterns only become relevant for certain time periods of the day [16]. The procedure of PPPM based prediction can be described as follows [16]:
  Step 1: Process the binary channel state values and generate candidate patterns;
  Step 2: Count the support of each candidate pattern;
  Step 3: Eliminate the redundant candidate patterns;
  Step 4: Generate the prediction rules and calculate the probability of the future channel states.
  Additionally, the algorithm based on PPPM was also used for predicting the channel state duration in [16] so as to reduce the collision probability owing to the PU's short absence.

5) Other Algorithms: Other relevant temporal methods found in the literature include Bayesian inference (BIF), learning automata (LA) and support vector machines (SVM). BIF is known as a classic method of solving the state prediction problem in CRNs as a critical part of the Markov systems, like the aforementioned NS-HMM and POMDP. It provides a general unifying framework for sequential state estimation. The procedure of BIF based prediction continuously updates the a posteriori distribution in a recurrent manner, based on the influx of spectrum data. Assuming that the evolution of the state is Markovian, BIF can make predictions based both on the observations and on the a posteriori distribution. BIF-based prediction is proposed in [17] [187] for estimating the distribution of idle durations in the PU's traffic. The algorithm proposed in [17] combines BIF with NS-HMM to predict the channel quality, which is capable of improving the efficiency of dynamic spectrum access. Compared to the traditional maximum likelihood technique, the BIF technique is capable of performing better, when processing a limited number of samples, and the channel availability may be reliably predicted after estimating the prevalent spectrum usage patterns [188]. In [157], a LA technique is utilized for predicting the spectrum opportunities in CRNs. The LA technique first generates the PU's activity model according to the characteristics of the PU's behavior. Then, the training and testing stage updates the parameters of the models, and finally the performance of the model is assessed in order to correct the prediction of the system's behavior. In comparison to the MFNNs, the LA has shown a high performance, despite its simple structure [157].

The SVM technique has been widely used to make time series predictions in many scientific fields, such as financial marketing, power supply and medical sciences [189] as well as for spectrum prediction in CRNs. The application of SVM to solve regression problems is termed as support vector regression (SVR). In [190], SVR is used for predicting the probability density of the idle/busy CR state duration. In [191], SVR is applied for processing the spectrum occupancy data.

B. Spectrum Inference in Frequency Domain

Section III-A has reviewed some of the popular techniques conceived for predicting the future spectrum occupancy in the time domain. Further studies are well dedicated to inferring the states of other channels in the light of already acquired sensing or predicted results [93], [119], [130], [192], [193]. The spectral occupancy correlation between adjacent channels has been evaluated by experiments in [194]–[196]. This correlation serves as the most important information representing the relationship of different channels within the same services. In other words, the more correlated two channels are, the more accurate predictions will be made. The authors of [192] exploited the spectral correlations for inferring the availabilities of other channels in order to improve the throughput. The new concept of channel availability vector was introduced for characterizing the spectral occupancy information.

In [193], predicting the states of unsensed channels is formulated as a matrix completion problem. The classic technique of belief propagation (BP) [197] is applied to fill the matrix with predicted states. It is found that the BP scheme is more suitable for specific matrix types, where the adjacent elements are highly correlated [29]. In [198], Bayesian networks are proposed for jointly modeling the spectral-domain and spatial-domain correlations, where the authors introduced statistical inference for evaluating the spectrum occupancy. The correlation across the frequency dimension was exploited to enhance the estimation of spectrum occupancy in wideband spectrum sensing [195], [196].

Yin *et al.* [119] has proposed a frequency pattern matching algorithm operating in two-dimensions (FPM-2D) for spectrum inference, which searches through all relevant 2D patterns [119]. Once these patterns have been obtained, we can compute the probabilities of future channel states and estimate the channel's availability. Their algorithm outperforms the first-order HMM-based predictor in terms of its prediction accuracy. Similarly, frequency domain correlation techniques were also introduced in [93] by modeling the neighboring channels in pairs. Simultaneously considering multiple frequency bands, the classic AR models which do not need a priori knowledge on the communication environment were also employed to reduce the complexity [93]. This algorithm performs well for deterministic usage patterns.

The investigations of [93], [119], [192], [196] clearly quantify the performance improvements achieved by spectral correlation based inference.

C. Spectrum Inference in the Geographic Spatial Domain

From a spatial-domain perspective, there are two directions for spectrum inference:

- One of them aims to infer the spectrum state information, while taking both the positions and movements of CRs into consideration;
- The other one infers geographical information, including the primary system's coverage contours, service areas and so on.

1) The first direction: In the first direction, both the BP technique and the Bayesian networks discussed in the frequency domain are also capable of taking the spatial correlations into account for inferring the channel states from those of other locations.

In the static spectrum environment, the interference powers experienced at different CR nodes are inferred by exploiting the spatial variation of interference. Specifically, both semi-supervised dictionary learning [200] and compressive sensing are employed for the interpolation of unobserved interference in the spatial domain, incorporating the CR network topology.

Since the movement of CRs directly affects the spectrum availability in a specific geographic area, spectrum prediction in the time-space domain constitutes and important research area. The traditional static model is extended to a dynamic mobililty model in [201]. The CRs' mobility and the PUs' activity can be jointly considered to infer both the spectrum occupancy and the interference constraints for a certain period under different relative positions between the PUs and CRs. Based on this scheme, both a greedy and a fair prediction algorithms were proposed in [201] to make the spectrum exploitation more effective, hence maintaining fairness in spectrum allocation. A SVM is used for inferring the spectrum occupancy evolution considering both the time-domain and geographic distribution characteristics [202]. A joint feature-vector extraction method is designed by analyzing both the CRs' movement and the PUs' behavior. Again, a SVM based inference mechanism is introduced for expediting the convergence speed, which is shown to have a better inference performance than the algorithms solely depending on the speed and location information, as in [202]. It was found that carefully choosing the parameters is capable of mitigating the performance loss caused by high-speed CRs having erratic movements. In [203], the SVM was invoked both for predicting the handoff point and the idle channels with a high precision. In addition to the spectrum availability, the link availability between the CRs was also inferred by the authors of [204]. By invoking this novel approach, a more reliable path can be found for dynamic routing in CRNs.

2) The second direction: For the TV services, the primary receivers must be protected from harmful interference [18]. This approach makes full use of the effective antenna height, effective isotropic radiated power and terrain information to map the primary users' coverage contour through Fresnel diffraction theory. The Google Earth software plays an indispensable role in TV white space prediction. Based on the primary users' coverage contour inference, the potential interference and the collisions imposed by the CRs may be significantly reduced. In [205], a location predictor is proposed, where the historical changes of the PU's geographic locations are represented by a directed graph having weighted edges. Once a spectrum occupancy prediction is requested, all the edges originating from the starting point are listed and then the destination is predicted according to the calculated maximum weights.

D. Spectrum Inference in Joint Multiple Domains

In addition to spectrum inference techniques in single domain (i.e., time, frequency and space) mentioned above, there are also recent studies on joint multiple-domain spectrum inference. Specifically, the work in [119] is one of the first studies to develop joint time-frequency spectrum prediction algorithm, where two-dimensional frequent pattern mining is proposed to analyze binary historical spectrum occupancy data. In [210], the authors develop an algorithm for spectral-temporal two-dimensional spectrum prediction with incomplete historical data by exploiting the approximate low-rank property of real-world spectrum measurement matrices. In [211], a robust spectral-temporal two-dimensional spectrum prediction algorithm is proposed under an assumption on the sparsity of abnormal or corrupted historical data. In [212], a matrix completion-based algorithm is developed for TV white space database construction via joint spectrum sensing in time domain and spectrum inference in spatial domain. In [213], the authors propose the concept of spectrum tensor and develop a multi-dimensional (including, time, frequency, and space) spectrum inference algorithm for spectrum map construction by invoking the recent advances in tensor completion. Moreover, the recent tutorial papers [214], [215] propose to combine spectrum sensing and spectrum inference into spectrum database for providing spectrum services for users, and also highlight that joint multiple-domain spectrum inference is an active research trend.

