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A REVIEW OF SPECTRUM HOLE PREDICTION SCHEMES

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ABSTRACT

The administrative approach to spectrum allocation coupled with rapid advances in mobile and wireless communication has led to a perceived spectrum scarcity. This has given birth to the idea of dynamic spectrum access with the proposal of cognitive radio technology. This novel idea allows licensed and unlicensed users to share the spectrum in a non-interference manner. For this to be possible, the users must be able to sense the channels to check whether they are busy or idle. In this paper, we present an overview of the most promising spectrum hole prediction schemes available. Theory and applicability to spectrum hole prediction of these schemes are presented. Their advantages and shortcomings are highlighted. Further discussion on future research direction is finally given.

KEYWORDS: *Spectrum, Cognitive radio, Spectrum prediction, channel.*

I. INTRODUCTION

Since the early days of radio communication, spectrum has always been allocated to users (such as land mobile services broadcasting, aviation and others) over large geographical area and usually for long period of time. This form of spectrum allocation is known as the administrative approach to spectrum management or command and control in some literature [1]. The process of spectrum allocation generally involves dividing the available spectrum into blocks or bands for particular service. This procedure is usually done by international and national bodies. At the world stage, the international telecommunication union ITU is responsible for coordinating the use of spectrum all over the world. The main idea behind this form of allocation is to minimize interference amongst adjacent users [2] (even though a band gap is provided between them). However, this approach has been shown to be inefficient. Recent spectrum occupancy measurements have shown that the spectrum is highly underutilized both spatially and temporally [3-8]. Moreover, recent advances in the field of wireless and mobile communication which has led to faster speeds and bandwidth has also resulted in a situation whereby the available spectrum is perceived to be scarce. The reality is that even though the demand for bandwidth has increased due to advent of several bandwidth-hungry technologies which have led to a perceived spectrum scarcity; the main problem has been in the manner the spectrum is allocated since recent research has shown that most of the spectrum allocated is actually idle. Therefore, it has become necessary to devise ways of maximizing the limited spectrum resource. This has led to the concept of dynamic spectrum access which could be achieved through Cognitive Radio (CR) which was envisioned by Mitola in 1999[9].

Several dimensions have been used for transmitting information over a wireless channel. Time, frequency, code and space have all been dimensions used in transmitting information in a multi-dimensional radio spectrum space. The advent of Cognitive radio technology promises to provide solutions to the problem of spectrum underutilization by providing the means of transmitting information simultaneously over both time and frequency domain [10].Cognitive radio includes four main functional blocks: spectrum sensing, spectrum management, spectrum sharing and spectrum mobility. Spectrum sensing aims to determine spectrum availability and the presence of the licensed users (also known as primary users PU).Spectrum management is to predict how long the spectrum holes are likely to remain available for use to the unlicensed users (also called cognitive radio users or secondary users SU). Spectrum sharing is to distribute the spectrum holes fairly among the secondary users bearing in mind usage cost. Spectrum mobility is to maintain seamless communication requirements during the transition to better spectrum. Among all other functions, Spectrum sensing is believed as the most crucial task to establish cognitive radio networks which is the main focus of this work.

In a traditional CR network, a SU sharing a particular channel allocated to a certain PU is supposed to vacate the said channel whenever a PU returns and initiates a transmission. This is supposed to be achieved through spectrum sensing where by the SU senses the spectrum to determine the feasibility of initiating a transmission. Sensing a whole band is time consuming and results in non-negligible time delays [11, 12]. Prediction based spectrum sensing has been shown to decrease energy consumption and also reduce the time required to sense by skipping those bands that have been proven to be busy at all times[13]. One of the key functions of cognitive radio is that it can learn from past experiences, therefore any approach being considered for prediction of spectrum usage must be able to incorporate that feature [14]. It has therefore become imperative to develop models capable of predicting the channel state accurately.

Spectrum prediction in CR is a complex area with a lot of branches such as channel status prediction, transmission rate prediction, radio environment prediction, and Primary User (PU) activity prediction [15]. Due to hardware limitation, the secondary user (SU) might not be able to sense the whole spectrum band, the idea has always been for the SU to scan bands that have been found to be less busy based on historical data available thereby avoiding the busy potions of the spectrum which will in turn help in conserving SU energy[14]. It has therefore become imperative that channel state prediction be devoid of any errors so that interference can be minimized to the minimum. In this paper spectrum prediction techniques or channel state prediction techniques (these two terms might be used interchangeably) will be discussed. Specifically their theory, advantages and disadvantages will be discussed and open research challenges will be presented at the end.

