Asian Journal of Information Technology 15 (11): 1816-1824, 2016
ISSN: 1682-3915

Adaptive Phase Adjustment and Channel Prediction Strategies (APA-CPS) in MIMO-OFDM Based Cognitive Radios

[1]R. Sarankumar, [2]P. Poongodi and [3]G. Umamaheswari
[1]Department of Electronics and Communication Engineering,
Sri Ramakrishna Institute of Technology, 641010 Coimbatore, India
[2]Professor, Department of Electronics and Communication Engineering,
Karpagam College of Engineering, 641032 Coimbatore,
[3]Department of Electronics and Communication Engineering, PSG College of Technology,
641004 Coimbatore, India

Abstract: MIMO (Multiple Input Multiple Output)-OFDM (Orthogonal Frequency Division Multiplexing) based Cognitive Radio (CR) systems has received great attention in dynamic spectrum access for the wireless communication. Cross-band Interference and channel feedback delay are the serious problems particularly in the cognitive radio applications. In this study, an innovative technique called Adaptive Phase Adjustment and Channel Prediction Strategies (APA-CPS) in MIMO-OFDM based cognitive radio networks is introduced. In the adaptive phase adjustment method, the phase of every OFDM symbol is adjusted to reduce the cross-band interference. Additionally, the smooth windowing is used instead of rectangular window to diminish the out-of-band radiation. For enhancing the spectral efficiency, accurate channel state information without any feedback delay is mandatory. An Auto Regressive (AR) model is used to select the most supportive data for predicting the channel. A Bidirectional Reduce Complexity Stepwise Subset (BRCSS) prediction algorithm is used to diminish the complexity of the channel prediction. In the BRCSS prediction algorithm, both forward selection and backward elimination are considered. The main idea is to concurrently remove the data from the correlation's point of view in a bidirectional manner. Experimental results show that the proposed method achieves less bit-error rate and Minimum Mean Square Error (MMSE) when compared to the existing method.

Key words: MIMO-OFDM, cognitive radio, channel prediction, phase adjustment, interference cancellation

INTRODUCTION

Radio spectrum has become a highly demanded resource because of their enormous growth in the Internet-enabled mobile devices (Bansal *et al*., 2010). The Industrial, Scientific and Medical (ISM) radio bands are the frequency bands that allocate the radio spectrum to different applications for industrial, scientific and medical purposes other than telecommunications. The ISM band is highly crowded because a high number of wireless technologies accommodate the frequency bands. If the frequency spectrum is not correctly managed, the high demand for wireless broadband and the ever-growing volume of data traffic are not accommodated. The measurements show that some of the frequency bands are frequently used while some are infrequently used. The usage of frequency bands depends on the location, time of the day and frequency bands (Mahmoud *et al*., 2009) which shows they are underutilized. The vacant portions of the spectrum are licensed yet it cannot be utilized by the licensed users. To solve these problems, a novel technology is developed called Cognitive Radio (CR) which is also used to solve the spectrum efficiency problem. This technology allocates the unused spectrum for the opportunistic users.

Moreover, MIMO-OFDM based CR systems have momentous application for usage in revolutionary dynamic spectrum access based wireless networks. In MIMO-OFDM based CR systems, the licensed primary users are preserved by switching off the equivalent subcarriers of the secondary user. On the other hand, OFDM has some drawbacks like large peak-to-average power ratio and high out-of-band radiation. This is particularly caused by the side lobes of the subcarriers that are generated because of the symbol truncation in the time domain. Due to the out-of-band radiation,

Corresponding Author: R. Sarankumar, Department of Electronics and Communication Engineering, Sri Ramakrishna Institute of Technology, 641010 Coimbatore, India

interference is caused to the primary users. Numerous side lobe suppression methods are presented for MIMO-OFDM based CR systems. A simple and efficient method called time domain windowing (Tan and Beaulieu, 2004; Assalini and Tonello, 2004) that extends the window by using the smooth shaping windows. The problem in this method is it decreases the data rate. Another method called Subcarrier Weighting (SW) (Cosovic *et al*., 2006) is used to reduce the side lobe power. But, this method has the side-effect of increasing the Bit-Error-Rate (BER) of the system.

Spectral efficiency improvement is also an important concern in MIMO-OFDM based CR systems. The spectral efficiency and system performance (Sampath *et al*., 2002) can be improved by some of the techniques like adaptive multi-user resource allocation (Wang and Giannakis (2011) and precoding (Joham *et al*., 2012) techniques. But, the benefits of these methods depend on the precise Channel State Information (CSI). The CSI is only computed at the receiver and it is given as the feedback to the transmitter. But due to the high feedback delay, there is high performance degradation.

Hence, it is necessary to predict the future channel coefficients based on the previous data. The channel prediction methods are categorized into two types: the parametric autoregressive model and the parametric radio channel model. Mostly traditional Autoregressive (AR) models are used which considers the channel as a Wide Sense Stationary (WSS) stochastic process (Hallen, 2007; Heidari *et al*., 2010).

