Multiple Antenna (MA) for Cognitive Radio Based Wireless Mesh Networks (CRWMNs): Spectrum Sensing (SS)

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Abstract. The concept of cognitive radio (CR) rings a big paradigm shift to the wireless communication domain. Extending this concept in to wireless mesh networks (WMN) results a CRWMN which alleviates the pragmatic spectrum congestion in the ISM bands. The assimilation of MAs technology in to CRWMN brings an astonishing system performance improvement. The use of MAs in WMN improves system capacity and reliability, increases coverage area and spectrum usage efficiency; and result in lower power consumption, better interference cancellation, efficient spectrum sensing, and spectrum sharing. In spite of the significant advantages, the use of multiple antennas has considerable limitations. In this paper, we investigate the challenges, opportunities, and the possible research directions that the cognitive radio network (CRN) in general and the CRWMN in particular experience while incorporating MAs to the system and its effect on spectrum sensing.

Keywords: Multiple antennas · Beamfoming · WMN · CRN
CRWMN · Spectrum sensing

1 Introduction

Capacity, flexibility, reliability and security are the most pressing problems of the current wireless networks. In these respect, WMN is a superior networking paradigm with huge network capacity and reliability gains. WMN is a better network paradigm because it is a dynamically self-organized and self-configured, with the nodes in the network automatically establishing and maintaining mesh connectivity among themselves.

The design of WMNs has evolved from single-radio single-channel architecture to single-radio multi-channel architecture then to multi-radio multi-channel (MRMC) architecture to bring considerable capacity gain, but connectivity and interference still remains being the most critical challenges for the WMN. These problems can be alleviated by availing additional bandwidth. The ideal solution for these problems is to add cognition flavor to the conventional WMNs architecture, i.e. to help conventional

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WMNs evolve to CRWMN. CRWMN is a marriage of WMN and CR technology where the active players of the WMN are equipped with CR technology. The integration of CR in to the WMNs brings many advantages, among others reduced spectrum scarcity, increased network, integration of heterogeneous wireless access networks [1–6].

In this paper we are interested to explore the impacts of MAs in terms of capacity gain and, SS on CRN in general and to the CRWMN in particular. Therefore, the challenges, opportunities, and future directions of MAs technology for CRWMN are investigated in detail.

2 Multiple Antenna (MA) Technology

The use of MAs has three fundamental benefits:- array gain, diversity gain and multiplexing gain. Multiple small antenna elements can be arranged in space and interconnected to produce a more directive radiation pattern which is called array gain. Spatial diversity (SD) and spatial multiplexing (SM) gains are obtained by taking advantage of the spatial signature and sending a replica of the same message by all the elements to reduce BER (SD gain), and by sending different messages concurrently (SM gain) [8, 11].

2.1 Array Gain

Array antenna technology is a more practical way of producing highly directive radiation pattern and it brings the following advantages: narrow beams, low side lobes, steerable beams, tracking multiple targets, it can be conformed to surface, and it scans/steers electronically. In [11], a reference antenna which is located at the origin radiates an electromagnetic field with far field components that are proportional to $F_0 = I_0 \frac{e^{-jkr}}{r} f(\theta, \varphi)$, Where: I_0 is complex amplitude, $f(\theta, \varphi)$ is the radiation pattern, r is the distance of observation, and k is the wave number which is equal to $2\pi/\lambda$. For an N number of identical radiating elements placed in parallel to each other within a volume of radius a, which is much smaller than the distance r (a/r < < 1). The far field components of the ith antenna element, whose position vector with respect to the origin $\bar{r}_i$ is proportional to

$$F_i = I_i \frac{e^{-jkR_i}}{R_i} f(\theta_i, \varphi_i), \quad \text{where} \quad R_i = |r - r_i| = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)}$$

The far field due to all of the antenna elements by using superposition principle becomes [8, 11]

$$S(\theta, \varphi) = I_0 \frac{e^{-jkr}}{r} f(\theta, \varphi) \sum_{i=1}^{N} \frac{I_i}{I_0} e^{j\psi_i(\theta,\varphi)} = F_0 AF(\theta, \varphi), \qquad \text{Where} \qquad AF(\theta, \varphi) = \sum_{i=1}^{N} \frac{I_i}{I_0}$$

$e^{j\psi_i(\theta,\varphi)}$ is array factor, $\psi_i(\theta, \varphi) = 2\pi d_i/\lambda$, Where d_i is the projection of $\bar{r}_i$ on $\bar{r}$, and λ is wave length.