II. SPECTRUM PREDICTION

CR technology addresses the problem of spectrum scarcity by sensing and occupying spectrum holes without causing interference to the PU [16]. This scheme also known as dynamic spectrum access is depicted in figure 1. Spectrum hole prediction should be done seamlessly and without causing interference amongst the PU and SU's. The two major reasons that necessitates the importance of spectrum hole prediction are;

1. The whole concept of DSA/CR lies in its ability to provide a dynamic means of sharing spectrum amongst licensed and unlicensed users without causing interferences amongst them. There should be a way that the SU will be able to sense to spectrum band for spectrum opportunities so that transmission can be started or vacate a spectrum channel when a PU wishes to initiate transmission.
2. Secondly, sensing the whole wideband spectrum when a transmission is to be initiated will be time consuming which will ultimately lead to draining of SU's power. Through a prediction mechanism like Artificial Neural Network based scheme, data could be stored that will help in restricting the sensing of spectrum bands to portions of the spectrum that have been found to be less busy through learning.

Several schemes for spectrum hole prediction have been proposed over the years. In the next section we are going to discuss these schemes and how they are applied in spectrum hole prediction.

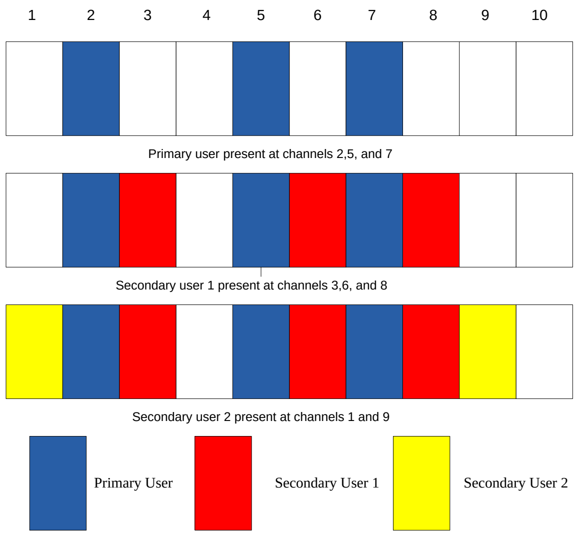

Figure 1. Dynamic Spectrum Access by cognitive users

III. Spectrum Hole Prediction Schemes

In this section, spectrum hole prediction schemes will be discussed. Some of these schemes have been widely researched. In total we are going to present, discuss and analyze five spectrum hole prediction schemes. Some of the earliest schemes include Hidden Markov Model and Artificial Neural Network based schemes. Others include Binary Time Series, Pattern Mining and Moving Average schemes.

3.1 Artificial Neural Network Scheme

Artificial neural networks are man-made systems that tend to imitate the natural neural structures of organisms through software programs running on computers. Studies have shown that ANNs have the ability to approximate any nonlinear function to an acceptable degree of accuracy given the right composition i.e. sufficient number of neurons [17]. Artificial Neural Networks (ANNs) are non-linear mapping structures based on the function of the human brain. They are powerful tools for modelling and are widely used in prediction problems due to their simplicity in terms of training. Whereas other prediction schemes require continuous training, neural network are trained once in an offline fashion when the observed process is stationary [14]. Basically, a neural network is a learning machine where the procedure used for learning is called the learning algorithm. The function of this algorithm is to modify the weights of the system so as to achieve a particular design goal. The process involved is simple: the input and output data is fed into the ANN system for training, afterwards, the trained network is used to predict the output of the network.

Many real life problems are generally non-linear in nature. The spectrum strength measured during spectrum occupancy campaigns (which constitutes the data) also falls into this category [18]. Several works [14, 19] have applied Multi-layered Perceptron (MLP) as the training algorithm in spectrum hole prediction. MLP has over the years been widely used in non-linear prediction.

