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Article *in* Wireless Personal Communications · May 2017

DOI: 10.1007/s11277-017-4487-6

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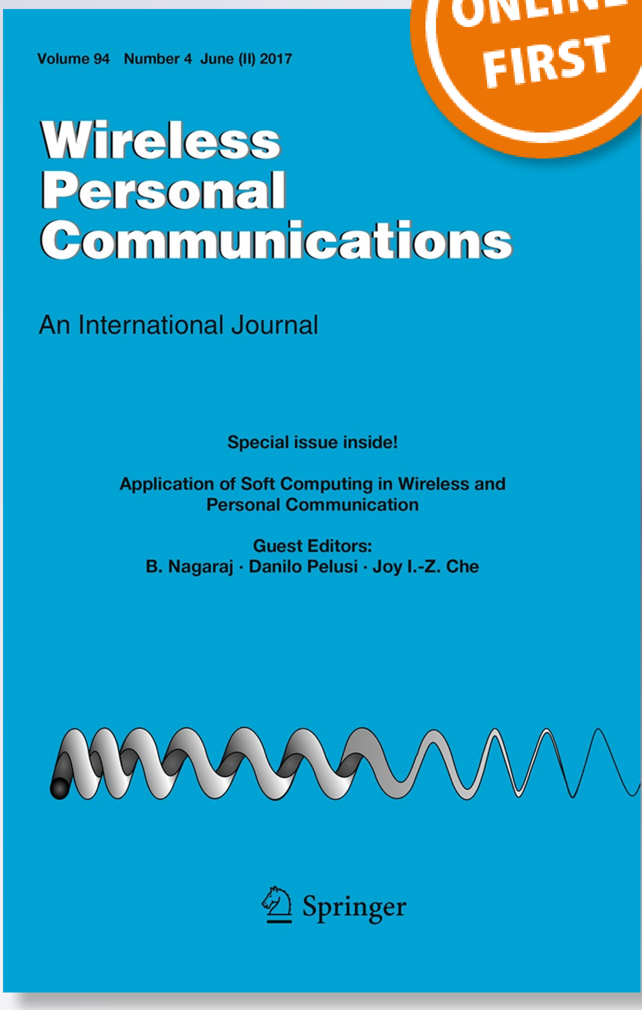
Wireless Personal Communications
An International Journal

ISSN 0929-6212

Wireless Pers Commun
DOI 10.1007/s11277-017-4487-6



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Wireless Pers Commun
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From Sensing to Predictions and Database Technique: A Review of TV White Space Information Acquisition in Cognitive Radio Networks

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Abstract Strategies to acquire white space information is the single most significant functionality in cognitive radio networks (CRNs) and as such, it has gone some evolution to enhance information accuracy. The evolution trends are spectrum sensing, prediction algorithm and recently, geo-location database technique. Previously, spectrum sensing was the main technique for detecting the presence/absence of a primary user (PU) signal in a given radio frequency (RF) spectrum. However, this expectation could not materialized as a result of numerous technical challenges ranging from hardware imperfections to RF signal impairments. To convey the evolutionary trends in the development of white space information, we present a survey of the contemporary advancements in PU detection with emphasis on the practical deployment of CRNs i.e. Television white space (TVWS) networks. It is found that geo-location database is the most reliable technique to acquire TVWS information although, it is financially driven. Finally, using financially driven database model, this study compared the data-rate and spectral efficiency of FCC and Ofcom TV channelization. It was discovered that Ofcom TV channelization outperforms FCC TV channelization as a result of having higher spectrum bandwidth. We proposed the adoption of an all-inclusive TVWS information acquisition model as the future research direction for TVWS information acquisition techniques.

Keywords Cognitive radio · Prediction algorithm · Spectrum sensing · TVWS · White space · Geo-location database

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Published online: 27 May 2017

1 Introduction

Spectrum measurement campaigns conducted globally conform to the notion that allocated spectrums are heavily under-utilized, leading to the notion of white space [1, 2]. The term TV white space (TVWS) implies white spaces observed in the UHF TV channels and TVWS networks, the wireless networks specifically designed to use TVWS frequency bands [3, 4]. The demand and consumption of spectrum-hungry applications are the key drivers of the current spectrum crunch. Hence, there is a need for a paradigm shift from the current fixed spectrum assignment regime to flexible spectrum regime capable of accommodating more users per unit Hertz. To this end, several candidate solutions have been proposed. Among the many candidate solutions, cognitive radio (CR) remains an attractive choice because it can intelligently utilized spectrum channels in the absence of assigned licensed users and thereby increasing spectral efficiency in wireless networks [5]. For CR technology to be deployed, it must be equipped with capabilities to guarantee provisioning of reliable information about the presence/absence of licensed users often referred as primary users (PU). The core of CR technology lies in the detection of the presence/absence of licensed users. The three PU detection techniques are: (1) spectrum sensing [6], (2) geo-location database [7], and (3) spectrum prediction techniques [8]. Spectrum sensing is by far the most extensive researched topic in CR technology [9, 10]. The selection of the appropriate white space information acquisition technique is based on the utility function $\log U(s, p, d)$ subject to s—spectrum sensing, being reliable, d—database technique being affordable, and p—prediction techniques being accurate to a certain threshold. In this case, $\arg \max_{s,d,p} U$ represents a maximization of the utility function. The use of a logarithmic function is common among researchers in the literature [11]. The main reason behind this logarithmic use is to ensure a certain level of fairness among different the optimization parameters. Separately, maximizing the utility function (without log) may lead to a solution that is purely dependent on a small subset of optimization parameters. For example, maximizing the utility function (without log) may return a result that is solely dependent on one of these parameters (i.e., s, d or p). However, the returned solution should be ideally dependent on these parameters in a balanced manner, which explains why $\log U(s, d, p)$ is maximized instead of $U(s, d, p)$. Spectrum sensing is a familiar topic in the cognitive radio environment and it is expected that, the reader have an in-depth knowledge of the topic. Therefore, our discussion on spectrum sensing is restricted to the core spectrum sensing techniques, comparison studies and limitations. For detailed information on spectrum sensing, the reader can consult several established review papers on spectrum sensing [12, 13].

As presented in Fig. 1, several review papers have analyzed white space information acquisition in a parallel and independent manner. As a result, creating a myopic and distorted viewpoint of all potential approaches that are currently in use. Hence, there is a need to present all the available techniques in a single paper. Based on this distinct research gap, this study reviews the white space information acquisition techniques in TVWS. Table 1 compares the three available white space information acquisition techniques based on some parameters.

In summary, this review paper makes the following main contributions:

- Provisioning of a classification model (taxonomy) for white space information acquisition techniques focusing mainly on TVWS technology.

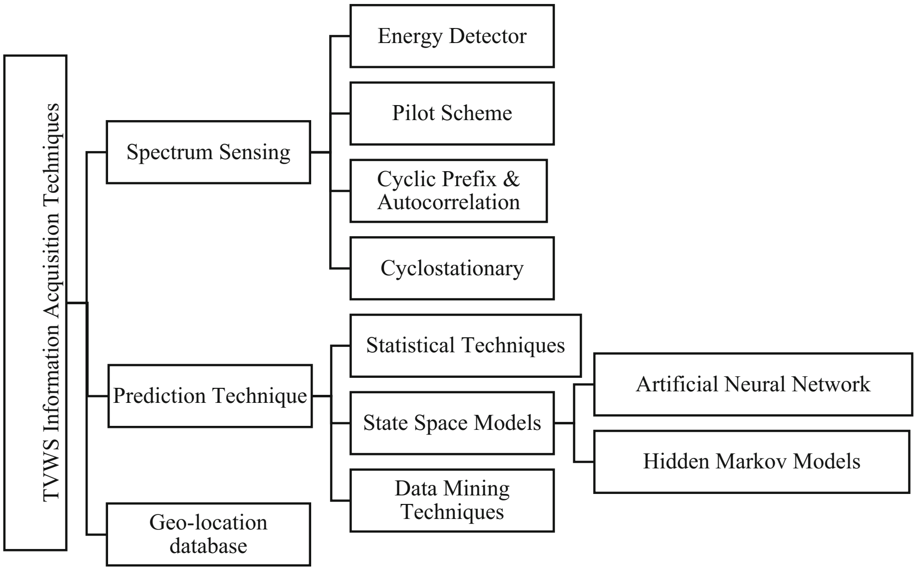

Fig. 1 Taxonomy view on TVWS information acquisition techniques

- Presenting a comprehensive literature review of three approaches for white space information acquisition—namely, sensing, prediction, and geo-location databases—and comparing the advantages and disadvantages of each approach.
- Outlining challenges, open issues, and future research directions for TVWS information acquisition in CRNs.