Consider uniform linear antenna (ULA) with N number of elements and uniform distance of separation d with phase $\psi_i(\theta, \varphi) = (i-1)kd\cos\theta$, and the exciting current $I_i = I_0\, e^{-j\beta_i}$ at the i[th] element the array factor expression could be rewrite as

$$AF(\theta) = \sum_{i=1}^{N} e^{j(i-1)(kd\cos\theta - \beta)}$$

Using Taylor Series and trigonometric identity, we can have a closed form expression for the array factor expression which is given by [7–11]

$$AF(\theta) = e^{j(N-1)\frac{\xi}{2}} \frac{\sin(N\xi/2)}{\sin(\xi/2)}$$

Where $\xi = kd\cos\theta - \beta$ and β is the current phase reference, and it is periodical for $\xi = 0, \pm 2\pi, \ldots$

The effect of varying array parameters on the radiation pattern of ULA which holds true for other variants of array antenna is presented both in rectangular and polar plot using simulation in Fig. 1. The simulations show that increased number of array element results narrower beam, increased number of side lobes and nulls; increased distance of separation results in a narrower beam but it is obtained at the cost of antenna size, and excitation phase has no effect on the beam width but it controls the direction of the beam.

2.2 Spatial Multiplexing (SM) and Spatial Diversity (SD) Gains

A system which uses MAs at transmitter (TX) and receiver (RX), known as Multiple-Input Multiple-Output (MIMO) system, is a promising way to augment data rate for the same spectrum and power. The MAs in MIMO systems can be used to achieve diversity and/or multiplexing gains. In SM there is a linear increase in channel capacity with the minimum number of transmit (N) and receive (M) antennas. MIMO systems can be grouped into two groups based on the channel state information (CSI). The first group requires CSI at the receiver, but not at the transmitter. The second group requires CSI both at the transmitter and the receiver ends (beamforming). In MIMO systems, beamforming separates the MIMO channel into parallel independent sub-channels. When the best sub-channel is used, the technique is called single beamforming, and when more than one sub-channel is used it is called multiple beamforming. The output of a MIMO channel is modeled by [12–14].

$Y = HX + n$, Where X is the transmitted signal, H channel transition matrix and n is additive Gaussian noise.

The capacity of MIMO channel is an extension of SISO (single input single output) channel capacity to a matrix form which is given by