E. Summary and Insights

As discussed above, there are a wealth of contributions on spectrum inference. In this subsection, we offer a brief summary and discussions of the existing spectrum inference algorithms. First of all, the major developments of spectrum inference/prediction techniques are summarized at a glance in Tables II and III in the chronological order. Then, the advantages and technical challenges of various spectrum inference algorithms are summarized in Table IV, according to a priori information concerning the processed data and to the resultant complexity and accuracy constraints.

Furthermore, there are also several major insights based on the comprehensive survey of the existing studies detailed as follows. Firstly, while the majority of the existing studies focused on spectrum inference in the time domain, in the past decade, spectrum inference in joint multiple domains has been gaining increasing research interests. For instance, the

TABLE II: Major developments of spectrum inference techniques (Part 1) (T/E: Theoretic/Experimental work; U/O/I: Underlay/Overlay/Interweave).

Year	Dimension	Algorithm	Reference	Key Contribution(s)	T/E	U/O/I
2007	Time	HMM	[95]	proposed to use the HMM based prediction algorithm in comparison with traditional CSMA based algorithms.	T	I
		AR	[130]	proposed an AR algorithm with different orders in predicting spectrum occupancy status.	T	I
		AR	[135]	proposed an AR algorithm to predict channel state transitions over fading channels.	T	I
2008	Time	FFNNs	[168]	proposed a spectrum prediction algorithm using multilayered feedforward neural networks for better PHY rate adaption.	T	I
		SVR	[191]	proposed SVR-based prediction for nonlinear, non-stationary and complex data series.	T	I
		ARIMA	[206]	proposed a seasonal ARIMA algorithm to analyse the spectrum occupancy and make forecasts.	T	I
		AR	[15]	applied the AR model presented in [135] and a Kalman filter to predict spectrum holes.	T	I
		MA	[207]	proposed an exponential weighted moving average based approach to predict spectrum occupancy.	T	I
2009	Time	FFNNs	[167]	adopted the approach of [168] for channel selection.	T	I
		HMM	[140]	validated the Markov chain-based modeling of the spctrum usage.	E	I
		POMDP	[154]	proposed a POMDP framework for DSA considering the energy constraint.	T	I
		BIF	[208]	provided a fast Bayesian statistical approximation method to infer the radio signal's power.	T	U/O
		MA	[128]	discovered that the usage pattern of all Chinese TV band channels can be modeled by the MA modeling method.	T	I
		MA	[129]	presented the EMA based prediction approach to improve energy detection in order to reduce the sensing time.	T	I
2010	Time	BIF	[198]	invoked a Bayesian network to infer the spectrum occupancy.	T	I
		FFNNs	[163]	designed a MLP to predict the channel status without requiring a priori knowledge of the statistics of channel usage.	T	I
		HMM	[146]	extended the standard HMM prediction method of [140] by considering the latency between spectrum sensing and data transmission.	T	I
		BIF	[187]	proposed a BIF method to estimate the distribution of state duration.	T	I
	Space	SNG	[205]	proposed the SNG algorithm for predicting the mobility of cognitive users.	T	U/O
	Frequency, Space	MC	[193]	proposed an efficient framework of BP for matrix completion to achieve a reduced error rate.	T	U/O
2011	Frequency, Time	AR	[93]	took the frequency dependence into consideration to optimize the performance of the AR model.	T	I
	Time	SVM	[203]	introduced the SVM model to infer the handoff point to reduce the collision rate.	T	I
		ERNN	[178]	proposed an ERNN approach and modeled the features of the PUs' activity as a multivariate chaotic series.	T	I
		FFNNs	[162]	applied the MLP to measured data.	E	I
		HMM	[14]	modified the HMM approach for single-user prediction and considered the time delay of hardware platforms.	E	I
2012	Time	PPPM	[216]	introduced a PPPM algorithm to mine the underlying spectrum occupancy patterns to make forecasts.	T	I
		ARMA	[217]	proposed a multichannel ARMA prediction filter based on a particular lattice filter structure.	T	I
	Frequency, Time	FPM	[119]	developed a two-dimensional FPM algorithm for exploiting the spectral correlations.	E	I
2013	Space	DL	[200]	proposed a specific dictionary learning framework to predict the interference power levels in various locations.	T	U/O
	Time	FBNNs	[183]	proposed a ESN method to predict the state duration with the aid of an improved parameter selection algorithm.	T	I
		HMM	[111]	applied the HMM algorithm in the HF spectrum for activity prediction.	E	I
		HMM	[144]	proposed a hidden bivariate Markov model (HBMM) prediction method which allows a phase-type dwell time distribution.	T	I
		HMM	[17]	proposed a NS-HMM to predict the channel quality.	T	U/O
2014	Space	SVM	[202]	proposed a SVM based spectrum mobility prediction algorithm.	T	I
	Time	LA	[157]	proposed the LA technique to predict spectrum holes.	T	I
		HMM	[118]	extended the NS-HMM method with an expectation maximization based parameter estimation algorithm.	T	I
	Time, Frequency	MC	[210]	developed a joint spectral-temporal spectrum prediction from incomplete historical observations.	E	U/O

authors of [209]–[211] proposed various joint two-dimensional spectral-temporal spectrum prediction algorithms by leveraging the low-rank nature of the spectral data. The authors of [213] developed a multi-dimensional (time, frequency, and space) spectral map construction method.

Second, there are some quantitative comparisons among different spectrum inference techniques. Specifically, it was reported in [20] that under the same traffic scenario, an ANN based predictor performs slightly better than the HMM predictor owing to having a flexible number of states and

TABLE III: Major developments of spectrum inference techniques (Part 2) (T/E: Theoretic/Experimental work; U/O/I: Underlay/Overlay/Interweave).

Year	Dimension	Algorithm	Reference	Key Contribution(s)	T/E	U/O/I
2015	Time	ELM	[225]	proposed to use ELM to predict the spectrum data obtained from frequency monitoring system of high-frequency radar.	E	I
		BPNN	[226]	designed an improved-back-propagation neural networks to perform spectrum prediction.	T	I
		SVR	[227]	performed spectrum prediction and channel selection using online learning techniques.	T	I
		HMM	[228]	applied the HMM approach for spectrum occupancy prediction.	T	I
		AR	[229]	proposed forward-backward-AR to perform spectrum prediction.	T	I
	SpacE	MC	[212]	developed a low rank matrix completion-based algorithm to enable efficient TV white space database construction via spectrum sensing and spatial inference.	T	U/O
2016	Time	HMM	[230]	proposed to use a high-order hidden bivariate Markov model to inherit the strengths of HBMM and high order and enhance the prediction accuracy by combining observing multiple previous states and the underlying process.	T	I
		HMM	[231]	provided a thorough analysis on hard fusion-based cooperative spectrum occupancy prediction where the local prediction utilizes HMM.	T	I
		NN	[232]	studied spectrum prediction in cognitive radio systems using a wavelet neural network.	T	I
		HMM	[233]	introduced a HMM-based spectrum prediction algorithm for industrial applications that predicts multiple slots in the future.	T	I
	Space	MC	[213]	developed a low rank tensor completion-based algorithm to enable multi-dimensional spectrum map construction.	E	U/O
	Time, Frequency	MC	[232]	studied spectrum prediction in cognitive radio systems using a wavelet neural network.	T	I
2017	Time, Frequency	MC	[209]	developed a robust online spectrum prediction algorithm with incomplete and corrupted historical observations via matrix completion and recovery.	E	U/O

TABLE IV: Discussions on advantages and challenges of various spectrum inference algorithms.