The AR coefficients can be calculated by using the Minimum Mean Square Error (MMSE) criterion which requires the knowledge of the channel correlation function. Some of the adaptive filtering methods like Least Mean Squares (LMS) (Hallen *et al*, 2002), Recursive Least Squares (RLS) (Hallen, 2007) and Kalman filter (Heidari *et al*., 2010) are suggested to track the modifications in the channel coefficients.

The motivation of this research is to improve the spectral efficiency and enhance the network performance for the MIMO-OFDM based CR systems. In this research, a new technique called Adaptive Phase Adjustment and Channel Prediction Strategies (APA-CPS) is introduced for improving the spectral efficiency and the bit-error rate. The adaptive phase adjustment approach adjusts the phase of the OFDM symbols while smooth windowing, used instead of rectangular window, reduces the cross-band interference.

Furthermore, the CSI information is given to the transmitter without feedback delay for the prediction of channel status. The main contributions are:

- An adaptive phase adjustment method is proposed to adjust the phase and smooth windowing is applied instead of rectangular window which permits high and controlled out-of-band roll-off
- Spectral efficiency is important in the MIMO-OFDM based CR systems. A Bidirectional Reduce Complexity Stepwise Subset (BRCSS) prediction algorithm is presented to predict the channel with less complexity. This algorithm considers both forward selection and backward elimination methods
- Experimental results prove that the proposed APA-CPS method has less feedback delay and high spectral efficiency when compared to the existing methods

Literature review: In this study, various methods are suggested for improving spectral efficiency and channel prediction in the MIMO-OFDM based CR systems.

Wang and Giannakis (2011) discussed the resource allocation problems of the multi-user wireless transmissions in OFDM. A new method is suggested for resource allocation that develops an optimal subcarrier that provides power and rate allocation for improving the sum-rate. Shen and Fitz (2008) suggested MIMO-OFDM beam forming design that is used to enhance the channel state estimation performance. After beam forming is performed, the Smoothed Singular Value Decomposition (SSVD) is firstly presented to get the near efficient channels. Then, the Frequency Smoothed Beam (FSB) former design is utilized to improve the channel estimation performance.

Hwang and Winters (1998) presented a linear complexity channel parameter tracking method inorder to incessantly adapt to the time-varying channel model parameters. The Cramer-Rao Lower Bound (CRLB) and asymptotic CRLB (ACRLB) parameters are derived for computing the Mean Squared Error (MSE) for the OFDM channel prediction. Schafhuber and Matz (2005) presented decision-directed channel predictors for OFDM communications over time-varying channels.

Wong *et al*. (2004) presented a novel Long Range channel Prediction method (LRP) for the adaptive transmission approaches. This method computes the linear Minimum Mean Squared Error (MMSE) computation of the future fading coefficients based on the past interpretations.

Tan and Beaulieu (2004) presented a method called pulse-shaping orthogonal frequency-division multiplexing. This method is better than raised cosine method and can be used to minimize the interference because of the frequency offset.

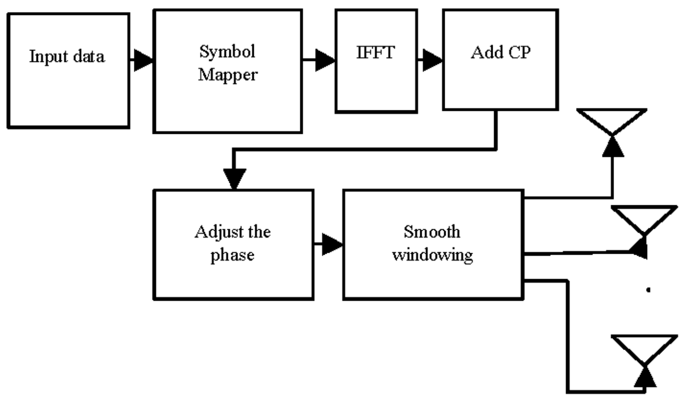

Fig. 1: MIMO-OFDM transmitter

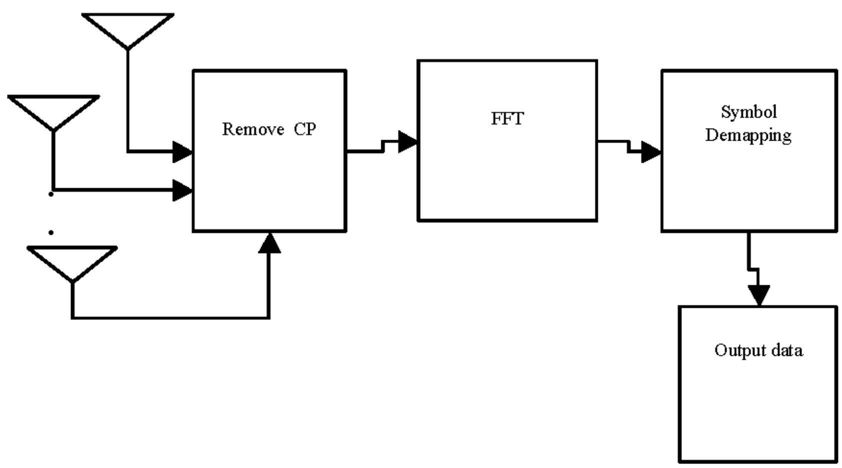

Fig. 2: MIMO-OFDM receiver

Cosovic *et al*. (2006) suggested a method for side lobe suppression in the OFDM systems. This method is based on the multiplication of the utilized subcarriers with subcarrier weights. For channel prediction, a conventional prediction method called SISO predictor (Li and Wang, 2003) is used that eliminates the spatial correlation and considers only the temporal correlation.