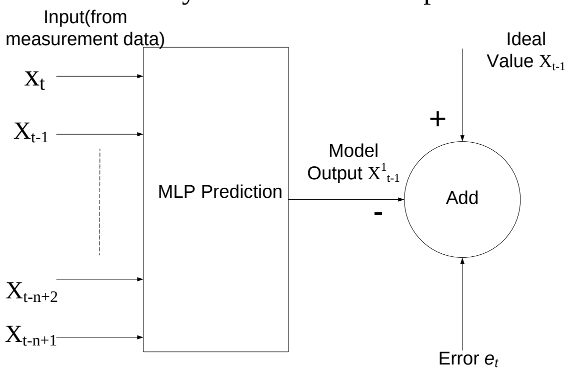

Figure 2. MLP Prediction Model

The MLP structure consists of an input layer, hidden layer and an output layer. The hidden and output layers contain neurons which are connected by adaptive weights. The non-linear transformation is achieved using a hyperbolic tangent function. The number hidden layers and the number of the neurons generally depend on the application [20]. In prediction problems, two hidden layers have been found to be sufficient. Figure 2 describes a typical spectrum hole prediction network using MLP. The input and output vector which is basically a data from spectrum occupancy measurements fed into the system. The learning process is done using the MLP learning algorithm. The output of the MLP is termed as the MLP output. The difference between the ideal value and the MLP output is the error which is continually updated until the desired value is obtained. The process can be itemized as follows

1. The time series power level data is converted into a binary time series of 0's and 1's using thresholding.
2. The data from step one is then grouped into the different services examined. The training and validation and testing data sets are then obtained.
3. The training and testing data for the service to be predicted are selected; architecture and training parameters are also selected.
4. The network is trained using MLP
5. The network was then validated using the validation data
6. The network is tested with the testing data to ascertain the prediction accuracy

Spectrum hole prediction using ANN has been found highly reliable with less errors. Its ability to learn from historical data and previous experiences makes it an ideal candidate for application in CR based prediction schemes. It will ultimately help to reduce power consumption of base stations as well as SU nodes since lesser time will be spent during sensing. However, ANN has been found to run into partial optimization therefore reducing the probability of optimal results. Even though this problem has been researched in [21], further works still needed to be done to ensure that fewer errors occur. In addition, ANN based models generally suffer from generalization, this problem is also an open research area in spectrum hole prediction which needs to be thoroughly looked into so as to enhance the quality of the prediction process.

3.2 Hidden Markov Model Scheme

Markov chain have been defined as a group of random processes possessing a specific form of dependence among current and past samples [22]. A process is termed a Markov process if it satisfies the Markov property that: given a present state, the probability distribution of the next state depends on the present state and not on the states preceding the current state [23]. This is known as the memoryless property of Markov chain. An HMM is formed by incorporating an observable process with an underlying Markov chain. The underlying Markov chain is said to be hidden, and it can be observed only through the observable process. Given the underlying Markov chain, the observed process is conditionally independent. HMMs consist of a rich family of parametric processes that has been applied in many applications especially in speech recognition. The hidden process can be either discrete-time or continuous-time finite-state homogeneous Markov chain [23]. The output of the observable process can have either finite-alphabet or general-alphabet; and thus, it can be characterized by a probability mass function or a probability density function appropriately.
In spectrum hole prediction, the spectrum occupancy pattern of a radio channel can be modeled by a two state Markov chain since the channel can either be busy or idle [24].

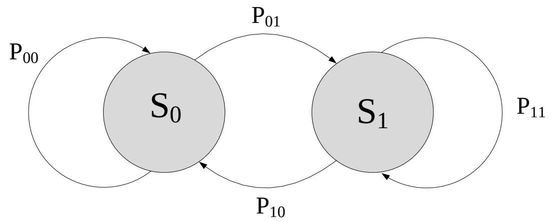

Figure 3. Discrete-Time Markov Chain Model

Let's denote $S = \{s_0, s_1\}$ the space state of a primary radio channel with s_0 indicating the state when the channel is free and s_1 when the state is occupied. Therefore the channel state $S(t)$ at any given time t can either be $S(t) = s_0$ or $S(t) = s_1$.The behavior of a Markov chain can statistically be described with a set of transition probabilities among states. If the state space S is finite with n states, the transition probability distribution can be described with a $n \times n$ square matrix. Therefore the states can be modeled as a discrete time Hidden Markov Model (DHNN). This model is important as it allows us to make prediction of the location and duration of the spectrum holes [25]. A typical DHNN model consists of a $N \times N$ state transitional matrix P, and $N \times M$ emission matrix Q; where N is the number of possible states and M is the number of possible emission symbols. Since our model has two states, the state transmission matrix is given as;

$$P = \begin{bmatrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{bmatrix}$$