TYPEs		Advantages	Challenges
Markov	*HMM*	1. solid statistics foundation 2. robustness in time sequence processing 3. flexibility in non-stationary scenarios	1. complex matrix operations and a large number of previous data needed 2. large memory 3. hard to find the optimized number of states 4. high computational complexity 5. cannot capture the rich temporal covariance of activity on the channel at multiple delays 6. discrete Gaussian models of observations is not suitable
	POMDP	adapt to uncertain information in the environment	1. difficult to model the environment of dynamics (estimate the probabilities of action outcomes and the accuracy of data) 2. lacking efficient resolution algorithm
LP	*AR*	1. low complexity for low orders 2. convergence guaranteed 3. needs no thresholds	1. requires some training data 2. dependent on stationary processes (except ARIMA) 3. high accumulated errors for high order 4. computationally expensive for high order
	ARIMA	1. able to process non-stationary sequences	1. needs considerable statistical skills 2. not suitable for fast learning
FFNN		1. flexibility in non-stationary scenarios 2. need no priori knowledge of the observed process distribution 3. does not need to set parameters 4. needs no thresholds	1. computationally expensive training process 2. hard to identify the optimal number of intermediate layers and neurons in each layer 3. large number of free parameters 4. local minima problem during training
FPM		1. robustness in time sequence processing 2. easy to implement 3. convergence guaranteed	dependent on stationary processes
BIF		dynamic prediction for even incomplete data	1. no feedback 2. requires the knowledge of distribution
SVM		1. flexibility in non-stationary scenario 2. guarantees to converge to optimal solution 3. small number of free parameters 4. computationally efficient	1. requires prior knowledge of the observed process distribution 2. computationally expensive training process
LA		1. simple structure	increase model complexity

a more efficient training mechanism. Although having more intermediate layers in the ANN increases their computational complexity, the prediction results are improved [157]. As expected, there is a tradeoff between the complexity and the accuracy. Moreover, it is reported in [139] that the short-term prediction performance of the ANN based predictor is better than that of the ARIMA predictor, but their performance degrades, when predicting further into the future. The performance of the HMM predictor suffers from two inherent limitations [218]. Since the radio environment is changing all the time, the fixed states assumed in Markov modeling fail to capture the rich temporal variations of the channel activities. Another limitation of the HMM aided predictor is that discrete or univariate Gaussian models of observations often fail to adequately characterize the general situations. The POMDP predictor gives full cognizance to random actions, to incomplete information and to noisy observations of the environment, but it may not be able to accurately calculate the probabilities of specific action outcomes [219]. When it comes to pattern mining based schemes, the partial periodic pattern mining predictor is more robust than the HMM predictor owing to extracting more channel state prediction rules, which reduces the probability of spectrum usage prediction compared to traditional frequent-pattern mining [16].

IV. Algorithm Analysis of Spectrum Inference in CRNs

A. Performance Metrics

When evaluating or choosing a prediction algorithm, carefully selected metrics should be considered. Typically the notion of detection probability (P_d) representing the correct prediction of the busy states and the false-alarm probability (P_{fa}) representing the rate of incorrect prediction of idle states are used for studying the performance of algorithms in spectrum occupancy prediction. A combination of a higher P_d and lower P_{fa} suggests a better prediction performance. Some other statistical criteria like the normalized mean square error (NMSE), the mean absolute percentage error (MAPE), and the root mean square error (RMSE) can also be introduced to quantify the adequacy of prediction. In order to demonstrate the advantage of using spectrum prediction, both the percentage improvement in spectrum utilization and the percentage reduction in sensing energy can also be invoked.

Spectrum inference/prediction is an efficient technique complementary to other techniques, such as spectrum sensing, geolocation spectrum database, and radio environment map, for capturing the relevant information about the spectral evolution and identifying spectrum access opportunities. In this subsection, we first briefly present the key ideas of each technique one by one. Then, we discuss the relationships between spectrum inference and the other techniques.

B. Relationship with Spectrum Sensing

Spectrum sensing determines spectrum state in a *passive* manner using various signal detection methods. This approach, however, suffers from the hidden node problem because of shadowing [239]. In the past decade, intensive studies have been carried out across the globe to improve the detection performance of spectrum sensing. Excellent survey papers in this direction can be found in [25]–[27]. Briefly, existing studies on spectrum sensing in CRNs can be classified into two groups: quiet-periods-based (see, e.g. [26]) and non-quiet-periods-based spectrum sensing (see, e.g. [291]), also known as spectrum monitoring in the literature. As the name implies, in the former studies, a cognitive radio first spends a time duration (known as quiet period) to perform spectrum sensing and then determines whether to transmit based on the sensing results. By contrast, spectrum monitoring in CRNs is a relatively new technique, where the cognitive radios can continue their communications while simultaneously monitoring the band to detect any transmissions that are initiated by primary radios. More specifically, the spectrum is monitored by the cognitive radio receiver during reception and without quiet periods [290]–[292]. So far, spectrum sensing has not been widely accepted by regulatory bodies to ensure non-harming the primary/licensed users. It is challenging to meet the strict rules required by the regulators from FCC, such as the detection of a primary signal at -114 dBm by FCC.

C. Relationship with Geolocation Spectrum Database

By contrast, according to the regulations of FCC [240], [241], the geolocation spectrum database approach seems to provide a technically feasible and commercially viable solution in the near future. This approach provides a service ensuring that an unlicensed device can inquire the spectrum availability from a geolocation database, which predicts the spectrum availability at any location using propagation modeling combined with terrain data [242], [246]. Based on the guidelines provided by FCC [240], several TV white space database systems have been developed by companies [247]–[250]. A specific limitation of this approach is that the accuracy of the spectrum availability provided by the geolocation database depends crucially both on the quality of the propagation modeling and on the granularity of the terrain data. To resolve this issue, a data-driven approach is presented in [5] to build a spectrum database by learning the spectrum availability from mobile crowd sensing and big spectrum data analytics. Another limitation of this approach is that the update speed of the spectrum availability provided by the geolocation database is relatively slow (e.g., in the time scale of hours or days).

D. Relationship with Radio Environment Maps

The radio environment map (REM), concept was originally proposed by scientists from Virginia Tech [251]–[253], which is a promising tool that provides a practical realization of CRNs, explicitly, it constructs a comprehensive map of the CRN by utilizing multi-domain information from geolocation databases, characteristics of spectrum use, geographical terrain models, propagation environment and regulations [254]. In contrast to the geolocation spectrum database, REM is an advanced knowledge base that stores live multi-domain information on the entities in the network as well as on the environment [255], [256].

Spectrum inference is an efficient technique complementary to the above techniques. Spectrum inference, with spectrum prediction in the time domain as a special case, infers an unknown spectrum state from known spectrum data, by effectively exploiting the inherent statistical correlations of spectrum data in time, frequency and spatial domains. A key distinguishing feature of spectrum inference is that it presents a proactive view of the spectrum state. In terms of the relation with spectrum sensing, spectrum inference can reduce the sensing time and energy consumption [127]. Spectrum inference (e.g., in time domain) can also be fused with spectrum sensing to improve the detection performance of spectrum access opportunities [12]. In terms of the relationship with a geolocation spectrum database, spectrum inference (e.g., in spatial domain) can be further used to calibrate the propagation models and to improve the update speed of the database. In terms of its relationship with REM, spectrum inference in multiple domains (i.e., time-frequency-space) can be used to construct dynamic interference maps for each frequency at each location of interest [254], in a proactive and energy-efficient manner.

V. Experimentation-Based Approaches in CRNs

Although the majority of the existing spectrum inference algorithms are mainly studied from a theoretical perspective, there are some studies that aim for bridging the theory and the practice. In this section, we present discussions regarding real experimentation-based spectrum inference approaches in CRNs. We begin with presenting several well known spectrum-related experimental projects, which serve as the hardware/software basis for the development of spectrum inference algorithms. Then, we briefly comment on the analysis of real-world spectrum measurements. Furthermore, we discuss the experimental results reported in the literature.

A. Spectrum-Related Experimentation Projects

During the past two decades, quite a few spectrum-related experimental projects have been carried out all over the world, which collected empirical real world spectrum measurements and supported the development of spectrum inference techniques. Excellent surveys and tutorials on the latest advances of worldwide spectrum projects and occupancy measurements can be found in [23] and [24]. In the following, we provide a brief review of several well-known spectrum occupancy evaluation projects to assist the readers.