MIMO-OFDM System model and channel model: Consider a MIMO-OFDM based CR system that includes a Base Station (BS) and sub channels for the CR users. A cognitive system is included with one transmit antenna that employs the non-contiguous OFDM signaling. The receiver contains many numbers of antennas. The OFDM system contains total of N subcarriers and based on the primary user usage of the spectrum, some of the subcarriers are switched off. Fig. 1 and 2 shows the MIMO-OFDM transmitter and receiver.

The input data stream is given to the symbol-mapper. The symbol-mapper is used to mapping from the denoised signal to the modulation symbols and the output of the symbol mapper is series of complex constellation points $\{S_i\}$ that are to modulate the active subcarriers.

Then the constellation points are given to input as the serial-to-parallel converter that converts the stream of constellation points $\{S_i\}$ into the complex-valued vector $X^{(n)}$ where n denotes the symbol index. The cognitive engine is used to deactivate the subcarrier based on the channel sensing which is used by the licensed primary users. Then, the $X^{(n)}$ is given to the IFFT block. The output of the IFFT block is given as:

$$\hat{x}^{(n)} = \frac{1}{N} W^{t}_{N,N} x^{(n)} \tag{1}$$

In this Eq. 1 where $W_{N,N}^{(L)} = [\omega^{kl/L}]$, k = 0, ..., N-1, l = 0, ..., NL-1 is the N×N Discrete Fourier Transform (DFT) in which $\omega = e^{-j\pi/N}$ and $(.)^t$ represents the conjugate transpose. L is the unsampling factor. The inter-symbol interference is reduced by adding the last G samples of $\tilde{x}^{(n)}$ at the initialization of IFFT output. As a result, the time domain OFDM signal is represented as:

$$x_i^{(n)} = \frac{1}{N} W^t_{N,N+G} X_i^{(n)} \tag{2}$$

In Eq. 2, $W_{N,N+G} = [A.\ W_{N,N}]$ is a modified upsampled DFT matrix with the cyclic prefix in which A is the sub matrix of $W_{N,N}$ which includes the last F columns of $W_{N,N}$. Further to reduce the interference of the primary user $x_i^{(n)}$ is given to the phase adjustment block that alternates the each OFDM symbol by an appropriate phase.

The unsampled FFT matrix is defined for compute the spectrum in the primary band in-between the subcarrier frequencies:

$$W^{(L)}_{N,N} = \left[\omega^{kl.1}\right], k = 0,\ldots,N-1, l = 0,\ldots,NL-1 \tag{3}$$

In Eq. 3, L is the unsampling factor. Therefore, the unsampled spectrum of the n^{th} OFDM symbol is evaluated as:

$$X_L^{(n)} = \frac{1}{N} W^{(L)}_{N,N+G} W^t_{N,N+G} X_i^{(n)} \tag{4}$$

MATERIALS AND METHODS

Adaptive phase adjustment process

Phase adjustment method: The main intent of the phase adjustment technique is to diminish the interference of the primary users by adjusting the OFDM symbols. In the phase alteration method, the entire subcarriers of every OFDM symbol are rotated in the complex space by the similar optimal phase for reducing the interference level. Let us consider m+1 successive OFDM symbols in every step, the optimal rotation phase of the last m symbols are evaluated in such a way that the entire interference of the m+1 symbols is diminished.

The spectrum of the resulting symbols is evaluated by using Welch's method in which a window length is equal to m+1 OFDM symbols is considered for every spectrum measurement segment and amount of overlap of the segments is one OFDM symbol. As a result, in every step the first symbol's phase shift is acquired by optimization of the previous step and thus m optimal phases are to be computed. Therefore the (m+1)th symbol in the current step will be considered as the first symbol in the next step.

Let $x_{(n)}, x_{(n+1)}, \ldots x_{(n+m)}$ denote the m+1 consecutive OFDM symbols in the current step. The upsampled spectrum of the m+1 symbol is then calculated as:

$$S^{(n)} = W^{(L)}_{N,2(N+G)} \begin{bmatrix} x^{(n)} \\ \vdots \\ x^{(n+m)} \end{bmatrix} \tag{5}$$

$$= \sum_{i=0}^{m} D_i W^{(L)}_{N,N+G} x^{(n+i)} \tag{6}$$

In this Eq. 6, D_i = diag{e-2πjki (N+G)/NL}, k = 0, ..., NL-1 the licensed primary user occupies a bandwidth equivalent to B successive subcarriers $[X_{t+1}, X_{t+2}, \ldots X_{t+B}]$, in which B<N. So, the interference vectors are denoted as:

$$d^{(n+1)} = \hat{D}_i \hat{W}^{(L)}_{N,N+G} x^{(n+1)}, i = 0,1,\ldots,m \tag{7}$$