$$C = \max_{p(x)} I(X, Y)$$

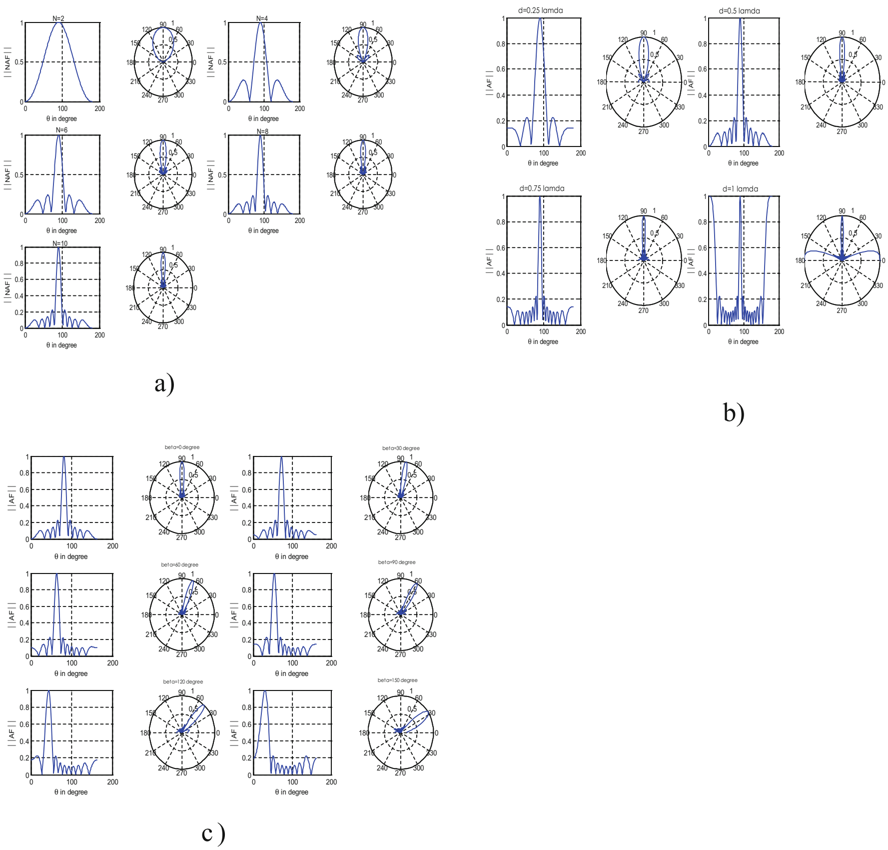

Fig. 1. The effect of varying (a) number of array elements for β = 0^0 and d = 0.5λ, (b) distance of separation for $\beta = 0^0$ and n = 10, (c) excitation phase between adjacent elements, d = 0.5λ on the radiation pattern.

The maximization of I(X,Y) for full channel state information (CSI) only at the receiver with uniform power allocation yields the capacity expression

$$C = w \log_2 \det(I_m + \frac{P}{N\delta^2} Q),$$

Where Q = HH*, for M < N and H * H for M $\geq$ N, P it the total transmitted power, w is the bandwidth.

Using singular value decomposition (SVD) we can write H as $H = UDV^*$. Where D is M $\times$ N diagonal matrix, U and V are M $\times$ M and N $\times$ N unitary matrices respectively. For M $\times$ N matrix H, the rank is at most equals to m = min(M,N). This implies that there are at most m non-zero eigenvalues. The capacity expression then reduces to [12]

$$C = w\sum_{i=1}^{r}\log_2(1+\frac{p_{ri}}{\delta^2}) \;= w\log_2\prod_{i=1}^{r}(1+\frac{\lambda_i P}{n_T\delta^2}), \qquad p_{ri} = \frac{\lambda_i P}{n_T}.$$

Whereas SISO's channel capacity is given by

$$C = w\log(1+\frac{P}{\delta^2}|h|^2), \text{where } |h|^2 \text{ is the path gain.}$$

Therefore, MIMO's channel capacity can be interpreted as the sum of the channel capacities of the sub-channels with channel path gain λ_i, i = 1,2,…r. i.e. we can have a maximum of min(M,N) independent paths through which independent information can be sent. If the channel coefficients are random variables, the above channel capacity expressions give instantaneous capacity values and the ergodic channel capacity becomes $C = E[w\log_2\det(I_m + \frac{P}{N\delta^2}Q)]$, Where E is an expectation operator.

The simulations shown below in Fig. 2 show the capacity gain observed for different SNR values for MISO, SIMO, and MIMO system.