- *ORCA*, which stands for Optimization and Rational use of wireless Communication bAnds [294], is a project with the general scientific objective of extensively evaluating the spectrum occupancy in order to study the potential for its exploitation by innovative wireless services. This project developed DTV coverage prediction algorithms by exploiting for example the Longley-Rice propagation model [295], [296].
- *WiSHFUL*, which stands for Wireless Software and Hardware platforms for Flexible and Unified radio and network controL [297], is a project funded by the European Commission's Horizon 2020 Programme with the following objectives: i) to offer open, flexible and adaptive software and hardware platforms for radio control and network protocol development; ii) to offer portable facilities that can be deployed at any location; iii) to attract and support experimenters for wireless innovation.
- CREW, which stands for Cognitive Radio Experimentation World [298], is a project with the main target of establishing an open federated test platform, which facilitates experimentally-driven research on advanced spectrum sensing, cognitive radio and cognitive networking in view of both horizontal and vertical spectrum sharing in licensed and unlicensed bands. Parts of the research outputs of this project focus on constructing radio environment maps using various spatial inference techniques [299].
- FARAMIR, which stands for Flexible and spectrum-Aware Radio Access through Measurements and modeling in cognitive Radio systems [300], is a project making CRs a reality, with the main goal of developing techniques for increasing the radio environmental and spectral awareness of future wireless systems. Parts of the research outputs of this project focus on constructing radio environment maps using various statistical inference techniques [301], [302].

B. Predictability Analysis of Real Spectrum Measurements

With respect to spectrum inference/prediction, there is a fundamental question: To what degree is the spectrum state evolution predictable? In other words, the predictability of spectrum evolution reflects the upper-bound performance of all potential spectrum inference/prediction techniques. When considering the temporal spectrum usage evolution for a given frequency band in a given location as a random time series, the entropy is the most fundamental quantity characterizing the degree of predictability for this random variable. In general, having a lower entropy implies a higher predictability and vice versa. Entropy-based analysis has indeed been introduced in diverse prediction scenarios, such as for the atmosphere [6], in finance [7], for network traffic [8] and for human mobility [9]. The basic idea is that the entropy offers a precise definition of the information content of predictions and it is renowned for its generality due to relying on minimal assumptions concerning the model of the scenario studied.

Recently, in [127], we have invoked an information theoretic methodology of using statistical entropy measures and Fano's inequality to quantify the degree of predictability underlying real-world spectrum measurements. We found that despite the apparent randomness, a remarkable 90% predictability may be achieved, in real-world RSS dynamics over diverse spectral bands for several popular services, including the classic TV bands, cellular bands, the (Industrial Scientific Medical) ISM bands, etc. Similarly, Olivieri *et al.* [123] have applied the information theoretic entropy as a measure of predictability in the process of generating the ON- and OFF-period durations. In [124]–[126], the authors have used state-of-the-art multi-scale entropy metrics in order to examine the predictability of the spectrum measurement traces recorded as a function of the prediction complexity.

C. Experimental Spectrum Inference Approaches

As shown in Tables II and III, although the majority of the existing spectrum inference algorithms are predominately studied from a theoretical perspective, there are some studies in the open literature that implement and test spectrum inference approaches from an experimental perspective.

To the best of the authors' knowledge, [140] is one of the earliest studies of this kind, where the Markovian property

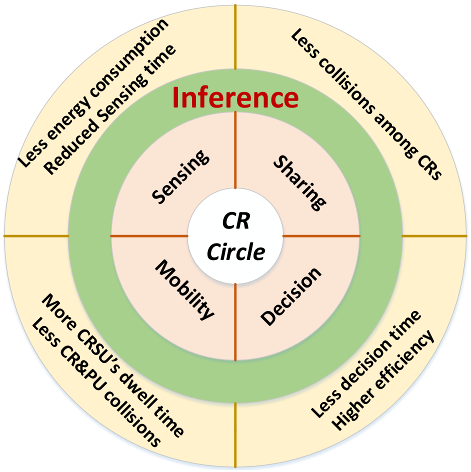

Fig. 9: Illustration of the applications and benefits of spectrum inference in CRNs.

of the spectrum usage has been validated by analyzing real-world measurements in the paging spectrum band (928-948 MHz). Experimentally, the HMM is used for predicting the ON-OFF activity of the PU with a prediction accuracy of about 76%. Similarly, Z. Chen, *et al* [14] verify the HMM method using measured WiFi data instead of artificial data, where the numerical results show that the prediction accuracy for a single device is above 70 %, which can be improved by cooperative prediction of multiple devices. In [111], the authors train and validate the HMM model with the aid of real measurements collected from the 14 MHz HF amateur band, where an average of 10.3% prediction error rate is achieved.

In [162], a multi-layer perception ANN is applied to forecast the idle or busy state of different channels, where the performances are evaluated for a seven-day spectrum dataset collected in a metro city located in south China and the empirical results show a high prediction accuracy having a mean RMSE as low as 0.04. In [119], based on spectrum measurements ranging from 20 MHz to 3 GHz at four locations in Guangdong province of China, the authors develop a 2-dimensional frequent pattern mining (FPM) algorithm to predict the availability of multiple channels simultaneously, where the numerical results show that the prediction accuracy is higher than 95% for the GSM900/1800 downlink and for the TV bands.

In [210] the authors develop a joint spectral-temporal prediction from incomplete historical observations, where real measurements of TV bands (614 MHz-698 MHz) are used for quantifying the improvements over the one-dimensional neural network-based temporal prediction scheme. In an extended work [209], the authors develop a robust online spectrum prediction algorithm relying on incomplete and corrupted historical observations, where the real measurements of TV bands, ISM bands and GSM bands are used for demonstrating that the proposed algorithm performs well in the presence of missing data.

VI. Applications of Spectrum Inference in CRNs

The specific benefits of cognitive radio networks depend on our ability to infer/predict the unknown/unmeasured spectrum states from known/measured spectrum data. To portray the various applications of the spectrum inference technology, in this section we first review the existing use cases and then we portray spectrum inference in the context of: i) 5th generation mobile communications (5G) spectrum sharing, ii) next-generation high-frequency (HF) automatic link establishment (ALE), and iii) several other potential applications in various future wireless networks, such as cognitive smart grid networks, cognitive radio sensor networks, cognitive cellular networks (CCN), and cognitive machine-to-machine communications (CM2M).

Based on the spectrum management framework proposed in [4], the existing applications of spectrum prediction in CRNs can be classified into four basic categories, namely, spectrum sensing, spectrum decisions, spectrum evolution upon handover and spectrum sharing [21]. The corresponding example applications of the inference algorithms discussed in Section VI on each category are summarized in Table V. Moreover, the applications and benefits of exploiting spectrum inference/prediction in CRNs are presented in Fig. 9, Table VI and briefly summarized as Section VI-A to Section VI-D.

A. Spectrum Inference for Sensing

Spectrum sensing is a critical aspect of spectrum inference applications that aim to explore idle spectrum slots. In the emerging spectrum sensing paradigms in the time, frequency and spatial dimensions, inference techniques are widely used to infer the most possible vacant channels for improving the detection performance and reducing the energy and time consumption of sensing.

In terms of spectrum inference in the time domain for spectrum sensing, refs. [15], [93], [128], [129], [139], [187], [220] use various linear prediction techniques, such as AR, MA, ARMA and ARIMA to perform spectrum prediction, where the output is used to improve the sensing accuracy and reduce the sensing cost. In parallel, Markov models such as HMM [14], [17], [20], [95], [111], [118], [140], [142], [144], [146], [218], [221], [222] and POMDP [153] are also widely used to perform similar tasks. These kinds of models work well under the assumption of memoryless or Markov property existing in the spectrum state evolution. That is, the future state depends only on the relevant information about the current, not on information from further in the past. ANN models are another kind of techniques that are widely investigated (see, e.g. [20], [119], [139], [158], [160]–[162], [167], [168], [178], [183], [223], [224]), which show relatively better prediction accuracy over other mondels. In addition, pattern mining methods [119], [216], BIF methods [17], [187] and SVM methods [190], [191] are also investigated.

In terms of spectrum inference in the frequency domain for spectrum sensing, the spectral occupancy correlation between adjacent channels has been evaluated by experiments in [194]–[196]. Related studies are well dedicated to inferring the states of other channels in the light of already acquired sensing or

TABLE V: Existing applications of various spectrum inference algorithms.