In Eq. 7, $\hat{W}^{(L)}_{N,N+G}$ is a sub matrix of $\hat{W}^{(L)}_{N,N+G}$ including only the two rows which correspond to the primary band, i.e., rows (t+1) L through (t+B) L and $\hat{D}_i$ is defined as:

$$\hat{D}_i = \text{diag}\left\{e - \frac{2\pi jki(N+G)}{NL}\right\}, k = (t+1)L,\ldots,(t+B)L \tag{8}$$

The main intent of the phase adjustment method is to identify the optimal rotation phase of the OFDM symbols $x^{(n)}, \ldots x^{(n+m)}$ to reduce the total interference $[x^{(n)t}, x^{(n+1)t} \ldots x^{(n+m)t}]^t$ to the primary user. As a result, using a least square minimization criterion, the optimal rotation phase is computed as:

$$\theta_{opt} = \arg\min_{\theta} \left\| d^{(n)} + e^{j\theta 1} d^{(n+1)} + \ldots + e^{j\theta m} d^{(n+m)} \right\|^2 \tag{9}$$

Equation is a Least Squares (LS) optimization problem in which $\theta_{opt} = [\theta_{1opt} \ldots \theta m_{opt}]^T$ denotes the set of optimal rotation phases of the considered symbols. The LS problem is denoted as:

$$\theta_{opt} = \arg\min_{a} \left\| d^{(n)} + Pa \right\|^2 \tag{10}$$

$$|a_i|^2 = 1, i = 1,\ldots,m \tag{11}$$

In this Eq. 9 and 10 $a = [e^{j\theta 1}, \ldots e^{j\theta m}]^T$ and $P = [d^{n+1} \ldots d^{n+m}]$. As a result, $\theta_i = \arg(a_i)$. The optimization problem is defined as a least squares problem with multiple equality constraints. In the special case of m = 1, the problem is specialized as:

$$\theta_{opt} = \arg\min_{\theta 1} \left\| d^{(n)} + e^{j\theta 1} d^{(n+1)} \right\|^2 \tag{12}$$

This is the single constraint LS minimization.

Smooth-windowing technique: In the OFDM-MIMO based CR systems, the unlicensed secondary users send the asynchronous signals to the primary licensed users. So, there is loss in subcarriers orthogonality leads to less spectral efficiency. To diminish the harmful interference of the secondary users to the primary licensed users, it is mandatory that the Power Spectral Density (PSD) of the primary user's subcarriers discloses a quick decay when out of band.

While the primary users are licensed an opportunistic user has to give assurance for non-harmful interference. Instead of using rectangular window in the traditional OFDM, a smooth window is used that authorizes high and prohibited out-of band roll-off.

The smooth windowing technique is same as the traditional OFDM but the difference is only replacement is being window at the end of the block of the MIMO-OFDM system. The windowing length required in the smooth window is $(1+\beta)\ T_0$ for the symbol instead of T_0 in the rectangular window. β represents the roll-off factor of the window. This symbol period extension involves a diminution of the transmission bit-rate.

The design of soft window is according to the uniqueness of functions with vestigial symmetry. The vestigial symmetry is used that these compromise orthogonal waveforms with perfect synchronization so that recover the data symbols without any interference. In addition to that by necessitate at the boundaries of the window several null derivatives; it is probable to direct a fast out-of-band decay.

If a limited pulse has its first P derivatives at the extreme points equal to zero then the asymptotic slope in the transform domain is at least of the order x^{-2P-2}. The postulations for the signal in windowing system are:

- The normalized duration of the window is $1+\beta$ which is equal to one of Raised Cosine (RC) with a roll-off factor of, i.e., there is expansion by β of the window length compared to the traditional rectangular window
- The function can be decomposed in a cosine series of period $1+\beta$. i.e:

$$w(t)=\begin{cases}\sum_{k=0}^{N}a_k, & |t|\le\frac{1-\beta}{2}\\ \sum_{k=0}^{N}a_k\cos\left(\frac{k\pi}{\beta}\left(|t|-\frac{1-\beta}{2}\right)\right), & \frac{1-\beta}{2}<|t|\le\frac{1+\beta}{2}\\ 0, & \text{otherwise}\end{cases} \tag{13}$$

It is clear that for N = 1 and $a_0 = a_1 = ½$ this diminishes to the RC with a roll-off of β. The vestigial symmetry:

$$w(t)+w(t-1)=1,\forall y\in[0,1] \tag{14}$$

Implies that $a_0 = ½$ and $a_{2k} = 0$, $k\ge1$. The use of window that normalized values between 0 and 1 denotes that the diminution of power. For acquiring the values for the asymptotic performance, the expression of the analogue multicarrier signal is considered:

$$x(t)=\sum_{k=0}^{N-1}a_k e^{j2\pi\left(f_0+\frac{k}{NT}\right)^t}w(t) \tag{15}$$

In this Equation f_0 represents the frequency of the first carrier. Using the independent data with unit power, the average power value is acquired:

$$<E\left[|x(t)|^2\right]>_t=N<|w(t)|^2>_t \tag{16}$$

In this Equation, $<.>_t$ denotes a time averaging operation and IE [.] represents the expectation operator:

$$<|w(t)|^2>_t=\begin{cases}1, & \text{rectangular window}\\ \frac{4-\beta}{4(1+\beta)}, & \text{RC}\beta\text{ window}\\ \frac{128-23\beta}{123(1+\beta)}, & \text{NP}\beta\text{ window}\end{cases} \tag{17}$$

it is easy to deduce that by using the NP with a roll-off factor β the performance is improved.