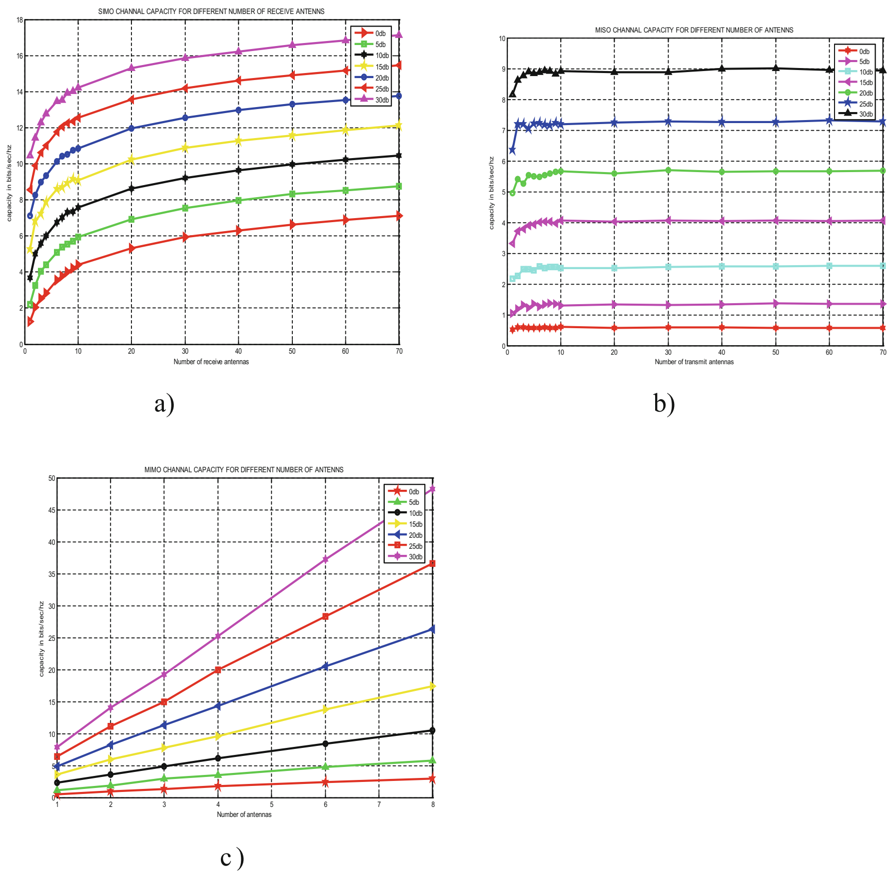

Fig. 2. (a) Capacity of receive diversity for different SNR values, (b) Capacity of transmit diversity for different SNR values, (c) Capacity of MIMO channel for different SNR values

3 Impact of MAs on the Capacity of CRNs and WMNs

In the wireless domain the impact of MAs on network performance is astonishingly immense. Now we shall examine the influence of MAs on the performance of CRNs in general and on the CRWMN in particular.

In [15], the upper and lower bound capacity for MAs based CRs have been developed. In [16], the authors analyzed the sum throughput of an underlay multiuser CR system with MA base stations operating either in the multiple access channel (MAC) or broadcast channel (BC) mode where both the users are equipped with MAs. In the model, there are N (primary) and n (secondary) users with their base stations having M and m antennas, respectively. For primary BC network with a set of interference power constraints on the primary, the maximum throughput of the secondary MAC grows as $\frac{m}{N+1}\log n$ and for primary MAC it grows as $\frac{m}{M+1}\log n$. For the secondary BC they have shown that the throughput can grow as $m \log\log n$ in the presence of primary BC or MAC, thus the growth rate of the throughput is unaffected by the presence of the primary system.

In [17], they have shown that directional antenna (MA) improves the performance of WMNs in contrast to the omnidirectional antenna. It is also observed that increasing the number of antennas and decreasing the beam width increases the capacity of the WMN. Moreover, in [18] it is shown that there is a capacity gain by using directional antennas (MA) in random adhoc network both at the transmitter and receiver. In [19], it is also shown that using directional antennas in MRMC WMN improves the throughputs by up to 231% and reduces packet delay drastically compared to omnidirectional MRMC WMN. In [20], the advantages of smart antennas to the WMNs are explored and it is noted that the use of smart antennas enhances the capacity of WMNs.

4 Spectrum Sensing (SS) Using MA for CRWMNs

SS in CR is a process of detecting the primary transmitter. Sensing time, system complexity, and probability of false alarm, detection and miss detection can be used to evaluate the performance of different SS techniques. The most common SS methods for CRNs are Likelihood Ratio Test (LRT), Matched Filter (MF), Energy Detection (ED), and Cyclo-Stationary feature Detection (CSD) and Eigenvalue based Detection (EVD).