Methodology \ Application			For spectrum sensing	For spectrum decision	For spectrum mobility	For spectrum sharing
Time Inference	*LP*	*AR*	[15], [93], [128], [187]			
		MA	[128], [129]			
		ARMA	[128]			
		ARIMA	[139], [220]	[220]		
	Markov Models	*HMM*	[14], [17], [20], [95], [111], [118], [140], [142], [144], [146], [218], [221], [222]	[17], [95], [111], [221]		
		POMDP	[153]	[153]		
	ANNs	*FFNNs*	[20], [139], [158], [160]–[162], [167], [168], [223], [234]	[161], [167], [168]		
		FBNNs	[178], [183], [224]	[178]		
	PM	*FPM*	[119]	[119]		
		PPPM	[216]			
	BIF		[17], [187]	[17], [208]	[174]	
	SVM		[190], [191]	[190], [191]	[202], [203]	
	LA		[157]	[157]		
Frequency Inference			[12], [93], [119], [192], [193], [195]	[119], [198], [199]	[175]	
Geographic Inference			[212], [213]	[198], [201]	[204], [205]	[5], [18], [176], [200], [238]

TABLE VI: A List of Reported Benefits/Gains of Exploiting Spectrum Inference in CRNs.

Reference	**Domain**	**Application**	**Benefits/Gains**
[234]	Time	Sensing	Spectrum prediction is designed to select the most likely idle channel for sensing and brings 10-30% throughput improvement.
[237]	Time	Decision	Spectrum prediction is introduced to be fuzed with sensing to improve the detection of PU and enhance the throughput as large as 50%.
[192]	Time, frequency	Sensing	Spectral correlation is introduced to prediction to decrease the time consumption in spectrum sensing and brings roughly 20% throughput improvement.
[12]	Time, frequency	Sensing	Spectrum prediction is introduced to select channels for sensing only from the channels predicted to be idle and brings 5-30% throughput improvement when the probability of wrong prediction is no larger than 0.2.
[236]	Time, frequency	Sensing	Spectrum prediction is introduced to rank channels according to the availability and quality and brings about 15% reduction of the link establishment time.
[5]	Space	Sharing	Compared with the traditional propagation model-based approach, spectrum inference in spatial domain brings roughly 20% improved spatial reuse between the PU and the CRs and 15% reduced interference to the PU.
[212]	Space	Sensing	Spatial inference is invoked as a complimentary method of spectrum sensing for enabling efficient TV white space database construction with a 2-6 dB gain in terms of root square error, compared with the traditional approach.
[175]	Time	Mobility	Spectrum prediction and monitoring are jointly used via OR/AND fusion to improve the perform of spectrum mobility/handoff, which brings 5-25% throughput improvement by reducing the resource wastage.
[205]	Space	Mobility	Moderate accuracy predictors improve routing reliability and bandwidth efficiency by 11% and 8%, respectively.

predicted results [93], [119], [192], [193]. Specifically, the authors of [192] exploited the spectral correlations for inferring the availabilities of other channels in order to improve the throughput. In [193], predicting the states of unsensed channels is formulated as a matrix completion problem and the technique of belief propagation (BP) is applied to fill the matrix with predicted states. Yin *et al.* [119] has proposed a frequency pattern matching algorithm operating in two-dimensions (FPM-2D) for spectrum inference, which searches through all relevant 2D patterns. Similarly, frequency domain correlation techniques were also introduced in [93] by modeling the neighboring channels in pairs, where the classic AR models which do not need a priori knowledge on the communication environment were also employed to reduce the complexity.

The existing studies on spectrum inference in the spatial domain for spectrum sensing are relatively limited. In [212], a matrix completion-based algorithm is developed for TV white space database construction via joint spectrum sensing in time domain and spectrum inference in spatial domain. In [213], the authors propose the concept of spectrum tensor and develop a multi-dimensional (including, time, frequency, and space) spectrum inference algorithm for spectrum map construction by invoking the recent advances in tensor completion.

B. Spectrum Inference for Decision

Spectrum inference for decision has been investigated in various aspects such as, centralized spectrum allocation, decentralized channel selection, physical layer rate adaption, dynamic spectrum access, to name just a few. In the following, we introduce several representative examples.

Akbar and Tranter in [95] proposed to use the HMM based prediction algorithm for dynamic spectrum allocation, where the superiority in terms of system throughput is presented by comparing with traditional CSMA based algorithms. Qin *et al* in [199] and Melián-Gutiérreza *et al* in [111] respectively studied the problem of spectrum inference-based channel selection in the HF spectrum. The authors of [153] proposed an approach for channel state prediction based on POMDP by finding the optimal policy that maximizes some aspect of the reward. The authors in [167], [168] proposed to use neural networks based cognitive controller for dynamic channel selection and adaptation. In [178], Elman recurrent neural networks was used for radio frequency multivariate time series modelling in order to predict the spectral evolution, which leads to intelligent CR decisions for exploiting the expected spectrum opportunities, optimized spectrum usage and interference avoidance.

C. Spectrum Inference for Mobility

The mobility terminology in the CRNs has double meanings. On the one hand, it refers to 'spectrum mobility or spectrum handoffs' from one spectral band to another, for example, due to the appearance of PUs or owing to interference avoidance for other CRs. One the other hand, the 'mobility of CRs and/or PUs', for example in vehicular CRNs, may also affect the surrounding geographical spectral environment in terms of imposing additional interference, hence changing channel conditions and spectrum availability, etc.

An excellent survey paper on spectrum mobility in CRNs was conceived by [170], which starts from the consideration that in highly dynamic environments, CR-aided communication is often interrupted and hence spectrum mobility is recognized as a pivotal feature of enabling continuous CR data transmission, by transferring ongoing sessions to an idle channel. A recent classification and survey was provided by [171]. In [172], a Poisson distribution based model of spectral resources relying on a cross-layer spectrum handoff protocol optimized for the minimum expected transmission time was developed for cognitive LTE networks. However, the fluctuating nature of the available spectrum makes it difficult to support seamless CR communications. To address this problem, a spectrum-aware mobility management scheme is proposed in [173] for CR cellular networks, where a unified mobility management framework is developed for supporting the diverse mobility patterns in CR networks, which consists of spectrum mobility management, user mobility management and inter-cell resource balancing.

Over the years, most of the existing studies have been focused on so-called reactive spectrum mobility, where the CR switches its communication once a PU becomes active, where the detection of the PU relies either on spectrum sensing or on monitoring. However, there are also some emerging proactive spectrum mobility solutions, based on prediction or inference techniques. For instance, Bütün *et al*. [205] propose a static neighbor graph (SNG) algorithm for predicting the mobility of cognitive users. Wang *et al*. [202] proposed a support vector machine (SVM) based spectrum mobility prediction algorithm for mobile CRNs. In [203], the SVM was invoked both for predicting the handoff point and the idle channels with a high precision. In addition to the spectrum availability, the link availability between the CRs was also inferred by [204], where by invoking this novel approach, a reliable path can be found for dynamic routing in CRNs. In [205], a location predictor is proposed, where the historical changes of the PU's geographic locations are represented by a directed graph having weighted edges. Once a spectrum occupancy prediction is requested, all the edges originating from the starting point are listed and then the destination is predicted according to the approximately calculated maximum weights. Huang *et al.* [174] propose a Bayesian inference-based prediction algorithm for spotting the specific channel that is most likely to be available for the CR-aided vehicular ad-hoc networks, where the most critical challenges are the high-speed mobility of vehicles and the dynamically-fluctuating channel availability. As a further advance, P. Thakur *et al.* [175] propose a proactive spectrum prediction technique, where the emergence of PU is predicted before its true emergence, in order to avoid dropping even a single packet.

D. Spectrum Inference for Sharing

In the context of spectrum sharing, there are different understandings in the literature. In the generalized sense, the concept of spectrum sharing is inter-changeable with the concepts of dynamic spectrum access or cognitive radio, which consists of three paradigms of spectrum usage: underlay, overlay and interweave [120]. This kind of understanding of spectrum sharing makes its meaning too board to cover every aspects of CRNs. On the other hand, in the narrow sense, spectrum sharing focuses on the underlay mode, which allows CRs to operate in the same band at the same time if the mutual interference among them is below a tolerant threshold. Spectrum inference for sharing is invoked for supporting/facilitating the coexistence of CRs with the PUs.