Channel prediction method: Channel prediction is a method to reduce the performance degradation because of the predictable feedback delay of the Channel State Information (CSI) in the wireless systems. In the channel prediction framework, the spatial and temporal correlations among the antennas are exploited.

In the MIMO-FDM system model, M transmitting antennas, K receiving antennas and N subcarriers are considered. The transmitted symbol $X_{i,\ k}$ is considered which is transformed into the time domain signal at the mth transmit antenna, ith symbol time in Nth subcarrier using IFFT. The cyclic prefix is additionally added to the data symbol for reducing inter-symbol interference. The received symbol is represented by:

$$Y_n(i,k)=\sum_{m=1}^{M}H_{n,m}(i,k)X_m(i,k)+Z_n(i,k) \tag{18}$$

In this Equation, $H_{n,\ m}$ (i, k) denotes the frequency response of the channel impulse response at the k-th subcarrier and ith symbol time for the (m, n) th antenna pair. Z_n (i, k) represents the background noise plus interference. The channel impulse response is represented by:

$$h_{n,m}(t,\tau) = \sum_{l=0}^{Ln,m-1} h_{n,m}(t,l)\delta(\tau - \tau_{n,m}(l)) \quad (19)$$

In this Equation $L_{n,m}$ (I, k) represenst the number of multiple radio path for the antanna pair (m, n), δ (.) denotes the Kronecker delta function, $\tau_{n,m}$ (l) and $h_{n,m}$ (t, l) represents the delay and complex-value CIR at time at t of the l-th path from the (m, n) antenna pair correspondingly. $h_{n,m}$ (t, f) represents the frequency response of the time domain CIR $h_{n,m}$ (t, τ). T_S is the duration of one OFDM symbol. The frequency domain CIR is represented in discrete form is as follows:

$$H_{n,m}(i,k) = H_{n,m}(iT_s, kf_s) \quad (20)$$

The time domain CIR is represented as:

$$h_{n,m}(i,l) = h_{n,m}(iT_s, l) \quad (21)$$

A random Rayleigh fading channel model satisfying the Wide-Sense Stationary Uncorrelated Scattering (WSSUS) assumption is used as:

$$E\{h_{n,m}(i+\Delta i, l)h_{n,m}(i,l')\} = r_t(\Delta i)\delta(l-l') \quad (22)$$

In this Equation, r_t (Δi) represents the channel's time delay correlatio function. Because of the WSSUS property, $h_{n,m}$ (t+Δi, l) and $h_{n,m}$ (i, l) are un assoiated for l≠l. The channel association for the MIMO system is represented as:

$$E\{h_{n,m}(i+\Delta i, l)h_{n',m'}(i,l)\} = r_t(\Delta i) \\ r_s(n,m,n',m')\delta(l-l') \quad (23)$$

In this Equation n, n'∈{1, 2, ..., N}, m, m'∈{1, 2, ..., M} and r_s (.) represents the spatial correlation function. Due to the longer distance between the transmitter and receiver the correlation function is decayed into two correlation division at the transmitter and the receiver.

$$r_s(n,m,n',m') = r_{sr}(n,n')r_{st}(m,m') \quad (24)$$

The spatial correlation matrix of the MIMO channel is represented by:

$$R_{MIMO} = R_{MS} \otimes R_{BS} \quad (25)$$

In this Equation, ⊗ denotes the Kronecker product, R_{MS} and R_{BS} represents the spatial correlation matrices correspondingly.

Time-domain prediction method: The time-domain prediction of the MIMO-OFDM systems has accomplish better MSE performance when compared to the frequency domain predictor. By using the traditional methods, the time-domain channel coefficient of every channel pair (m, n) is estimated. For instance, a K-point IFFT is utilized to do the frequency-time transformation:

$$\hat{h}_{n,m}(i,l) = \frac{1}{k}\sum_{k=0}^{K-1}\hat{H}_{n,m}(i,k)ej2\pi lk/k = \\ \begin{cases} h_{n,m}(i,l) + z_{n,m}(i,l) & l = 0,...,L-1 \\ z_{n,m}(i,l) & l = L,...,K-1 \end{cases} \quad (26)$$

For every tap, the channel delay $\tau_{n,m}$ is an integer multiple of sampling interval. Then, the entire energy from the path will be mapped to zthe zero to L-1 taps. It can be effortlessly prove that $z_{n,m}$ (i, l) is also a zero mean AWGN with variance:

$$\beta^2 = \frac{\sigma_z^2}{k} \quad (27)$$

A MIMO predictor is performed to calculate the time domain channel impulse response $h_{n,m}$ (I+p, lf) for every delay l = 0, ..., L-1 where L-1 represents the channel's maximum delay and p denotes the prediction length. As a result, the MIMO predictor for the l-th tap only requires to consider the consequent tap of each channel pair (m, n). At last, the frequency domain channel coeficient is acquired from the predicted time-domain impulse response sample through the K-points FFT.