The paper takes the following structure based on the precedence of TVWS acquisition technique development: sensing, prediction, and geo-location databases. Section 2 presents related study to find the gap between existing studies and the current research. Section 3 discusses strategies to overcome some of the research limitations of spectrum sensing. Section 4 discusses prediction techniques by analyzing the two main approaches, namely, statistical and state space models. Spectrum mining, a new approach to spectrum prediction, is also discussed. Practical deployment of TVWS assisted by geo-location databases is discussed in Sect. 5. Section 6 suggests several potential research opportunities and application challenges of TVWS networks.

1.1 Related Studies

Several published review papers on spectrum sensing discuss white space information acquisition techniques focusing on either generic CR networks i.e. wireless networks whose operating radio frequency are other than the UHF TV bands (e.g., [25–28]) or CR networks operating over TVWS (e.g., [17, 19, 29–31]). From the perspective of generic CR networks, [13] highlights several aspects of spectrum sensing technology including: the challenges, enabling algorithms, multi-dimensional spectrum sensing, reactive/proactive sensing, approaches and cooperative sensing. [32] studied conventional spectrum estimation techniques based on short-time Fourier transformation. Furthermore, studies on wideband spectrum sensing algorithms for CR-based next generation cellular networks have been surveyed in [33], clustering techniques for cooperative sensing have been

Table 1 Comparison of the three white space information acquisition techniques

Features/capability	Spectrum sensing	Prediction	Geo-locational database
Technical complexity	Varies [14]	Complex [15]	Fairly low [16]
Accuracy and degree of reliability	Relatively low	Average	High
Modeling	Heavily relied on [17] probabilistic model	Reliance on probability density function [18]	Driven by protection contour
Process transparency	Low	Average	Extremely
Ease of deployment	High	Average	Low
Standalone capability	✔	X	X
Propagation technique	AWGN [19]	Not important	ITU-R-F(X, Y) [19]
Detection unit	dBm [20]	dBm [21]	dBu [19]
Detection of instantaneous spectrum usage	✔ [22]	X [23]	✔ [19]
Location awareness capability	X	X	✔
Currently deployed	N/A	N/A	✔ [24]
QoS and mobility supports	X	✔	✔
PU–PU/PU-SU interference avoidance possibility	X	✔	✔
Overhead channel planning	X	✔	✔
Handover functionality	X	Varies	✔
Physical infrastructure demands	X	X	✔
Market driven	X	X	✔
Transmit power reconfiguration based on location awareness	X	X	✔
Knowledge of consolidated database system (CDBS)	X	X	✔

covered in [34]. Cooperative spectrum sensing has exhibited capabilities to mitigate some of the noticeable spectrum sensing limitations such as: shadowing and hidden node problem. Several review papers specifically designed for spectrum sensing over TVWS have also been analyzed. Whereas [17, 30] were conducted based on the Ofcom spectrum sensing standard, [14, 19, 20, 31, 35] were based on FCC standards. The main difference between Ofcom based spectrum sensing techniques and FCC-driven standard is simply based on channelization. FCC adopts 6 MHz channelization scheme and Ofcom adopts 8 MHz scheme.

Similarly, there are several review papers on spectrum prediction techniques which are often referred as state space models [15, 21, 23, 36]. State space models are driven by the fact the future state of a model depends mainly on the present state and are rich in probabilistic models. As this is the main principle behind the Markovian models. HMM-based prediction techniques have been analyzed [23, 36]. A survey of artificial intelligence aided prediction technique was the focus of [15] and the application of neural network in spectrum prediction [21]. Studies focusing on database techniques include [24, 37–39] have been investigated. With the exception of [24], which focuses on a broker-based architectural framework, every other database technique mentioned here analyzed TVWS information acquisition aligned towards coexistence issues between PUs and SUs. Several published reviews have focused on both geo-location database and spectrum sensing techniques [14, 19, 35]. In [40–42], spectrum prediction and spectrum sensing were discussed. This review is different from previous surveys because it covers all three TVWS information acquisition techniques in a single paper.

2 Limitation on Spectrum Sensing

2.1 Spectrum Sensing: General Overview

A TVWS device must sense the TV bands and successfully detect white spaces in the TV spectrum. Notable licensed incumbent users include analog television systems—National Television System Committee (NTSC) and digital television systems—Advanced Television Systems Committee ATSC and DVB-T and wireless microphones [17, 30]. Unlike the other white spaces in the RF, TV signals are known to exhibit a high autocorrelation function (ACF), low zero crossing points, periodicity, and a high degree of signal differencing function in the presence and absence of TV signals. These characteristics make TV signals relatively easy to characterize and analyze. This partly explains why many vendors have concentrated their research efforts on TV frequency bands instead of other assigned radio spectrums. An ideal sensing device should maximize the probability of detecting PUs and reduce the probability of losing spectrum opportunities due to false alarms. Some selected spectrum sensing techniques, features and drawbacks are presented in Table 2. In addition, the SUs must adhere to the strict conditions as shown in Table 3. Several techniques to overcome some of the research challenges of Table 2 and actualize Table 3 are presented next.

2.2 Cooperative Spectrum Sensing

The spectrum sensing techniques implemented by the FCC tested prototypes in 2007 and those techniques shown in Table 2 are categorized as non-cooperative spectrum sensing (NCSS) techniques. In NCSS, the spectrum decision is made based on the sample of an individual SU [9]. The NCSS are considered unreliable as results are affected by channel impairments of fading, shadowing and receiver imperfections. To some extent, the shortcomings of NCSS can be overcome by cooperative spectrum sensing (CSS) [27, 45]. In CSS models, spectrum decision is made in alliance with other sensing nodes to improve sensing accuracy and the stringent conditions set by FCC in Table 3 by adopting the CSS. The CSS exploits the spatial diversity of the received PU signals to make informed decisions at the fusion center (FC). At the FC, PU signals are combined either by maximum ratio combiner (MRC), select combiner (SC) and equal gain combiner (EGC) [46]. At the FC, two decisions approaches are deployed which are hard or soft decision rule. Furthermore, the decision rule could be logical OR rule [47], logical AND rule [48] and majority rule [49]. It is advisable to use the OR rule in the case that the number of participating SUs are many.

On the other hand, when participating SUs are fewer, the AND rule shows superior performance [50]. While the logic OR and AND are suitable for the hard decision rule making, the MRC is an example of soft-decision. Several soft-decision making algorithms

Table 2 TVWS detection techniques

Technique	Features	Drawbacks
Energy Detector [43, 44]	Compares signal samples received over an observation interval with a threshold to detect white space Optimum non-coherent technique and the most commonly used in spectrum sensing Requires less computational resources and has minimum implementation complexity Suitable for detecting analog TV and wireless microphone signals	Exhibits low performance compared to other sophisticated techniques Inability to distinguish a licensed user's signals from other interference signals such as noise
Cyclic prefix and autocorrelation [17, 20]	Compares energy of cyclic prefix sequence of each OFDM signal segment with a threshold to detect white space Uses autocorrelation function of DVB-T signals to detect white space Coherent technique is able to distinguish target signals from other interference signals such as noise Suitable for detecting DVB-T signals	Exhibits relatively good performance under high correlated signals Exhibits moderate computational and implementation complexities
Cyclostationary feature [17, 20]	Exploits cyclic autocorrelation function of the received signals by correlating the received signals with a known TV signal to detect white space Coherent technique that can distinguish different transmission signals, e.g., weak signal at a very low SNR, noise with PUs' signals Requires short sensing time and can achieve high detection performance Suitable for detecting both ATSC and DVB-T signals	Implementation complexity is high Susceptible to synchronization error and requires high sampling rate Requires prior knowledge of PU signal features to demodulate the signal
Pilot based [17]	Uses pilot subcarriers of the received signals to set a threshold for detecting white space, channel estimation, and synchronization at the receiver Immune to noise uncertainty because the pilot's position can be accurately determined Achieves better sensing performance with short sensing time Suitable for detecting both ATSC and DVB-T signals	Requires prior knowledge of the target signals Sensing unit may be practically large Implementation complexity is relatively high

have been proposed [26, 45, 51]. While [26] focused on distributed energy based detectors for spectrum sensing in Nakagami-m small scale fading, soft decision sensing efficiency considering inhomogeneous background from quantization theory was studied in [51]. The hard decision based rules are relatively easy to implement compared to the soft decision because it is based on a given threshold. The threshold is adjudged by the output of a binary logic.