As shown in Table V, the research on inference-based spectrum sharing is relatively limited and mainly focused on spatial domain [5], [18], [176], [200]. In [5], a systematic approach is developed to enable efficient spectrum sharing between the PU (i.e., TV receivers) and the CR (e.g., smart phone, tablet, mobile vehicles, etc) where matrix completion-based spectrum inference technique is invoked to serve as a spatial interpolator of unmeasured spectrum data. In [18], the authors propose to predict the contour and service areas of the PU for enabling unlicensed CR systems operating in the TV white space without producing harmful interference to the PU receivers. Recently, Kim and Giannakis in [200] have proposed a dictionary learning framework to predict the interference power levels in various locations for enabling harmonious spectrum sharing between the PU and the CR. In [176], the authors formulate the adaptive vehicular data piping problem for dynamic spectrum sharing as a coalitional formation game and propose a near optimal coalitional formation approach for enabling vehicular data pipe selection partition in a distributed way.

E. Potential Use Case I: Spectrum Inference for Supporting 5G Spectrum Sharing

Radio spectrum sharing is an essential topic for 5G wireless communications [259], [260]. The explosive growth of data rates offered by smart phones, tablets, laptops, vehicles and many other wireless devices is about to overwhelm the allocated 2G-3G-4G radio spectrum. Spectrum sharing is emerging as an affordable, near-term method of meeting the 5G radio spectrum shortage and increasing the radio access network capacities for supporting 5G content delivery [261]. Spectrum sharing may occur between an incumbent user (e.g., commercial TV or public radars) and a secondary 5G user, when a 5G device uses a spectrum band allocated for an incumbent usage in a geographic place, time and RF channel that the incumbent is not using, subject to the tolerable interference imposed on the incumbent [5].

Fig. 10 presents a vision of spectrum inference/prediction-based spectrum sharing conceived for 5G wireless communications. Specifically, in the basic operation cycle printed in light color, the spectrum sensing module infers the observable RF stimuli from the radio environment and outputs the predicted RSS in various spectrum bands of the current time slot. Based on the input from spectrum sensing, the spectrum sharing module activates spectrum reuse and interference control to ensure the safe coexistence between commercial or public incumbent users and secondary 5G users. It may be deemed inevitable for 5G devices to explore and exploit the benefits of multiple (non-continuous) spectrum bands of a wide range, spanning from a few hundred MHz in the VHF/UHF band to the 30-300 GHz millimeter-wave length band. In this case, predictive schemes are expected to obtain the RSS of such wide spectrum bands and to enable wideband spectrum sharing in a timely and cost-efficient manner based on time domain or joint time-frequency domains spectrum inference algorithms discussed in Section IV. Specifically, in Fig. 10, a spectrum inference/prediction module is introduced, which infers the future RSS based on the historical RSS data acquired by spectrum sensing, which can further enhance 5G spectrum sharing for example by,

- supporting adaptive PHY-layer spectrum sensing, i.e. adaptive optimization of the sensing parameters, such as the sensing time duration in each time slot,
- facilitating resource-efficient MAC-layer spectrum sensing, for example by reducing the number of time-slots required for multi-band sequential sensing as well as scheduling and by reducing the energy consumption of multi-sensor cooperative sensing as well as scheduling,
- supporting high-data-rate spectrum sharing by combining the outputs of spectrum sensing and spectrum prediction, for example by guiding the selection of spectrum bands of high channel quality in carrier aggregation.

Specifically, in 5G systems, prediction-based spectrum sharing can be arranged at the base stations (BSs) of macro/small cells and at the access points (APs) of WLANs in a centralized manner as well as more aggressively, by the autonomous user equipment in a self-organized manner by relying on game theory and graph theory.

F. Potential Use Case II: Spectrum Inference for Next-Generation HF Automatic Link Establishment

High-frequency (HF) radio, also known as short-wave radio [262], operating in the 1.5-30 MHz spectrum band, is now widely used, not only by the amateur community, but also by worldwide governmental and non-governmental agencies as an alternative to satellites for over-the-horizon wireless communications. Typical application scenarios of HF radios include ships at sea, aircraft out of range of line-of-sight radio networks, disaster areas where the terrestrial communications infrastructure has been destroyed, and distant regions lacking other communications, to name just a few.

One of the key challenges in using HF communications is finding a frequency that will support the desired tele-traffic from a transmitter to a receiver. The reasons behind this challenge are mainly two-fold: Firstly, over-the-horizon HF communications often use skywave propagation paths provided by ionospheric refraction, which physically makes the window of usable frequencies time-varying throughout the day, the season, the subspot cycle, the weather environment, and the radio locations, etc [263], which is quite different from terrestrial wireless communications, such as cellular and WLAN systems. Second, there are many governmental and non-governmental HF radio systems in the HF band, which make it a nontrivial task for each transmission to find a frequency without interfering with other users [264].

To tackle the above critical challenge, ALE [263] is well-recognized as a promising technology, which automates the process of finding a usable frequency and setting up links between two or more radios. Since the late 1970s, three generations of automatic link establishment techniques have been developed. Briefly, the first generation ALE was independently developed by different manufactures to automatically identify suitable transmission frequencies using microprocessors, instead of the original manual operation. The second generation ALE focused on standardized, interoperable HF radio systems, relying on the standards such as MIL-STD-188-141A and FED-STD-1045. The third generation ALE operates at a lower SNR, carries more traffic and supports larger networks.

The ALEs of the first three generations are in essence narrowband ALE operating over 3kHz HF channels. However, in recent years we have seen an increasing demand for higher-data-rate transmission over HF links, supporting services ranging from voice and low-speed data to real-time video over HF skywave channels from aircraft, which motivates us to develop wideband ALE operating over HF channels wider than 3kHz, and up to 24 kHz [263]. Wideband ALE, also termed as fourth generation (4G) ALE, introduces an increased bandwidth flexibility as well as additional automated capabilities: i) detect and characterize the occupancy or interference within a wideband channel, and ii) coordinate the allocation of the clear subchannel.

The literature [264]–[267] reports on the potential application of cognitive radio techniques in 4G ALE, where consensus ensures that spectrum sensing will indeed be used for HF radios for detecting the occupancy or interference within any portion of channels up to 24 kHz. Based on data link quality

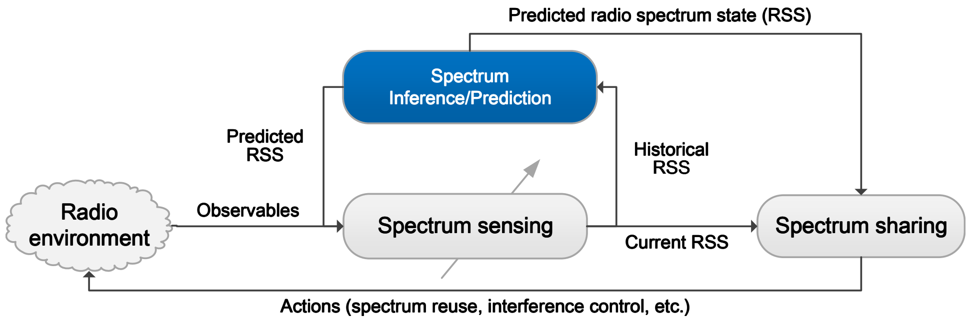

Fig. 10: Spectrum inference for spectrum sharing in 5G wireless communication systems. The basic operation cycle is in light color and the functionality of spectrum inference/prediction is in dark color.