In different literatures the use of MAs for spectrum detection has been explored and found to be a promising candidate in the spectrum detection process of CRNs. In addition to the conventional benefits of MAs, a CR equipped with MAs shows better detection performances and shorter sensing time than single antenna CR systems. Therefore, we have explored different literatures on the use of MAs in CRNs as follows.

In [21], the authors proposed a SS algorithm using MAs receiver. It is a statistical covariance based spectrum detection algorithm which compensate for the noise level uncertainty at the detector. Generally, they have extended the covariance-based detector for MAs receiver, they have derived the decision variable distribution for the case of signal in noise, and they have investigated the noise uncertainty impact to the detector's performance and gave guidelines on how to control the detection probability in case of noise uncertainty.

In [22], the authors presented SS using MAs where the noise and the PU signal are assumed to be independent complex zero-mean Gaussian random signals. They have made performance comparison for Rayleigh fading and AWGN channel. They have considered Generalized Likelihood Ratio (GLR) detectors for three different cases when: channel gains are unknown (GLRD1), channel gains and PU variance are unknown (GLRD2), and channel gains, PU and noise variances are unknown (blind GLR detector). Increasing the SNR, number of antennas, and number of samples improves the performance of all spectrum detectors. They have also shown that the optimal detector can outperform the GLR detectors provided that the optimal detector knows the noise variance accurately. Moreover, it is shown that the GLR detectors are more robust to the noise uncertainty than the optimal detector and ED, and in fact under noise variance mismatch, the optimal detector performs similar to the GLRD1, and the blind GLRD performs slightly better than the GLRD1. When the PU signal is not a Gaussian signal, the performance of the proposed detectors, i.e., blind detector and GLRD1, are acceptable, and the blind detector performs like and even slightly better that the CSD based detector. Generally, the proposed GLR detectors perform better than the ED and almost identical to the optimal detector under noise variance mismatch but it is complex than ED.

In [23], the authors studied the performance of ED using MAs at the CR receivers. They have considered two MA processing methods and analyzed their detection performance. They have derived closed form expressions for the probabilities of detection and false alarm maximum ratio, and selection processing. They have shown that using MAs for SS improves the probability of detection. Moreover, from the two MAs processing techniques maximum ratio processing performs better than the selection processing. For a finite number of signal samples, and in the presence of unknown parameters, the GLRT is optimal in detecting the PU.

In [24], the authors investigated the PU signal detection performance in an OFDM based primary and secondary networks where the secondary user (SU) receiver is equipped with MAs. The square low combining scheme in ED based MAs SS resulted in higher probability of PU detection even at low SNR, and increasing number of symbols increases the detection performance with higher sensing time. Generally, increasing the ratio of symbol period of the primary to the secondary subcarriers makes the probability of detection to decline, and the performance of PU signal detection using MAs is much more better than single antenna ED based OFDM CRN.

In [25], the authors proposed an ED SS which is a parallel, multi-resolution SS technique that uses MAs for the CR users. It has reduced the SS time in a significant way with respect to the serial, fixed-resolution technique, first by sensing the system bandwidth using a coarse resolution and then by performing fine resolution sensing over a small range of frequencies which eliminates sensing the entire system bandwidth at the maximum resolution. It is shown that increasing number of antennas decreases the sensing time approximately by a factor of the number of antennas on the receiver, whereas it is observed that number of antennas and the total number of blocks to be sensed at a fine resolution (α) are inversely related. For the number of points in FFT (N), they have revealed that sensing time decreases almost linearly with N until a point at which it begins to increase ($N = 4$), which is the optimum number of points for the FFT.