Once the conditions meet the given threshold, a decision is taken. Therefore, hard decision rule consumes less communication overhead. The drawback of this scheme lies on

Table 3 TVWS spectrum sensing requirements

Parameter	DTV (digital television)/ATV (analog television)	Part 74 (wireless microphone)
Channel detection time	≤2 s	≤2 s
Channel move time	2 s	2 s
Channel closing transmission time	100 ms	100 ms
Detection threshold (sensitivity) at 90% of detection probability and 10% of false alarm	114 dBm (DTV) −94 dBm (ATV)	−107 dBm >200 kHz
SNR	−21 dB (DTV) 1 dB (ATV)	−12 dB

the fact sensing result reliability is quite low as there is no opportunity to correct any miss detection. Moreover, there is no room for repeat computation in the case of wrong or false sensing report from the SU. A study has been conducted to compare soft decision and hard decision based on imperfect channel [52]. The simulated result showed that soft decision based CSS is bandwidth hungry as quantization bits increases. On the other hand, hard based CSS consumes more signal overhead when channel state information, channel occupancy and signal frame header are considered.

2.3 Energy Efficient Spectrum Sensing Approaches

Spectrum sensing was introduced to promote spectral efficiency in wireless communication. It is obvious that spectrum sensing consumes energy. Therefore, energy efficient approaches must be implemented. Several works considering energy constraint spectrum sensing have received attention lately [53–57]. The focus of energy constraint spectrum sensing is the best approach to implement a high spectrum sensing detection algorithm under low spectrum sensing energy consumption.

A novel energy based sensor selection technique for CSS in cognitive radio network considering energy consumption balance between the SUs has studied in [54]. The goal of the work was to ensure equal energy utilization among the participating CSS sensor nodes. Sleeping and censoring techniques which are strategies to conserve among the SUs in distributed topology have been proposed [55]. The primary purpose of the work is to reduce the maximum energy consumption of individual SU nodes during spectrum sensing. Considering the importance of relaying in prolonging wireless transmission range at a reduced power, the use of rateless coded relaying and an efficient user selection techniques has been proposed [56]. Clustering technique is another efficient technique to implement CSS and as such, several authors have adopted this technique [27, 45]. [27] proposed three strategies of reducing energy consumption in CSS sensing nodes which are pruning, selecting and clustering. Evidence based on simulated results indicate that there is 28% increase in energy saving as the number of clustered CR nodes increases from 20 to 60. Similarly in [45], there was 10% reduction in the power consumption for a 90% probability of detection criteria. The above works indicate that superior CSS can be obtained via CSS clustering techniques.

The major limitation of MUSIC is that it performs poorly in a low signal-to-noise ratio (SNR) regime. In order to overcome this performance limitation, special diversity across multiple SUs can be exploited. Alternatively, the proposal of [58] focusing on the use of distributed orthogonal matching pursuit (DOMP) technique which encourages independent estimation of the SU signal support using local compressed samples. Then, using majority voting rule, the final decision is made. Invariably, this approach lead to reduction in signal overhead and sensing time. The noticeable limitation of this approach is the loss of certain information as a result of non-optimal decision fusion.

2.4 Spectrum Sensing Time Reduction Techniques

There is no doubt that CSS will increase spectrum sensing time moreover as the number of participating nodes increases. It is plausible that spectrum sensing decision might fail to adhere to ≤ 2 s channel detection as indicated in Table 3. One of the limitations of cooperative spectrum sensing is that it requires a large sample size. In addition, there is an increase in the battery energy consumption, decision-making time, and computational processing power [29, 45]. There is a correlation between long sensing time and energy consumption. As sensing time increases, energy consumption linearly increases [9]. Though, it can as well be argued that longer spectrum sensing time can enhance spectrum sensing results. Therefore, there is a trade-off to be made between spectrum sensing time and spectrum accuracy. Driven by this goal, a spectrum sensing time reduction technique for cluster base CSS has been proposed [59]. An efficient way to reduce spectrum sensing time in CSS is to sample the spectrum sensing samples at sub-Nyquist rate. Sampling at sub-Nyquist rate involves the implementation of blind signal estimation techniques. Studies have shown that sampling a wideband spectrum at the Nyquist rate is quite expensive, power-consuming and highly computational intensive [33].

Earlier works have demonstrated that any it is possible to perfectly reconstruct any arbitrary wideband signal on the condition that the rate is no less than the total bandwidth of the occupied spectrum. This is motivated by the wireless signal sparsity in the frequency domain. To further reduce spectrum sensing time, comprehensive sensing has been introduced [60]. The major limitation of [60] is that it requires sampling at random sub-Nyquist rate [61]. As a result, the complex analog-to-digital converter (ADC) circuit is not capable of provisioning low-power utilization, therefore, limiting practicability [62]. In a recent work [29], the authors showed a departure from the conventional sub-Nyquist approach by locating the PU occupied channels blindly via utilization of signal support system. The SUs exploit the joint sparse nature of the multiband signals properties. The signal support scheme enables the efficient wideband signal acquisition, detection, processing and transmission to be implemented in reduced time. While guaranteeing signal detection within a time window. This signal support approach is based on subspace signal decomposition techniques. Simulated results showed that proposal performs relatively well over existing algorithms. Direction-of-Arrival (DOA) estimation of the PU signals is a robust technique which can be implemented using less complex hardware. In DOA technique, the SU can detect the PU's signal direction by Multiple Signal Classification (MUSIC) algorithm [63].

3 Prediction Techniques

- Radio intelligence can be exploited by the CR to perform white space information prediction. White space information prediction is the act of using already existing information on spectral holes to forecast/predict the availability of spectrum holes in a given RF channel. Prediction capability is designed for CRN operational improvement as indicated in Fig. 2. Prediction algorithms are performance enablers to infer the future state of spectral holes given the present conditions. Considering that the operational framework of CRNs is principally divided into spectrum hole detection and spectrum management, prediction techniques have found applicability in both domains. Enhance and improve radio resource utilization via the offline exploitation of unused frequency bins considering OFDM PU networks [64];

- Promote seamlessness in CRN by the systematic avoidance of channels with high PU activities and holding time leading to a reduction in CRN transmission loss [8, 65];
- Extend the CRN device battery life for sensing individual CRN devices because spectrum sensing is tightly correlated with sensing energy [66];
- Enable traffic planning in a dynamic spectrum environment utilizing predictability gain and consequently reducing spectrum reconfigurability [67].

Given the importance of spectrum hole detection, most CRN prediction-assisted functionality focuses on spectrum detection [36]. However, CRN prediction-assisted spectrum management has also received research attention [68]. In this section, we discuss prediction techniques and particularly interested in spectrum hole detection techniques.