Bidirectional Reduce Complexity Stepwise Subset (BRCSS) prediction method: The channel prediction approach is started with the Auto Regressive (AR) model that captures the fading dynamics. The p is defined as the prediction length. For each and every tap of the channel, Q current and previous computed coefficients of the channel are considered. Denote:

$$\hat{h}_{n,m}(i,l) = \left[\hat{h}_{n,m}(i,l), \hat{h}_{n,m}(i-1,l), ...\hat{h}_{n,m}(iQ+1,l)\right]^T \quad (28)$$

The prediction of $\hat{h}^{pre}_{n,m}(i+p,l)$ the data set $\hat{h}$ is utilized where:

$$\hat{h} = \begin{bmatrix} \hat{h}_{1,1}(i,l)^T, \hat{h}_{1,2}(i,l)^T, \ldots, \hat{h}_{1,M}(i,l)^T, \\ \hat{h}_{2,1}(i,l)^T, \ldots, \hat{h}_{N,1}(i,l)^T, \ldots, \hat{h}_{N,M}(i,l)^T \end{bmatrix}^T \quad (29)$$

The BRCSS prediction method is used for predicting the channel with less feedback delay and with less computational burden. In this method, the observations are not considered to be uniformly significant for prediction.

Some of the observations provide little information for the AR method. Specifically if a datum is independent with the predicted datum then the datum has no use for the prediction. So, it is necessary to select the most helpful data for the AR prediction method which considers the spatial and temporal correlations.

In the BRCSS prediction algorithm, both forward selection and backward elimination are used. The main idea is to concurrently remove the data from the correlation's point of view in a bidirectional manner. The main concept in the BRCSS prediction algorithm is to test the data in forward and backward by using the correlation. If the second data in the subset is highly correlated than the first data, check the Mean square error value of the data symbol. If the Mean square error value is high than the threshold, the data symbol is removed.

It is necessary to find the most associated datum. Suppose, we have already chosen Q' data from $\hat{h}$ where Q' is a tradeoff between the prediction precision and complexity to form a Q'×1 vector $\hat{h}$. The prediction AR model is as follows:

$$\hat{h}^{pre}_{n,m}(i+p,l) = w_B^H \hat{h} \quad (30)$$

Based on the MMSE criterion:

$$W_B = \text{argmin}_{WB}\, E\left\{ \left\| h_{n,m}(i+p,l) - W_B^H \hat{h} \right\|^2 \right\} \quad (31)$$

Similarly, using the orthogonal principle, it can be written as:

$$W_B = E\left[\hat{h}\hat{h}^H\right]^{-1} E[h_{n,m}(i+p,l) * \hat{h} \quad (32)$$

Where the MSE is given as:

$$\varepsilon_B = r_t(0) - E\left[h_{n,m}(i+p,l)\hat{h}*\right]^T E\left[\hat{h}\hat{h}^H\right]^{-1} E\left[h_{n,m}(i+p,l)\hat{h}*\right] \quad (33)$$

Instinctively, the prediction model with the lowest MSE is the best. Thus, we derive the criterion for choosing $\hat{h}$. Choose Q' data point so as to get the minimal MSE.

In this subsection, a prediction algorithm is introduced which aims to further reduce the computational complexity of BRCSS method. The key idea is to select the data incrementally for prediction from the correlation's view. If the new observation has a high correlation with the selected data in previous steps then the new observation cannot provide more new information and may help little.

Therefore, the considering value $\hat{h}_k$ in the k-th step can be chosen by the analysis of the selected data $\left[\hat{h}_1, \ldots, \hat{h}_{k-1}\right]$. Based on this idea, the k-th element is chosen as follows.

First step: according to MMSE criterion and AR model $\hat{h}^{pre}_{n,m}(i+p,l) = W_R^H \hat{h}$, we get W_R where $\hat{h} = \left[\hat{h}_1, \ldots, \hat{h}_{k-1}\right]^T$.

Second step: define resdual = $h_{n,m}$ (I+p, l)- $W_R^H \hat{h}$, the $\hat{h}_k$ is the selected data which is most correlated with the residual.

The proposed reduced-complexity BRCSS predictor is used to diminish the times of computing MSE to Q' and only requires time inversion of a Q'×Q' matrix in each and every selection.

Steps in BRCSS:

- Consider MIMO-OFDM system with M transmit antennas, N receive antennas and K subcarriers
- Transmitted symbol is transformed into time domain and frequency domain by using IFFT
- Generate the subset of data symbols for MIMO-OFDM system
- //Testing the data in a bidirectional manner
- Check the data symbols in a forward and also backward wise
- If the second data is highly correlated than the first data, then the second data cannot provide new information for channel prediction
- //Check the MSE
- If the Mean square error value of the data symbol is high than the threshold, the data is to be eliminated

Bidirectional reduce complexity stepwise subset (brcss) predictor algorithm:

- Identify the datum which is most associated in a bidirectional manner with $h_{n,m}$ (I+p, l) and denote by $\hat{h}_1$, initialize $\hat{h}_{ul}=\hat{h}$.
- Minimize MSE to find:

$$\hat{h}_j = \arg \min_{hj \in \hat{h}/\hat{h}_{old}} \begin{pmatrix} r_t(0) - E\left[h_{m,n}(i+p,l)\hat{h}^*_{new}\right]^T \\ E\left[\hat{h}_{new}\hat{h}^H_{new}\right]^{-1} E\left[h_{n,m}(i+p,l)\hat{h}^*_{new}\right] \end{pmatrix}$$

- $j = j+1, \hat{h}_{old} = \hat{h}_{new}$. If j<Q', turn to step 2
- The final selected data set is $\hat{h}$ which is a Q'×1 vector. Then the desired Q' order AR prediction model is:

$$\hat{h}^{pre}_{n,m}(i+p,l) = w^H_B \hat{h}_{new} \text{ where } W_B = E\left[\hat{h}_{new}\hat{h}^H_{new}\right]^{-1} E\left[h_{n,m}(i-p,l) * \hat{h}_{new}\right]$$

RESULTS AND DISCUSSION

In this study, the numerical results are evaluated for the existing and the proposed method. In the existing method, MIMO-OFDM beam forming is used for channel prediction or estimation. This method eliminates the spatial correlation and only considers the temporal correlation. In the proposed method, Adaptive Phase Adjustment and Channel Prediction Strategies (APA-CPS) in MIMO-OFDM based cognitive radio networks. The performance is evaluated in terms of Normalized Mean Square Error (NMSE) and uncoded Bit Error Rate (BER). The effect of different receiver elements is also taken into consideration by estimating the changes caused by the elements.

Normalized Mean Square Error (NMSE): The Normalized Mean Square Error (NMSE) is used to evaluate the prediction accuracy and it is defined as:

$$\text{NMSE} = 10\log\left\{\frac{E\left\{\left\|h_{n,m}(i+p,l) - \hat{h}^{pre}_{n,m}(i+p,l)\right\|^2\right\}}{E\left\{\left\|h_{n,m}(i+p,l)\right\|^2\right\}}\right\}$$

The noise variance β^2 and the correlation matrix $E\{h_{n,m}(i+\Delta i, l)\, h_{n',m'}(i, l)$ are known in all the simulations. Figure 3 shows the normalized mean square error comparison for the existing and proposed system. In the X-axis Signal-to-Noise Ratio (SNR) is in dB is taken. In the Y-axis NMSE in dB is taken. In the existing method, MIMO-OFDM beam forming technique is used for channel prediction. This method eliminates the problem of spatial correlation but the method has large amount of errors in prediction. In the proposed method, adaptive phase adjustment and channel prediction strategies (APA-CPS) in MIMO-OFDM based cognitive radio networks. When compared to the existing system, there is less mean square error in the proposed system. When the effect of different receiver elements is considered it is found that the error rate is affected by the external noises in the receiver elements.

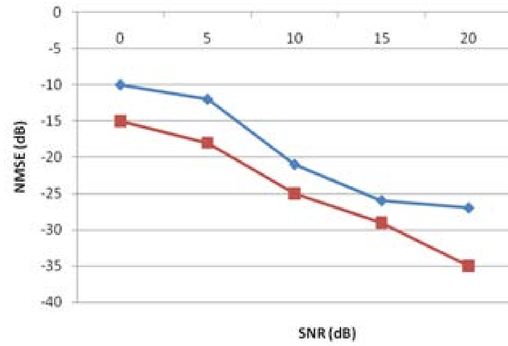

Fig. 3: The NMSE

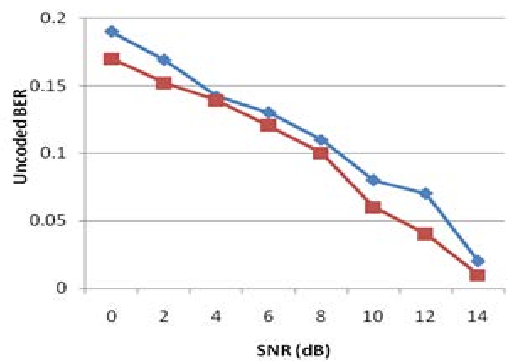

Fig. 4: Uncoded BER

Table 1 shows the normalized mean square error comparison for the existing and proposed system. If the SNR value is 20 dB, the NMSE in the existing MIMO-OFDM beam forming technique is-26 dB and for the proposed APA-CPS method is-33 dB.

Uncoded BER: The uncoded Bit Error Rate (BER) performance is compared to the existing and the proposed method in the MIMO-OFDM based CR systems.

Figure 4 shows the uncoded BER comparison for the existing and proposed system. In the X-axis signal-to-noise ratio (SNR) is in dB is taken. In the Y-axis uncoded BER is taken. In the existing method, beam forming technique is used for channel prediction. In the proposed method, Adaptive Phase Adjustment and Channel Prediction Strategies (APA-CPS) in MIMO-OFDM based cognitive radio networks. When compared to the existing system, there is less uncoded BER in the proposed system. When the effect of different receiver elements is considered it is found that the uncoded bit error rate is increased with the receiver elements. Table 2 shows the uncoded BER comparison for the existing and proposed system. If the SNR value is 14 dB, the uncoded BER in the existing beam forming technique is 0.03 and for the proposed APA-CPS method is 0.016.