In [26], the authors proposed MA based SS using the GLRT paradigm that make use of eigenvalues of the sample covariance matrix of the received signal vector. By making different assumptions on the availability of the white noise power value at the CR receiver, they have derived two algorithms that do not require prior knowledge of the primary signals which outperform the conventional ED with or without noise power uncertainty. The proposed algorithms are computationally complex but it has shorter sensing time for a given probability of detection and false alarm.

In [27], the authors proposed a suboptimal MAs detector under unknown noise which does not require obtaining the eigenvalues of the spatial correlation matrix. The performance of the proposed detector is better than many EVDs. However, its performance degrades when the noise variance is not uniform across the antenna elements. They proposed another MAs detector based on GLR which performs better for two antennas.

In [28], the authors proposed an affordable CSD based spectrum sensor using smart antenna which is less computationally complex in relative to the conventional SCD spectrum detector but not the ED. It is assumed that the SUs have limited priori knowledge of the PUs' signal characteristics. They have used an adaptive beamforming algorithm for the proposed SS, and it is called the adaptive cross-self-coherent-restoral (ACS) algorithm. They have proposed a universal spectrum sensor that uses ACS algorithm to extract the desired signal from the antenna array measurement and able to decide whether the spectrum is occupied by the PU or by the SU or vacant which is not possible for ED.

In [29], the authors studied the effect of secondary receiver antenna correlation on the performance of ED based SS using MAs. They have derived the detection and false-alarm probabilities, and have shown that the presence of antenna correlation decreases the performance of the spectrum detector by increasing the false-alarm probability, however they have also shown that even if the antenna correlation degrades the performance of the spectrum detection, it can be compensated by increasing the number of antennas of the secondary receiver.

In [30], the authors proposed spectrum detection technique that overcomes the noise uncertainty problem observed in ED while maintaining its advantages using MAs receiver. The proposed spectrum detection method is based on eigenvalues of the covariance matrix of the received signal. It is the ratio of the maximum eigenvalue to the minimum eigenvalue that is used to detect the signal existence. Based on random matrix theories (RMT), they have quantized the ratio and find the threshold. In general, the method can be used for various sensing applications without knowledge of the signal, the channel and noise power.

In [31], the authors proposed a simple non-iterative GLRT sensing algorithm which is obtained based on a fast-fading signal model, offers the best performance in all systems under considerations, including slow-fading channels, fast-fading channels, MIMO systems, and OFDMA systems. For a small number of signal samples, non-iterative GLRT sensing algorithm significantly outperforms several state-of-the-art SS methods in the presence of noise uncertainty. Its complexity is very small in relative to the computational complexity of the iterative GLRT sensing algorithms.

5 Opportunities, Limitations, and Research Directions on the Use of MA for CRWMN

The use of MAs significantly improves the node capacity and reliability, and in terms of SS MA brings many advantages such as shorter sensing time, robustness to noise uncertainty, better probability of detection, and reduced probability of false alarm. The limitations and possible research directions can be summarized as follows:-

- It is still critically challenging to come up with a low cost reconfigurable, multi-band, and wideband MA systems which can better suit the basic nature of CRWMN.
- So far there is no literature on capacity analysis of MA based CRWMNs. To observe the capacity gain due to MAs in CRWMNs, it is important to make capacity analysis.
- Designing less computational complex SS system using MAs could be a new direction.
- Lack of comprehensive study on MAs based SS in terms of sensing time, robustness to noise uncertainty, increased number of antennas and samples, impact of antenna correlation, computational complexity, and noise variance mismatch.
- There is no single study that evaluates the impact of SS on the performance of the different types of wireless networks.
- Investigating suitable SS technique which better ensemble the unique nature of CRWMNs. Therefore, investigation of suitable MA based SS is mandatory.

6 Conclusion

In this paper one of the basic elements of CRN that is SS, is well explored being associated with MA system. Generally speaking, the use of MA has many advantages like network capacity improvement and connection reliability among others. Besides, the use of MA in SS could bring magnificent advantages to the CRN by providing shorter sensing time, better probability of detection, and lower probability of false alarm. For these reasons, MA based SS particularly GLRT detector (non-iterative) is a promising candidate for CRWMN.

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