3.1 Prediction Techniques Overview

For spectrum prediction algorithms to be implemented, mathematical models are necessary. Mathematical models are thus derived with the knowledge of the PU activity model. The starting point of spectrum prediction model could be the result of spectrum measurement campaigns being conducted globally [40, 41]. The common denominator of prediction algorithms is to provide solution Eq. (1):

$$X_t = AX_{t-1} + BO_t + w_t \tag{1}$$

where O_t is the input observation vector, B is the input matrix, A is the state transition matrix, X_{t-1} is the previous state, and w_t is the prediction error. The goal of the optimal predictor is to minimize the prediction error, which enhances prediction accuracy. To drive this equation, two diverse but related approaches have been adopted: (i) statistical models

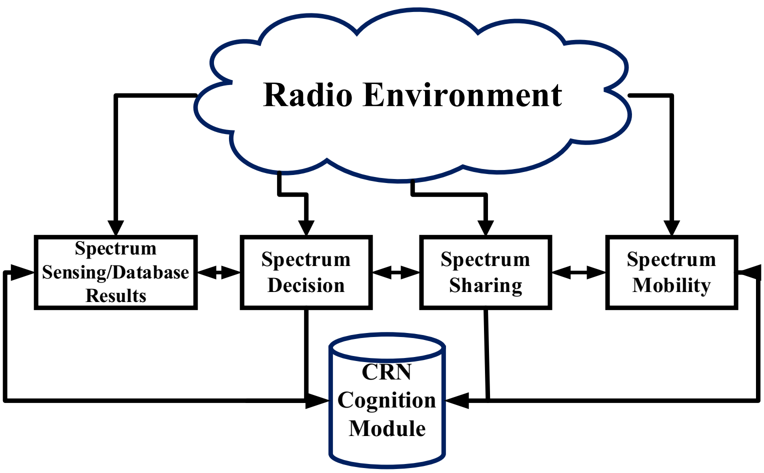

Fig. 2 Operational architecture of CRN

and (ii) state-space models. PU activity can be modeled as either deterministic or stochastic. Deterministic PU traffic revolves around PUs with a fixed known ON–OFF slot time pattern and high coherency constituting the basis for the deployment of a geo-location database scheme. Such deterministic traffic patterns are easily observed in TV transmitters. Conversely, stochastic traffic is characterized as highly randomized and difficult to predict. Some variables that can serve as PU traffic input prediction parameters include PU channel holding time, arrival rate, and departure time [69]. Others include channel capacity, cyclostationary, cyclic frequencies, and bandwidth efficiency.

3.2 Overview of Statistical Models

The design objective of stochastic processes is to infer the unknown distribution, $\{X_t\}$, using the available observed data samples $O_1, O_2, O_3, \ldots O_t$. Predicting a highly dynamic system over time is nearly impossible. Thus, stability is desirable. Stationarity has proven to be a useful attribute in studying statistical models and deserves investigation. Previous studies have suggested several definitions, but the most useful explanation of stationarity in the context of prediction is the notion of covariance stationarity in which the first two moments are time independent [70]. A stochastic process, $\{O_t\}$, is considered stationary if for all integers, t, k,

$$\begin{aligned} E(O_t) &= \mu \\ Cov(O_{t+k}, O_t) &= \gamma_k \end{aligned} \tag{2}$$

The first term in Eq. (2) indicates that $\{O_t\}$ fluctuates around a fixed mean,μ, and the second connotes that the variation around the mean is time independent. Hence, setting $k = 0$ yields

$$Var(X_t) = \gamma_0 \quad \forall t \tag{3}$$

The function $\{\gamma_k\}$ is defined on all the set of integers and by the second term in Eq. 2. This definition is called the covariance function of the stationary process $\{O_t\}$. Its autocorrelation function (ACF), denoted by $\{\rho_k\}$, is given as [70].

$$\rho_k = \frac{Cov(O_{t+k}, O_t)}{\sqrt{Var(O_{t+k})Var(O_t)}} = \frac{\gamma_k}{\gamma_0}, \quad k = 0, \pm 1, \ldots \forall t \tag{4}$$

As a result of stationarity, covariance and correlation between O_{t+k} and O_t depends only on *k,* which is their time separation or lag. This implies samples of closely related data in time domain exhibit the closely matched mean. Moreover, standard deviation increases as lag increases. Mean, covariance, and correlation functions are easily estimated for a stationary process. A common inference drawn from the stochastic parameters is their slow variance, which necessitates the use of historical data for parameter estimation and radio environment learning [71]. Stationary time series have been widely used to model PU activity. The widely adopted statistical modeling techniques are the autoregressive (AR), moving average (MA), and autoregressive and moving average (ARMA) [70]. The AR model of the order p is given by

$$O_t = \varphi_1 O_{t-1} + \varphi_2 O_{t-2} + \cdots + \varphi_p O_{t-p} + w_t \tag{5}$$

where $\varphi_1 + \varphi_2 + \varphi_p(\varphi_p \neq 0)$ denotes the model coefficients and is constant. When the mean of O_t is not zero O_t yields.

$$O_t = \alpha + \varphi_1 O_{t-1} + \varphi_2 O_{t-2} + \cdots + \varphi_p O_{t-p} + w_t \tag{6}$$

Conversely, a non-zero mean MA model of order q is denoted by

$$O_t = \beta + w_t + \theta_1 O_{t-1} + \theta_2 O_{t-2} + \cdots + \varphi_q O_{t-q} \tag{7}$$

where $\theta_1 + \theta_2 + \theta_q \left(\theta_q \neq 0\right)$ denotes the model coefficients and is constant. Similarly, a non-zero mean ARMA model includes AR and MA with model orders of p and q denoted by

$$\begin{aligned} O_t = \alpha + \varphi_1 O_{t-1} + \varphi_2 O_{t-2} + \cdots + \varphi_p O_{t-p} + \beta + w_t + \theta_1 O_{t-1}, \\ + \theta_2 O_{t-2} + \cdots + \varphi_q O_{t-q} \end{aligned} \tag{8}$$

The AR, MA, and ARMA models are filter circuits that are based on polynomials. The characteristic equation of a filter polynomial involves the selection of the appropriate filter model order of $a's$ and β's. Note that some assumptions regarding the noise (w_t) should be adopted. For example, Gaussian noise can be assumed to ease additional analyses. In statistical models, the choice of model order is crucial for model accuracy. Akaike Information Criterion (AIC) remains the most attractive technique [69, 72].

3.3 Practical Implementation of Statistical Models in TVWS Technology

Performance comparison between the AR model and the continuous Markov chain (CMC) model has been performed with vital results established [69]. The study highlighted that the AR modeling approach outperforms the CMC approach given that CMC needs to update its modeling parameters in a sequential manner until the end of the observation period. A slightly different approach for combining the AR process using the Kalman filter and a Bayes risk criterion was exploited for predicting the spectrum hole for CR systems [73]. From a theoretical point of view, AR and Kalman filtering enhances the robustness and subsequently improves PU prediction. The radio channel occupation time, which is calculated from the packet length and the transmission rate for IEEE 802.11, has been predicted using the AR model. The authors successfully proved the accuracy of their model by comparing the n-step-ahead prediction for a time series, which is calculated for a one-second interval, and the one-step-ahead prediction for a time series, which is calculated for an n-second interval using real world measurement data [74].

Similarly, MAC layer-based PU channel occupancy behavior in imperfect spectrum sensing has been successfully predicted using basic statistical approaches by estimating the minimum PU period and the first and second moment statistical parameters [75]. This experiment suggested that sensing accuracy significantly improves with high SNR values. A statistical framework consisting of model measurement, modeling, and emulation (MME) has been proposed [76]. The study was primarily concerned with the basic approach to conduct spectrum prediction. The time series approach using a sigmoid function to transform predicted results into distinct regions was exploited in [72], similar to [77]. However, the former study explicitly defines the prediction statistical ARIMA parameters. Motivated by the numerous studies in the statistical prediction model, a spectrum estimation and spectrum hole opportunities prediction for cognitive radios using higher-order statistics have been performed [78].

3.4 State-Space Prediction Models

State space models (SSMs) are machine-learning algorithms that improve their performance via experience gained over periods of time with or without complete information on the operational environment. The underlying principle of SSMs is that the transition matrix is used to decode the hidden state between the present state X_t and the future state X_{t+1}. SSM presents a generalized framework for analyzing deterministic and stochastic dynamical systems and is deeply rooted in probabilistic theory [79]. The two main types of SSM models currently in use in CR technology are (1) the hidden Markov model (HMM) and (2) the artificial neural network (ANN). SSMs can be generalized as prediction techniques processed from the wireless communication optimization toolbox.