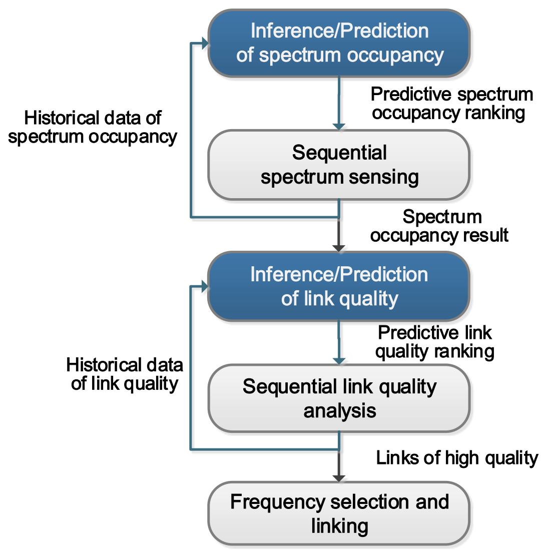

Fig. 11: A vision of spectrum inference/prediction-based wideband 4G HF ALE. The basic operating cycle is in light color and the functionality of spectrum inference/prediction is in dark color.

analysis (LQA), the associated frequency selection algorithm will be invoked for determining which channel(s) will be used for data transmission. The research and development of 4G ALE is still in its infancy [268].

Fig. 11 presents a vision of spectrum inference/prediction-based wideband 4G ALE. Specifically, in the basic operating cycle printed in light color, firstly sequential spectrum sensing is performed for detecting the occupancy or interference within each channel. Based on the output of spectrum sensing, sequential LQA is then performed on the particular channels, which are deemed to be unoccupied. Based on the LQA result, the frequency band(s) having a high quality will be selected as the active transmission link. One of the main problems of the basic operation cycle for wideband ALE is that the amount of time required both by the process of spectrum sensing and LQA increases proportionally with the number of frequencies sensed and analyzed. To reduce the associated delay, spectrum inference/prediction may be invoked as seen in Fig. 11. Specifically, spectrum inference can be employed in two specific ways:

- Inference/Prediction of spectrum occupancy, which outputs the predicted spectrum occupancy ranking. Based on this output, the specific frequency of the particular bands exhibiting a higher probability of being unoccupied will be sensed first in the following process.
- Inference/Prediction of link quality, which outputs the predicted link quality ranking. Based on this output, the specific frequency of the links having a higher predicted link quality will be firstly selected for LQA.

We note that in the basic operating cycle of wideband 4G ALE, the specific order in which spectrum sensing and LQA are carried out is generally random or predefined. By contrast, the introduction of spectrum inference/prediction is capable of providing an informative guidance considering the sensing order and LQA order. Therefore, the link establishment time is expected to decrease in 4G ALE, provided that the spectrum inference techniques summarized in the previous sections are invoked. To enable the vision shown in Fig. 11, time domain or joint time-frequency domains spectrum inference algorithms discussed in Section IV can be used.

G. Other Use Cases: The Applications of Spectrum Inference for Various Future Wireless Networks

In addition to 5G and HF communications, there are many other potential applications of spectrum inference for various future wireless networks, such as cognitive smart grid networks (CSGN) [269], [270], cognitive radio sensor networks (CRSN) [271]–[274], cognitive cellular networks (CCN) [275]–[277], and cognitive machine-to-machine communications (CM2M) [278].

Specifically, in cognitive radio-enabled smart grid networks, spectrum sensing and spectrum inference techniques are promising methods of providing timely smart grid wireless communications by utilizing all available spectrum resources. Besides the prediction of spectrum state evolution, various statistical inference techniques can also be utilized to predict the system state of the smart grid itself and the potential faults resulting from environmental disasters, cyber attacks and mechanical failures [269].

In CRSNs, wireless sensor networks benefit from the advantage of cognitive radio to overcome the spectrum scarcity by enabling dynamic spectrum access [271]. Among others, the limited energy/power supply and processing capability of wireless sensors impose additional constraints on the utilization of various cognitive radio techniques. More specifically, the design of spectrum inference in CRSNs should carefully balance the tradeoffs among the inference accuracy, the computational complexity, and the memory requirements.

In future CCNs, spectrum sharing-oriented cognitive radio techniques can be used to improve the spectrum utilization and to meet the dramatic increase of wireless data rate requirements. Most of the studies on spectrum sharing in future CCNs assume that the network will be i) multi-tier, including macro cells, small cells such as micro cells and pico cells, and device-to-device or machine-to-machine communications [275]; ii) multi-band, including both licensed and unlicensed bands [276]; and iii) software-defined, relying on various intelligent learning or data mining algorithms operated in the cloud radio access networks [277]. Inference of the spectrum usage state and the users' content demand will facilitate more proactive and efficient network operations.

VII. Open Issues and Research Trends

Although a number of studies have been carried out on spectrum inference in CRNs, this research topic has a great potential for future investigation. Actually, there are still a number of unsolved challenges waiting for solutions. Based on the above survey and tutorial, this section presents a range of potential open issues and future research trends as follows.

A. Fundamental Performance Limits of Spectrum Inference

First of all, the fundamental performance limits on spectrum inference are still unknown. Most existing work on spectrum inference focus on applying various statistical inference techniques for capturing the spectrum state's evolution. However, to the best of our knowledge, there is a paucity of studies focusing on the theoretical performance analysis of spectrum inference. Just as the Shannon capacity gives the upper bound of various modulation and coding schemes, there should be fundamental performance limits for the various spectrum inference techniques. These fundamental performance limits can guide the further development of spectrum inference algorithms.

As mentioned above, recently, Olivieri *et al.* [123] have applied the information theoretic entropy as a measure of predictability in the process of generating the ON- and OFF-period durations. In [124]–[126], the authors have used the multi-scale entropy, in order to examine both the complexity and the predictability of the spectrum measurement traces recorded. In [127], from an information theory perspective, the authors have introduced a methodology of using statistical entropy measures and Fano inequality to quantify the degree of predictability underlying real-world spectrum measurements. However, there is no commonly accepted limit on spectrum inference in the literature so far. Moreover, most of them have focused on the performance limits of time-domain spectrum prediction. No work has considered the limits of joint multi-domain spectrum inference, intuitively, which is expected to have a higher performance upper bound.

B. Spectrum Inference in Various Domains

Besides the time, frequency and spatial domains, in other dimensions such as the code- and angular-domain, to the best of our knowledge, inference/prediction of spectrum usage has not been proposed. Once the system becomes aware of the spreading code that the PU is going to use, the CRs become capable of choosing orthogonal codes to simultaneously transmit information with little or no interference. In the context of multiple input multiple output (MIMO) techniques, the PUs may transmit data within a narrow beam in a specific direction [282]. This provides opportunities for CRs to simultaneously transmit over the same frequency band in different directions. Inference/prediction techniques may help the CRs to infer the PU's transmit phase trajectory and pre-shift the phase accordingly.

Moreover, most of the existing spectrum inference studies focus on single domain spectrum inference, more specifically, time-domain spectrum prediction, but only very limited work consider joint multi-domain spectrum inference. Actually, no individual spectrum data exists in isolation, there are inherent correlations between this data and its neighbors in time domain, frequency domain, and space domain. Consequently, joint multi-domain spectrum inference is an active research direction, which is expected to bring more comprehensive, accurate and reliable spectrum information.

C. Spectrum Inference in Various Bands

Although there have been extensive spectrum measurement campaigns all over the world during the past decade, the majority of the efforts have been focused on TV bands to identify TV white spaces (see e.g. [86] and [87]), which to some extent represent the responses to FCC's spectrum policy task force in 2002 [57] and to FCC's adoption rule for unlicensed use of television white spaces around 2010 [240]. There is an urgent need to perform spectrum measurements and inference, in order to document the usage of spectrum bands that have attracted the recent interest of the regulatory bodies. For instance, FCC issued a report and order in 2015, adopting rules for the commercial use of 150 MHz of spectrum in the 3550-3700 MHz band (known as 3.5 GHz band), where the primary user is the US Department of Defense (DoD) radar systems. There are relatively few studies on the spectrum measurements in the new bands [285]–[287]. Interestingly, spectrum sharing between the incumbent radar systems and the Internet of Things devices or secondary WiFi networks have been recently studied in [287]–[289].