Table 1: Normalized mean squared error

	Normalized mean square error (dB)	
SNR (dB)	MIMO-OFDM beam forming	APA-CPS
0	-11	-14
5	-13	-16
10	-22	-24
15	-24	-29
20	-26	-33

Table 2: Uncoded BER

	Uncoded BER	
SNR (dB)	MIMO-OFDM beam forming	APA-CPS
0	0.189	0.167
2	0.169	0.152
4	0.142	0.139
6	0.135	0.112
8	0.117	0.100
10	0.0805	0.067
12	0.0700	0.042
14	0.0300	0.016

CONCLUSION

MIMO-OFDM based CR systems provide an opportunity for the users to use the spectrum very efficiently. But the cross-band interference is a main problem that is created due to the OFDM signal side lobes particularly in the cognitive radio systems. In addition to that, further improve the spectral efficiency channel prediction is an important method. Because of the high feedback delay there is significant performance degradation. In this research, Adaptive Phase Adjustment and Channel Prediction Strategies (APA-CPS) is proposed in the MIMO-OFDM based cognitive radio networks. This method adjusts the phase of every OFDM symbol and also uses the concept of smooth windowing instead of rectangular windowing in the conventional OFDM systems. Accurate channel state information without any feedback delay is an important concept. For the channel prediction, estimate the channel state information without any feedback delay is very important. The BRCSS prediction algorithm is used to predict the channel without any complexity. The main idea is to concomitantly eradicate the data from the correlation's point of view in a bidirectional manner.

REFERENCES

Assalini, A. and A.M. Tonello, 2004. Improved nyquist pulses. IEEE Commun. Lett., 8: 87-89.

Bansal, G., Z. Hasan, M.J. Hossain and V.K.Bhargava, 2010. Subcarrier and power adaptation for multiuser OFDM-based cognitive radio systems. Proceedings of the 2010 National Conference on Communications (NCC), January 29-31, 2010, IEEE, Chennai, India, ISBN: 978-1-4244-6383-1, pp: 1-5.

Cosovic, I., S. Brandes and M. Schnell, 2006. Subcarrier weighting: a method for sidelobe suppression in OFDM systems. Commun. Lett. IEEE., 10: 444-446.

Hallen, A.D., 2007. Fading channel prediction for mobile radio adaptive transmission systems. Proc. IEEE., 95: 2299-2313.

Hallen, H., A.D. Hallen, S. Hu, T.S. Yang and M. Lei, 2002. A physical model for wireless channels to provide insights for long range prediction. Proceedings of the Conference on MILCOM, October, 7-10, 2002, IEEE, Raleigh, North Carolina, ISBN: 0-7803-7625-0, pp: 627-631.

Heidari, A., A.K. Khandani and D. McAvoy, 2010. Adaptive modelling and long-range prediction of mobile fading channels. Commun. IET., 4: 39-50.

Hwang, J.K. and J.H. Winters, 1998. Sinusoidal modeling and prediction of fast fading processes. Proceedings of the IEEE Global Telecommunications Conference on the Bridge to Global Integration GLOBECOM, November 8-12, 1998, IEEE, Sydney, New South Wales, Australia, ISBN: 0-7803-4984-9, pp: 892-897.

Joham, M., P.M. Castro, W. Utschick and L. Castedo, 2012. Robust precoding with limited feedback design based on precoding MSE for MU-MISO systems. Signal Process. IEEE. Trans., 60: 3101-3111.

Li, Y. and H. Wang, 2003. Channel estimation for MIMO-OFDM wireless communications. Proceedings of the 14th Personal, Indoor and Mobile Radio Communications, September 7-10, 2003, Beijing, China, pp: 2891-2895.

Mahmoud, H.A., T. Yucek and H. Arslan, 2009. OFDM for cognitive radio: Merits and challenges. Wirel. Commun. IEEE., 16: 6-15.

Sampath, H., S. Talwar, J. Tellado, V. Erceg and A. Paulraj, 2002. A fourth-generation MIMO-OFDM broadband wireless system: Design, performance and field trial results. Commun. Mag. IEEE., 40: 143-149.

Schafhuber, D. and G. Matz, 2005. MMSE and adaptive prediction of time-varying channels for OFDM systems. Wirel. Commun. IEEE. Trans., 4: 593-602.

Shen, C. and M.P. Fitz, 2008. MIMO-OFDM beamforming for improved channel estimation. Sel. Areas Commun. IEEE. J., 26: 948-959.

Tan, P. and N.C. Beaulieu, 2004. Reduced ICI in OFDM systems using the better than raised-cosine pulse. IEEE. Commun. Lett., 8: 135-137.

Wang, X. and G.B. Giannakis, 2011. Resource allocation for wireless multiuser OFDM networks. Inf. Theory IEEE. Trans., 57: 4359-4372.

Wong, I.C., A. Forenza, R.W. Heath and B.L. Evans, 2004. Long range channel prediction for adaptive OFDM systems. Proceedings of the Conference Record of the Thirty-Eighth Asilomar Conference on Signals, Systems and Computers, November 7-10, 2004, IEEE, Austin, Texas, USA., ISBN: 0-7803-8622-1, pp: 732-736.