3.4.1 Hidden Markov Model and Its Practical Implementation in CRN

The Hidden Markov model (HMM) is a tool richly assimilated in the Bayes probabilistic models. Two properties shape HMM. First, observations at time instant t are a result of some process whose state, X_t, is hidden from the observer. Second, it assumes that the hidden states preserve the Markov property. That is, given the value of X_{t-1}, the current state X_t is independent of all the previous states. All we need to know about the history of data to predict the future has been capsulated in the present. Mathematically speaking, Markov properties mean that the joint distribution of a sequence of states and observations can be factored as:

$$P(X_{1:T}, O_{1:T}) = P(X_1)P(O_1|X_1)\prod_{t=2}^{T} P(X_t|X_{t-1})P(O_t|X_t) \tag{9}$$

where the notation X_{1-T}, means $X_{1,\ldots,}X_T$. The equation above is often included in studies using the graphical model that exploits the D-separation properties algorithm to solve the complex relationship. Previous studies often include Eq. 9 in compact form as $H = (\pi, A, B)$. The HMM captures the future state of a variable using a combination of (1) the initial state probability density π, (2) the state transition A, and (3) the emission probability B. In the Markov process, the decision maker may be confronted with partial information as information may not be totally transparent. The two distinguished cases are when the state the process occupies is not completely observed and the transition law is not completely known.

The former drives the partially observed Markov decision problems (POMDP) whereas the latter drives Bayesian Inference (BIF) decision problems. The former problem can be transformed to the Bayesian problem by relying on Bayes' rule. PU occupancy modeling using Markov models are either based on the discrete time Markov chain (MC) or continuous time Markov chain (CTMC) methods. The predicted observation is obtained by training the HMM with the Baum–Welch algorithm. The input to the algorithm is prior knowledge of any PU characteristics already mentioned. The output is the future state of the observation from which decisions are made. The design flow of HMM utilization is categorized as (1) HMM training, (2) channel decoding, and (3) prediction decisions. In HMM training, the observation sequence O is employed as the training sequence to train the HMM model and to make parameter estimations. The Baum-Welch algorithm is the most extensively used training algorithm. In channel state decoding, the Viterbi algorithm is used to decode the state of the observation data and make a state decision based on the posterior likelihood.

The HMM has been explored extensively for PU channel status prediction because it possesses strong theoretical foundations and tractability. As a result of the closed form of the algorithm, few variants of the model have been employed for PU prediction. The pioneering work with the HMM for the PU channel status prediction algorithm was discussed in [80, 81]. Whereas the former study investigated the mechanism of switching to a channel with high SNR likelihood, the latter focused on high BER throughput. From the mathematical perspective, the Markov process has been studied in the context of CRNs [82, 83]. Using advanced techniques, the probability distribution of PUs has been estimated from training data and observation sequence [36, 84]. HMMs are derived from Bayes' findings, and substantial infusion between HMM and Bayes' model results in several Bayesian-aided HMM prediction models [85–88]. Bivariate-HMM has been explored to predict *k-steps ahead* observation using Gaussian distribution [89]. The dwell time of PU under non-stationary HMM for interference reduction was studied in [90]. The implication of the preceding study is that, given the knowledge of the PU dwell time, the SU can plan its transmission schedules a priori. Posteriori estimation of the finite state Markov process has been analyzed [91]. Concentrating on posteriori estimation, a special case of the Gilbert-Elliot channel was researched in [92]. A recent study also analyzed an HMM-assisted spectrum prediction PU activity model with the attendant prediction and mean error [23].

3.4.2 Artificial Neural Network (ANN) and Its Practical Implementation in CRN

Artificial Neural Networks (ANNs) are computational tools modeled after neuroscience in which cells are connected in parallel. They are trained using input–output data to generate the desired mapping between the input stimuli and the targeted output. The artificial neuron is the unit of the neural networks model, which receives inputs from neighboring neurons. The output is derived from the synaptic bias and activation functions [93]. The most extensively used activation functions are the Tansig and Sigmoid functions. ANNs consist of the input layer, the hidden layer, and the output layer. The design analysis of the ANN is subdivided into (1) data training, (2) neuron testing, and (3) validation. ANN has been a model of choice for prediction purposes despite its highly prescriptive nature because it preserves offline training in which the algorithm is trained once and recursively reuses the same algorithm. Based on attractive properties inherent to ANN, there exist ANN variants such as Elman Recurrent ANN (ERANN) and Feed-Forward ANN (FFANN). In FFANN, the output of one layer constitutes the input to another layer connected via synaptic weight.

This outcome is in contrast to ERANN in which a compulsory feedback loop links neurons within the same layer or other layers depending architecture. A multilayer perceptron ANN was used to predict PU traffic; the result indicated similarity between the predicted data and the empirical data [66]. The ERANN model successfully implemented to predict the PU channel occupancy in the UMTS multivariate time series [94]. The preceding study was oriented towards the incorporation of another layer known as the recurrent unit (RU) between the input neuron and the hidden neuron unit in the ANN. The RU serves as a tracking module that iteratively updates the difference between the last input data and the current input data feed to the neuron. The performance analysis reveals similar prediction results. The comparison with other ANN models indicate some time delays as a result of the RU. The ANN was employed to predict the availability of the TVWS using some characteristics of the TV signals [95]. A survey of the prediction accuracy of various ANN training algorithms focusing on SU throughput has been conducted [15]. Multilayer FFANN based on empirical data collected from the frequency bands ranging from 410 MHz to 2700 MHz has been studied [96]. In a recent study, three models of ANN trained using compact differential evolutionary algorithms variants were used for PU channel prediction [21]. Migrating from "hard decision" approach, a "soft decision" approach has been proposed, leveraging on the ANN back propagation algorithm [97].

3.5 Spectrum Mining

A new dimension known as spectrum mining has been included in the conventional spectrum prediction techniques. Spectrum mining models exploit the attractive features of statistical models and Markov properties to develop a tractable prediction model [98]. Unlike other prediction models, spectrum mining tends to explicitly demonstrate the correlations between 3-D spectrum models consisting of spatial, temporal, and frequency factors. Spectrum prediction is executed based on the correlation analysis. Spectrum mining prediction consists of signal strength and occupancy prediction [99]. Predicted variables are mainly channel state information, channel vacancy duration distribution, and the service congestion rate. The two main algorithms in use are frequency pattern mining (FPM) and partial periodic pattern mining (PPPM). In FPM, predictions of future channel state information are generated based on previously collected data [98]. Meanwhile, PPPM is an enhanced version of FPM based on the addition of pruning techniques [99]. Several real-world based spectrum-mining exercises have been conducted. FPM algorithms were used in [98, 100, 101]. Based on the analysis of the various prediction techniques, we present a comparison of the techniques in Table 4.

Table 4 Quantitative comparison of prediction techniques in TVWS

	Statistical	ANN	HMM	Spectrum mining
Prediction accuracy	Higher than HMM [69, 88]	Highly accurate [21]	Not highly accurate [69]	Highly accurate using real-world data [98, 99]
Memory efficiency	No memory capacity [73]	Highly efficient [66]	One step backward [36]	No memory capacity [100]
Computational complexity	Trivial [72]	Highly complex [96]	Slightly [15]	Trivial
Multivariate analysis support	None	Yes [21, 96]	Bivariate [89]	None
Hybrid support		Yes [21]	Yes [23]	Yes [98, 99]
Unique parameters	Mean, Covariance, PACF	Hidden layers, bias, Tansig and Sigmoid functions	Probability density function (pdf), state transition, the emission probability.	Channel state information, service congestion rate, channel vacancy duration
Recent trends	On the decline	Has momentum	Gaining momentum	Not fully exploited

4 Tvws Geo-Locational Database

The geo-locational database is the most practical approach for white space information acquisition. It is dependent on predetermined frequency information and has attracted significant research and industrial attention [38]. Recall that the limitations of spectrum sensing to protect PUs from the interference of SUs are highly questionable. However, prediction techniques are not start-up processes but an enhancement and optimization technique [102]. Thus, the geo-locational database has been accredited as the most reliable and feasible techniques towards white space information acquisition [39, 103, 104]. Conversely, cloud-based spectrum management has been proposed as an approach that can handle the process of dynamic spectrum allocation more efficiently [105].

4.1 Overview of TVWS Implementation

The TVWS database is a detailed information set that contains all licensed PUs, which include TV transmitter operating frequencies and their locations, areas of operation, and operating schedules [31]. Roughly speaking, providing PU database requires complete information of the TVWSDs themselves. As such, the FCC rules specify a precision of ±50 meters for TVWSDs' locations, and the IEEE 802.22 standard has agreed to implement this specification. The locations are trivial to obtain for fixed TVBDs and do not present any technical challenge because TVBD installation is thoroughly planned and performed by a professional. As for personal/portable TVWSDs, if they are equipped with global positioning service (GPS) and located outdoors, obtaining their geo-locations present a less technical challenge. However, if they are not equipped with GPS, such as Mode-I devices described below, obtaining geo-locations becomes challenging. The TVWS database technique can be considered the industrial arm of a CRN because more industries are currently providing TVWS geo-location data services. These companies include Google, Microsoft, Fair Spectrum, Key Bridge, Spectrum Bridge Incorporated (SBI), and Iconectiv. See their respective websites for additional information, e.g., [106]. The geo-locational databases have effectively replaced spectrum sensing in frequency channels that exhibit a high degree of stationarity, predictability, and auto-correlation, such as TV transmitters.