Similarly, since our model has been defined as having perfect sensing, therefore the emission matrix will be the identity matrix given as

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

The parameters of the HMM are updated using the Baum-Welch algorithm. This algorithm uses the observed sequence of spectrum states to infer the underlying HMM transmission matrix.
The HHM based scheme has been used in several works to predict the presence or absence of spectrum hole in [24, 25]. One of the major shortcomings of this scheme is that unlike the ANN scheme, it cannot learn from previous experiences. Since CR systems are supposed to learn from previous experience, this is a major shortcoming in HMM based prediction model.

3.3 Summary of Other Methods

Several works [26, 27, 28] have attempted to model the variation of signal power on a channel. A second order autoregressive process (AR-2) has been used to model the channel variation. The channel state can be determined once the AR-2 model parameters have been found and the signal power predicted. A Kalman filter is finally used to determine the channel status. In [27], an autoregressive integrated moving average model was used to predict the signal power in a channel. The ARMA model was created by integrating a moving average (MA) model with an AR model. The results obtained indicated that the time series of all the TV channels fall into the moving average model. An ARMA model generally requires the time series to be stationary; a model was presented in [28] to handle non-stationary time series. Due to this a problem arose, that the time series must be converted to stationary and periodic time series to be analyzed.
In [29] a spectrum occupancy prediction model based on Partial Periodic Pattern Mining (PPPM) was introduced. The mining takes into account the irregularity of spectrum usage and thus mimics true traffic. The proposed PPPM algorithm combines the gap-constrained pattern growth, the head index list structure, the Apriori-like property, and the backward-extension pruning to achieve fast and reliable partial periodic pattern mining. The partial periodicity of spectrum occupancy patterns and the performance of PPPM are validated with real life Wi-Fi network activities and data collected in the PCS bands.
A binary time series approach to spectrum prediction was proposed in [30]. Time series models derived are tested in terms of raw residuals and Akaike Information Criteria (AIC). Two types of spectrum occupancy schemes, namely deterministic and non-deterministic schemes, are considered. It is observed that even without updating the model, this approach performs very well for deterministic occupancy schemes.

IV. DISCUSSION

As we have outlined earlier, several schemes have been deployed to predict the presence or otherwise of spectrum holes in a radio channel. The most promising schemes so far have been the ANN based scheme and the HMM scheme. The ANN scheme seems promising because of its ability to learn from previous experiences. Furthermore, once the model has been trained for the first time, there will be no need to train it again in the event that new information is available. The model will just be updated because of its ability to learn from previous experiences. The HMM scheme has also been shown to predict channel status with a high degree of accuracy. Recent research into channel status prediction has also shown that though there are ample spectrum holes, the pattern observed is highly irregular. From experimental results, it has been deduced that this phenomenon will lead to several collisions amongst the CR nodes thereby reducing the performance efficiency of the system. Though statistical methods have been used for prediction purposes, their implementation in real-life systems might be a challenge due to their inability to integrate new information into their model. The FCC has already presented a blueprint that future CR systems will be based on a geo-location database that CR nodes will query before initiating transmission, this requirement indicates that any prediction scheme must integrate database and machine learning into it. This feature is lacking in these schemes.

Lastly, most of these prediction schemes proposed were analyzed based on assumptions. Very few works were able to use real data to validate the proposed schemes. The ability of these schemes to work in real systems will depend on their suitability and performance using real-life data.

V. CONCLUSION

Several spectrum hole prediction schemes currently available in literature have been presented. The importance of spectrum hole prediction as it applies to CR technology cannot be overemphasized. Successful determination of the channel status will lead to fewer collisions between the several CR nodes. It will also help reducing he sensing time thereby reducing the power consumption of the SU and corresponding base stations. Schemes such as ANN , HMM and PPM show great potential in their applicability in real systems due to their ability to learn from past experience, high prediction accuracy and resolving the issue of irregular spectrum hole patterns observed during the spectrum occupancy measurements. A lot of work still needs to be done so that this novel idea could be finally actualized. Real data should be used in determining the performance of these schemes as most of these models performance were determined without real data.

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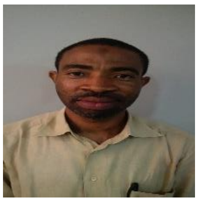

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