D. Cooperative Spectrum Inference

In scenarios where there are multiple PUs and multiple CRs, cooperative spectrum inference among CRs is a promising research direction. Cooperative spectrum inference can benefit from multi-user diversity gains since different CRs may face different shadowing and fading environments and have different spectrum consequences for inference. Furthermore, cooperative spectrum inference can enable different CRs to perform different inference subtasks, which may both reduce the computational complexity and the inference delay.

Moreover, the geographical movements as well as the data transmission trends of the CRs could be better predicted by cooperative schemes. There are several studies in this direction [258], [280], [281].

E. Deep Spectrum Inference

With the escalation of spectrum demand, there is a pressing need to recognize, classify and to activate the available bands. In fields like public health, economic development and climate forecasting, data mining has shown a beneficial predictive power [279]. Similar success may be anticipated in the radio environment conceiving the required transmission power, spectrum state, PU/CR location, as long as there is sufficient training data. To handle the flood of spectrum data, recent advances in artificial intelligence techniques, like deep learning and reinforcement learning [283], [284], are promising tools for improving the spectrum inference performance.

F. Spectrum Inference for Sensing

There are a number of interesting directions of exploiting spectrum inference for sensing. Firstly, as is known, wireless spectrum has a (time, frequency, space, etc) multi-domain space. Due to either the hardware limitations or sensor deployment cost, spectrum sensing can only capture the state of a partial of the spectrum space. To obtain a whole picture of the multi-domain spectrum space, spectrum inference can help to fill the unmeasured space via acting as an interpolator. Second, to find idle spectrum from a large number of candidate bands, the order of spectrum sensing is vital to minimize the sensing time overhead. Spectrum inference can provide a predictive input to spectrum sensing for enabling a better sensing order. In addition, spectrum inference can output a complementary spectrum state estimation to spectrum sensing. It's possible to fuze the output of spectrum inference and spectrum sensing to get a more accurate state estimation.

G. Spectrum Inference for Sharing

In the context of spectrum sharing, spectrum inference is invoked for supporting/facilitating the coexistence of CRs and PUs. The current research on inference-based spectrum sharing is limited and mainly focused on spatial domain [5], [18], [176], [200], where the inference of spatial signal coverage is used to improve the spatial reuse. One interesting direction is to jointly predict/inference the spectrum demand of CRs and the spectrum activities of PUs for proactively coordinating the spectrum sharing among them. Another direction is to predict/inference the statistical channel gains of CR links, PU links and CR-PU interference links, which can facilitate the resource allocation, especially when the channel gains cannot be obtained due to various practical constraints.

H. Spectrum Inference for Mobility

As mentioned above, spectrum mobility in the CRNs has a twin interpretation. On the one hand, it refers to spectral handoff from one band to another, due to the appearance of PUs or interference avoidance. One the other hand, the mobility of CRs and/or PUs, for example, in vehicular CRNs, may also affect the geographically surrounding spectrum environment in terms of imposing additional interference, changing channel conditions and spectrum availability, etc. Spectrum inference associated with in the former case has been extensively studied. However, in the latter case, there are only a few contributions.

Supporting high-throughput vehicular communications is important for safety applications, traffic management and mobile Internet access. One promising scenario of spectrum inference for mobility can be found in railway, highway or subway based cognitive communications, where the mobility trajectory is fixed and thus the spectrum demand may be relatively regular for inference. One interesting research direction is to jointly consider the spectrum mobility with the user mobility since the spectrum evolution patterns are generally determined by the human's usage of radio spectrum. Moreover, it is reported in [293] that a 93% potential predictability of human mobility can be expected, which in-turn can be exploited for supporting accurate spectrum inference.

I. Spectrum Inference for Decision

As mentioned above, spectrum inference for decision has been extensively investigated in various aspects such as, centralized spectrum allocation, decentralized channel selection, physical layer rate adaption, dynamic spectrum access, to name just a few. There are relatively few open issues found on this topic. However, one direction is to design demos or systems that utilizes the specific techniques with the well known example as DAPRA's spectrum challenges.

J. Applications of Spectrum Inference

Last but not least, more investigations on specific applications of spectrum inference techniques is also a fruitful research direction. Although there are several common rules for various applications, the requirements of spectrum inference in different application scenarios are rather diverse. For example, the spectrum occupancy state in TV bands changes relatively slowly on a time-scale of several hours, while the spectrum occupancy state in cellular bands or Wi-Fi bands changes within several milliseconds. Considering the fact that the outdated prediction or inference is useless, the tolerance to time delay in the corresponding spectrum inference is significantly different, which imposes different design constraints on the specific inference algorithms.

VIII. Conclusion

Spectrum inference is a promising technique of improving the spectrum exploitation in cognitive radio networks. In this paper, we reviewed the recent advances in spectrum inference based on an extensive study of the existing literature. We first introduced the preliminaries of spectrum inference, including the sources of spectrum data, the models of spectrum usage and the predictability of spectrum evolution. Then we explored various spectrum inference algorithms from a time-frequency-spatial domain perspective and presented an in-depth tutorial.

We proceeded by offering a comparative analysis of the advantages and challenges of various spectrum inference techniques. Additionally, we reviewed the applications of spectrum inference both in existing and in future wireless networks, including 5G cellular communications, next-generation HF communications, cognitive smart grid networks, cognitive radio sensor networks, etc. We also highlighted a range of open issues and research trends influencing the actual deployment of spectrum inference. We conclude that the main goal of the existing and forthcoming studies on spectrum inference in CRNs is to achieve a compromise amongst the conflicting objectives of improving the prediction accuracy, reducing its computational complexity and memory requirement. This forms a fruitful research area. Our hope is that this paper, with its interdisciplinary perspective, will stimulate the research and development of spectrum inference in future wireless networks.

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TABLE VII: ACRONYMS

5G	5th Generation Mobile Communications	LBT	Listen-Before-Talk
ALE	Automatic Link Establishment	LP	Linear Prediction
4G ALE	Fourth Generation ALE	LQA	Link Quality Analysis
APs	Access Points	MA	Moving Average
AR	Autoregressive	MAPE	Mean Absolute Percentage Error
AR-2	A Second Order AR Model	MC	Matrix Completion
ARIMA	Autoregressive Integrated Moving Average	MFNNs	Multilayer Feedforward Neural Networks
ARMA	Autoregressive Moving Average	MIMO	Multiple Input Multiple Output
BIF	Bayesian Inference	MLP	Multilayer Perceptron
BP	Belief Propagation	MM	Markov Model
BSs	Based Stations	MSE	Mean Square Error
CAV	Channel Availability Vector	NMSE	Normalized Mean Square Error
CDF	Cumulative Distribution Function	NS-HMM	Non Stationary Hidden Markov Model
CR	Cognitive Radio	OP-ELM	Optimally Pruned Extreme Learning Machine
CRNs	Cognitive Radio Networks	OSA	Opportunistic Spectrum Access
CTMC	Continuous Time Markov Chain	PCS	Personal Communication Service
CTSMC	Continuous Time Semi Markov Chain	PFA	Prediction Fairness Algorithm
DC	Duty Cycle	PGA	Prediction Greedy Algorithm
DL	Dictionary Learning	PM	Pattern Mining
DSA	Dynamic Spectrum Access	POMDP	Partially Observable Markov Decision Processes
DTMC	Discrete Time Markov Chain	PPPM	Partial Periodic Pattern Mining
ELM	Extreme Learning Machine	PSO	Improved Partial Swarm Optimization
ERNN	Elman Recurrent Neural Networks	PU	Primary User
ESN	Echo State Network	QoS	Quality Of Service
FBNNs	Feedback Neural Networks	REM	Radio Environment Map
FFNNs	Feedforward Neural Networks	RMSE	Root Mean Square Error
FPM	Frequent Pattern Mining	RSS	Radio Spectrum State
FPM-2D	FPM in Two Dimension	SLFNs	Single Hidden Layer Neural Networks
HBMM	Hidden Bivariate Markov Model	SNG	Static Neighbor Graph
HF	High Frequency	SVM	Support Vector Machine
LA	Learning Automata	SVR	Support Vector Regression

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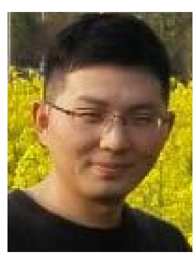

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