4.2 TVWS Device (TVWD) Description

Recommendations for FCC-US [107] and Ofcom—UK [31, 104, 108] have emerged as the de facto standards in defining TVWS band devices (TVBDs); operational modes; white space information acquisition techniques; reservation channels 3, 4, and 37; transmit power controls; and the antenna gain and specifications. Channels 3 and 4, which are located in the VHF band, are excluded from TVWS because they are utilized when connecting to a video home system (VHS) player, digital video disc (DVD) player or a set top box. The UHF channel 37 is reserved for radio astronomy [31]. The FCC has divided the TVWSDs into Fixed, Mode-I, and Mode-II classes. Ofcom, by contrast, produced a demarcation between the master and slave devices. The slave device is dependent on the master devices for operational parameters, such as power level and usable channels. No significant difference between the FCC and Ofcom specifications is detected. Additional details are provided in Table 5.

Table 5 Summary of the TVWS Modes

Type of white space device	Protection requirement
Fixed	Devices in this category must have geo-location database capabilities to ensure an interference-free environment among the TVWSDs and incumbent users. Devices use an outdoor antenna(s) and can transmit a maximum of 1 W into one or more 6 MHz TVWS channels. Maximum antenna gains of 6 dBi and a maximum of 4 W of effective isotropic radiated power (EIRP) are permitted [31]
Personal/portable	
Mode-I	This device operates at a lower power, may be mobile, and can operate only in the frequency band range of 512–608 MHz (TV channels 21–-36) and 614–-698 MHz (TV channels 38–51). Its maximum EIRP must not exceed 100 mW (20 dBm) per 6 MHz of bandwidth, and its power spectral density must not exceed 2.2 dB when measured in any 100 kHz band. It must be dependent on Mode-II for a list of usable operating channels [31]
Mode-II	This mode has the same parameters as the Mode-I devices. However, it must have geo-location capability with an accuracy of ±50 m and the ability to directly access TVWS database

4.3 The TVWS Database: How Does It Work?

To facilitate the concept of the TVWS database, we provide the following summary of its main components and their functions.

Figure 3 illustrates a typical example of a geo-location WSD approach that consists of the following main elements:

- TVWS database management is responsible for the spectrum allocation of the TVWS, the user's registrations, and the authorization.

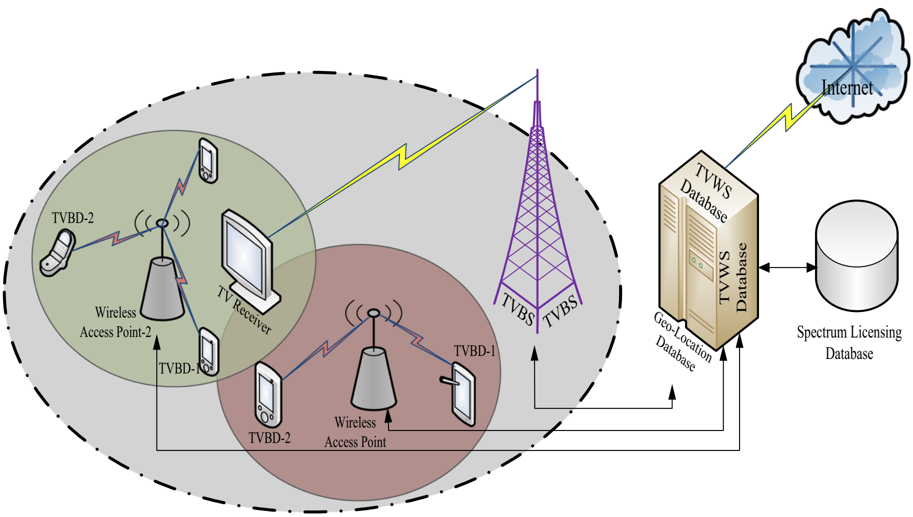

Fig. 3 Example of the TVWS database approach

- The primary spectrum database includes the data and activities related to the licensed users and information about the occupied spectrum.

Moreover, the secondary users in the TVWS approach should follow a certain etiquette to ensure smooth transmission service with the PUs. The following steps describe how TVWSDs function in a dynamic spectrum database.

- *Registration* In this step, the TVWSDs must register with the TVWS database of the certified database provider.
- *Updating* In the database approach, the locations of the TVWSDs should be updated to the database system with certain accuracy.
- *Request* The TVWSDs request available white space channels at their locations.
- *Authentication and Channel Allocation* The database provider authenticates the TVWSDs and assigns them to vacant channels based on their locations.
- *New Query* The TVWSDs make a new query occasionally or when they change locations.
- *Signaling* In this step, periodic updates and control messages occur between the TVWS database and the incumbent database to ensure free-interferences in all frequencies.

Furthermore, TVWSDs must adhere to draft specifications protocols discussed in IETF PAWS to be able to access the database [109, 110]. The TVWS manager accommodates several algorithms to estimate the estimated available TVWS based on the FCC's F-curve [111]. The F-curve models are specifically designed for TV-bands and find applicability in both analog and digital broadcast signals. The F-curves are statistical propagation models derived from actual measurements and are fully specified by operating band, effective isotropic radiated power measured in dB, and height above average terrain (HAAT). This implies that FCC's F-curve relies on location (l) and time (t) percentage reliability, and it is denoted in compact format by F(l, t). Predictably, higher location and time reliability levels will result in lower predicted E-field levels using these models. Based on the F-Curve, the desired-to-undesired signal levels are estimated.

4.4 Cloud-Based Spectrum Management (CBSM)

The geo-locational database suffers from uncertainty in allocating spectrum to real-time applications. To address this level of uncertainty, a cloud-based dynamic spectrum allocation has been developed to manage the spectrum allocation process, increase spectrum efficiency, ensure QoS, and provide comprehensive real-time spectrum allocations with interference-free operations, mainly driven by a spectrum-trading module. According to the US patent [112], cloud-based spectrum management can be defined as a process that not only manages and guides secondary users to use spectrums beyond their reach but also allows the users accomplish, for example, their download during congested times. Thus, CBSM is a service that employs cloud-based geo-location databases and broker engines to allocate available spectrum to secondary devices. Moreover, implementing CBSM comes with the following advantages [113, 114]:

1. *Instantaneous Spectrum Sharing* CBSM plays an important role in dynamic spectrum allocations by managing and optimizing the procedures associated with sharing the available spectrum instantaneously, which resulted in better spectrum sharing and utilization.

2. *New Resource Management Strategies* Transferring the information of spectrum occupancy to a cloud opens the possibility to implement more proper and accurate resource allocation strategies because all secondary devices are cloud-connected.
3. *Efficient Spectrum Sharing* The CBSM provides better spectrum utilization effectiveness because all secondary devices are connected to the cloud, which facilitates the instantaneous movement of the secondary devices from the spectrum hole to another hole in the case of sudden presence of the primary users.

Furthermore, the main components of CBSM can be highlighted as follows [105, 113, 114]:

- *Cloud-Based Spectrum Management System (CBSMS)* It offers all the required components to manage the dynamic spectrum allocation based on locations. Moreover, CBSMS facilitates communication among all the devices within the CSMS.
- *Cloud Spectrum Broker (CSB)* It is an entity that communicates with a CBSD to update information about the spectrum occupancy and communicates with primary spectrum owners to collect information about their vacant spectrum and make this spectrum available to any demand by secondary users.
- *Cloud Spectrum Database (CBSD)* It is used to store information, which is used by CSB, related to spectrum occupancy offered by the primary network to provide better radio spectrum resources management. Furthermore, it offers the available spectrum for rent in response to any call from a secondary user.
- *Coexistence Manager* It is used for spectrum occupancy analysis, interference detection and mitigation, and best available spectrum allocation for the secondary devices.

However, extensive studies have not been conducted in this area. Thus, adopting cloud-based spectrum management in TVWS remains an attractive issue that must be addressed in the nearest future.

4.5 White Space Information Trading Engine

One of the possible ways to actualize the deployment of TVWS technology is by the involvement of spectrum market models. Market models provide financial incentives for spectrum players consisting of PUs, database operators and TVWS networks to engage in short term spectrum trading motivated by financial gain. Spectrum auction has been adjudged as the best approach to implement short term spectrum trading as it provides to the participants platform to evaluate the spectrum independently. A comprehensive review of TVWS database assisted spectrum trading has been done in [7]. Using the trading module, achievable generic rate r of TVWS network $k \in K$ is denoted as

$$r_k = \frac{b_s}{N}\log_2\left(1 + \frac{P_k|h_k|^2}{N_0}\right) \tag{10}$$

where N is the sub-channel,P_k is user K's transmission power; b_s is the bandwidth which can be 6 MHz for FCC TV channelization scheme or 8 MHz for Ofcom TV channelization scheme, N_0 is the noise-power density; $|h_k|^2$ is the channel gain, modelled as Rayleigh The revenue-based utility model for secondary users is stated in Eq. (11):

$$U_s^{(k)} = \frac{b_s}{N} \log_2 \left(1 + \frac{P_T |h_s|^2}{N_0} - b_s p \right) \tag{11}$$

p is the spectrum price per TV channel. From Fig. 4, it could be seen that the data rate of Ofcom TV spectrum channelization is higher than that of FCC. The reason being that Ofcom TV spectrum channelization is higher that of FCC. Similarly in Fig. 5, it is observed that the spectral efficiency of Ofcom TV channelization in spectrum trading module is higher that of

FCC scheme. Furthermore, it could be seen as the spectrum price goes, data rate and spectral efficiency declined. In Fig. 6, the SNR of FCC and Ofcom channelization were compared using cumulative distribution function (CDF) plot. Ofcom TV channelization scheme.

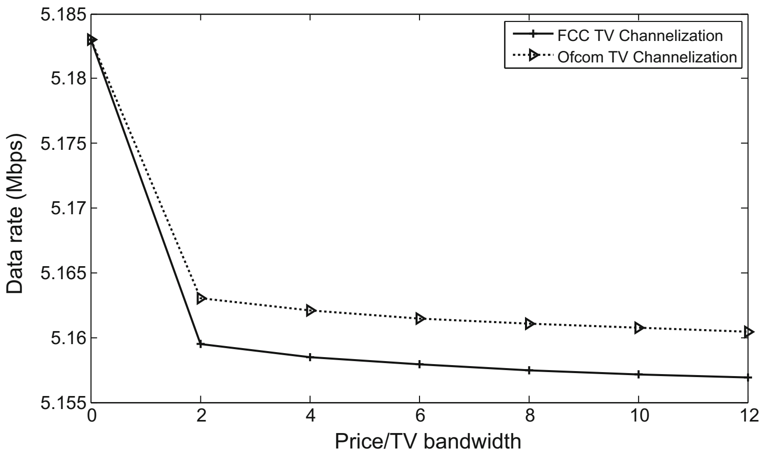

Fig. 4 Throughput comparison based on market driven TVWS database

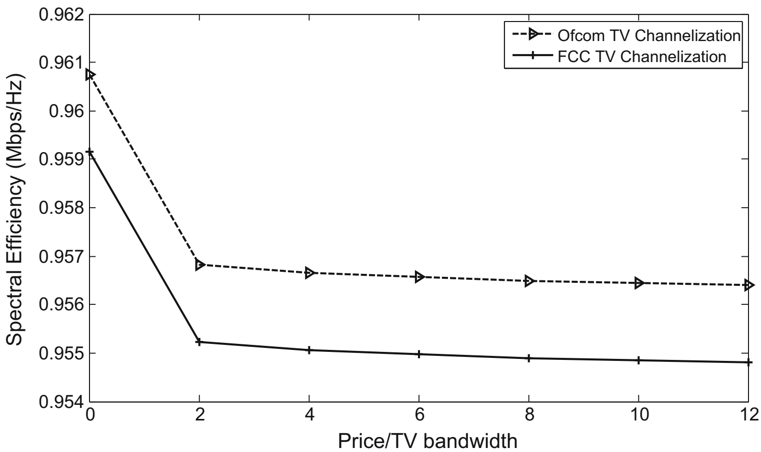

Fig. 5 Spectral efficiency comparison based on market driven TVWS database

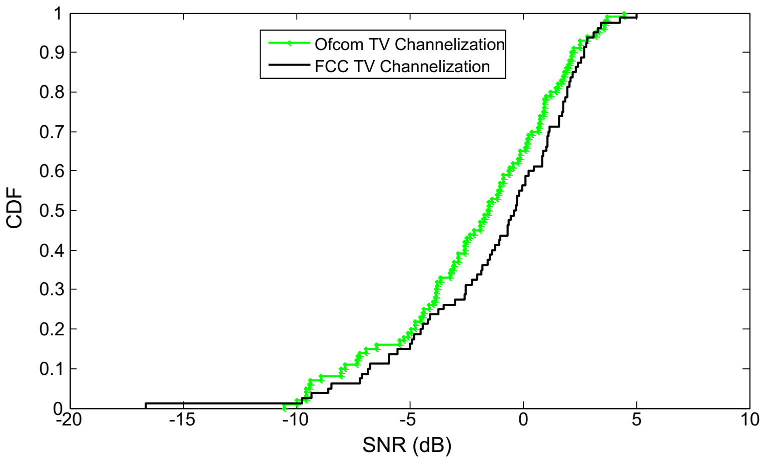

Fig. 6 SNR comparison between FCC and Ofcom market driven TVWS database

5 Potential Challenges and Research Direction

Although CR has existed for some time, numerous significant problems and issues remain unexplored. Most countries have completed or are on the verge of identifying white spaces in their frequency domains. Consequently, CR has evolved from a mere theoretical concept to a practical reality. CR is a unique wireless communication standard that thrives on intelligent decision-making and spatial–temporal functionality with an open and non-prioritized spectrum-sharing scheme. CR is envisioned to have sufficient ability to recognize common user activities, which enables it to learn to assist the user and the network with common tasks. Based on this brief description, other aspects of CRN research remain unexplored. Some of these issues are discussed in the subsequent subsection.

5.1 The Autonomous White Space Information Acquisition Regime and Proposed Solution

The three approaches to white space information acquisition techniques have been independently implemented, resulting in defective units that reduce the efficiency and seamlessness of TVWS information acquisition. Consequently, we propose a novel model called the "All Inclusive TVWS Information Acquisition Model". A flowchart of the proposed model is depicted in Fig. 7. The proposed All Inclusive TVWS Information Acquisition Model tends to exploit the desirable attributes of spectrum sensing, geo-location database, and spectrum prediction. Although the geo-location database has been determined to be the most reliable white space acquisition technique [38, 115], it does not support mobility across regions because it is location specific. This effect also implies that roaming services are not guaranteed. Furthermore, the technique requires an Internet backbone to acquire information about which channels are available for use. Conversely, spectrum-sensing techniques are not location specific and can be deployed for a TVWS network initial startup and while crossing over into a new territory in which the previous database operator has no footprint. This approach enhances TVWS network seamlessness while the TVWSD tries to establish communication with the approved TVWS network operator. Another

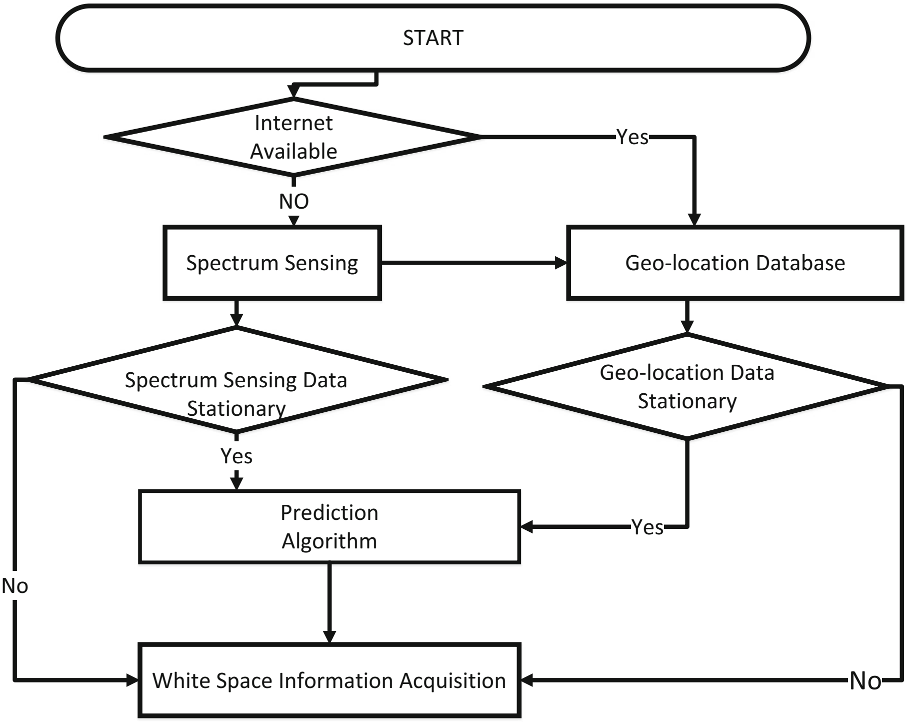

Fig. 7 All-Inclusive TVWS information acquisition model

scenario can be in a situation that TVWSD is able to predict their next destination, it can download the TVWS channels and operate in offline mode. However, care must be taken while operating in the offline mode to ensure that the downloaded TVWS information is used during their valid period to avoid causing harmful interference to the PU.

By design, TVWS devices are mandated to either sense the presence/absence of PU signals or contact the geo-location database for PU-free channels prior to transmitting any signal in the TV band. Spectrum prediction drives the TVWS information acquisition schemes into the domain of intelligent networks by extracting useful pattern recognition attributes in the already acquired TVWS information data stored in the device memory. Using the prediction algorithm, spectrum channels can be proactively selected to reduce the possibility of interference with the PU and increase the efficiency of the spectrum utilization. In addition, Mode II devices are dependent on Mode I or fixed TVWS devices for a list of available channels. Mode II devices must cease transmission within 5 s of not receiving a response from the master device to a transmission [31]. The prediction algorithm serves as a buffer to proffer solutions to the PU future spectrum profile in the case of a device communication failure between the TWSD and the database entity. This process ensures the continual usage and protection of the PU against interference from TWSD.

5.2 The Geo-Locational Database-Related Issues

In this subsection, some of the related issues concerning geo-locational database techniques are presented.

5.2.1 Geo-Location Interference

Interferences in geo-locational databases can be classified into two main classes: interference among secondary devices and interference due to incumbent users. The interference scenario becomes a challenging issue when the secondary devices move from one location to another that belongs to a different database provider. This move may result in a collision among the database providers.

5.2.2 Geo-Location Security

The database provider stores sensitive information about the incumbent users, including their location and transmission power and their allocated and vacant spectrum. Moreover, information about the actions of the secondary users is also available with the database provider. This situation allows for an open information exchange among incumbent users/ secondary users and the database provider, and this information must be protected. This line of thought has been proposed in the context of open-source spectrum sensing [116, 117]. Thus, the database provider must provide proper security tools, including authentication, integrity, privacy, and confidentiality. Common security attacks of spoofing and PU emulation attacks must be considered [117]. Providing the appropriate level of security is one of the most challenging aspects of the geo-location database approach.

5.2.3 Multi-Database Provider and Quality of the Spectrum

Another issue that should be considered by researchers is the multi-provider scenario in the geo-location database approach. Secondary devices may change their locations and need to address the new database's provider. This particular scenario produces another delay because the secondary devices must establish new cooperation/registration with the new provider. The quality of the available white space from the new provider may differ, which may result in poor service quality in certain cases.

5.2.4 Mobility/Handover/Handoff Supports in a Multi-user Environment

Handoff is the process that that permits this transition from a channel to another with minimum performance degradation [116]. Spectrum mobility issues for a Cognitive Radio Ad Hoc Network (CRAHN) will be an important research topic. IEEE 802.22 addresses the spectrum handoff with the Incumbent Detection Recovery Protocol (IDRP). The IDRP allows the network to restore its normal activity maintaining an acceptable level of QoS [117]. Two different strategies are presented: proactive spectrum handoff and reactive spectrum handoff. Secondary devices in the geo-location database mainly depend on the database's provider to collect information about the available white spaces. However, this activity also produces delays in the secondary devices to cope with changes in white space availability when secondary devices are in mobile status. Furthermore, in a situation where a mobile node is moving out of the coverage area of one provider, it is unclear how to arrange the best handover mechanism and information exchange to be used by TVWS different operators.

5.3 Indoor Location Awareness Updates

Additional challenges in the geo-location database approach include (1) the location awareness of the secondary devices and (2) the ability of the secondary devices to continually update their locations to the database provider. GPS provides reasonable accuracy in outdoor settings, but achieving the same level of accuracy in indoor scenarios remains an open question [118].

5.4 Autonomous Heterogeneous Coexistence Etiquette for TVWS Networks

TVWS is envisioned to be inhabited by heterogeneous networks, each acting selfishly. The current belief is that TVWS networks will form a collaborative network [16]. However, the reality is that the system will instead exhibit non-collaborative (autonomous) networks [119]. Thus, a need exists to develop autonomous coexistence etiquette capable of guaranteeing optimal QoS to end-users. Evidently, this process will involve the introduction of elements of artificial intelligent to implement learning automata in the TVWS nodes.

5.5 Interference Estimation

Interference is expected to mar the QoS of TVWS networks. The selection of the appropriate interference estimation model is therefore critical as highlighted in [8]. The 802.22 wireless regional area networks will be deployed with fixed high-power base stations serving fixed CPE and portable devices. Conversely, 802.11 WLAN networks are commonly deployed by consumers at home or small office settings. Moreover, the different TVWS wireless standards have varying cell radii, resulting in numerous overlapping cell edges among the TVWS networks. As such, there is a great need to develop a common platform for improved interference estimation among all the TVWS networks.

5.6 QoS Aware and Rate Adaptive Prediction-based Tools

It is equally possible to predict white space information on the availability of perfect channel state information. In this scenario, the TVWS networks must acquire all the relevant information pertaining a particular TV channel. If the rate drops below a predefined threshold, the likelihood of the presence of PU is confirmed. This analogue is based on the fact the PU signals are constitute of interference, which adds up to the spectrum noise to reduce signal strength. Effectively, instead of modelling signal-to-noise ratio, the appropriate metrics will be signal-to-noise plus interference ratio.

6 Conclusions

Cognitive radio through TVWS has been demonstrated to be a reliable and readily available wireless resource capable of mitigating the current spectrum crunch in the wireless system technology. This study has presented a review of the contemporary approaches to TVWS information availability techniques, the advantages and disadvantages of each technique, and possible solutions to the predominant white space information acquisition technique of spectrum sensing. We have also provided a classification model for white space information acquisition techniques. An overview of the current industrial trends in TVWS demonstrates that CRN is not merely a theoretical approach but is instead a practical technology. We believe that by sharing this information with the larger engineering and academic communities, this article will trigger analytical thought and discussion that may accelerate the development and improve the quality of modern TVWS technology.

Acknowledgements The authors would like to thank Malaysia's Ministry of Higher Education for their financial support under Grant Ref. No. ERGS/1/2013/ICT03/UKM/02/1.

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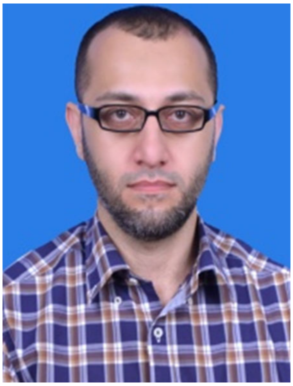

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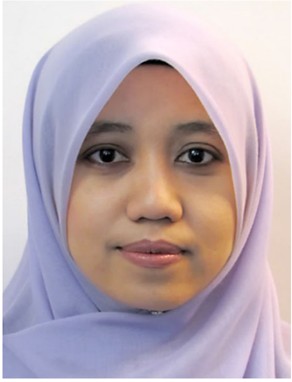

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