

# Performance Analysis of CBSS for CR Based 5G

Babji Prasad Chapa, Sasibhushana Rao Gottapu, Suresh Dannana



**Abstract:** With the rapid and continuous growth of mobile users and services across the world, 5G is anticipated to be the next step in the development of the cellular network. The conceptualized architecture for 5G uses a dynamic spectrum sharing (DSS) approach to include a common spectrum resources that is shared by a multitude of varied network entities and systems. While this proposed solution would vitally enhance the entire efficiency of spectrum. In this situation, the unique function of spectrum sensing (SS) that belongs to the cognitive radio (CR) paradigm is recently being introduced as one of the primary facilitators for effective DSS with less interference. The dissemination of the testing criteria for the detection problem is examined in this paper to get the precise formulas for probability false alarm ( $P_f$ ) and detection probability ( $P_d$ ). The performance of the covariance detector can be evaluated by using  $p_d$  and  $p_f$  expressions. Finally, theoretical  $P_d$ ,  $P_f$  expressions are verified with simulations.

**Index Terms:** Cognitive radio, Detection probability, Dynamic spectrum access, False alarm probability, Spectrum sensing.

## I. INTRODUCTION

In consideration of previous generations, the 5G abbreviation is now usually accepted to indicate conceptualized demands and potential alternatives together as the accelerated growth of cellular mobile services and devices necessitate the growth of a next generation of the cellular mobile networks. Three primary pillars make the next generation networks more demandable: (i) more transmission rates, (ii) very less latency, and (iii) global services [1]; in return, three classes note the probable solutions: (i) increased energy efficiency, (ii) enhanced spectrum and bandwidth efficiency, and (iii) substantial and heterogeneous densification of networks [2]. In all, the next generation network design will cover a multitude of varied system entities largely distributing a mutual frequency spectrum resource, organized by unlicensed and licensed band of frequencies, through a dynamic spectrum sharing (DSS) method in contrast to fixed band assignment which would be traditional but inefficient. While this proposed solution would enormously improve the entire spectrum efficiency, it further puts forth the trial of maximizing the coexistence between various entities that include systems, devices, and technologies.

Revised Manuscript Received on November 30, 2019.

\* Correspondence Author

**Babji Prasad Chapa\***, Dept. of ECE, Andhra University College of Engineering, Andhra University, Visakhapatnam, India.

**Sasibhushana Rao Gottapu**, Dept. of ECE, Andhra University College of Engineering, Andhra University, Visakhapatnam, India.

**Suresh Dannana**, Dept. of ECE, Andhra University College of Engineering, GMR Institute of Technology, Rajam, India.

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an [open access](http://creativecommons.org/licenses/by-nc-nd/4.0/) article under the CC-BY-NC-ND license <http://creativecommons.org/licenses/by-nc-nd/4.0/>

Accordingly, the technology that is conceptualized in [3] is cognitive radio (CR) is now being introduced as the primary facilitators for effective and spectrum sharing dynamically among various network entities. Recently, numerous cognitive radio based spectrum

resource organization processes have been put forth to this end. The aforementioned processes have been put at various stages of the 5G system architecture for effective DSS with slight interference. The fundamental concept of these processes is to take advantage of the cognitive radio ability of gathering the spectrum related data and to then implement the most suitable action plan. The function of obtaining data on the spectrum resource is typically called spectrum sensing (SS); spectrum sensing results are subsequently utilized for maximizing the sharing of spectrum among network entities. Various sensing methods of spectrum have been proposed in the previous works related to sensing of spectrum [4] and [5]. SS through energy detection (ED) approach provides a remarkable performance without necessitating a past information of licensed user signals among the low computational complexity detectors [6]. Nevertheless, ED requires the information of noise power and under noise (power) uncertainty, its performance quickly deteriorates [7]. In order to offset the uncertainty in the noise, sensing methods with estimation of noise power have been explored in [7]. In [8], the power of noise is first predicted by turning off RF stations, and then modified to noise samples from past detection periods. To get around the necessity of noise power, several antennas can be used for detecting the vacant spectrum by employing spatial antenna correlations [5]. Techniques that are using eigenvalues [9] and the covariance of the received signals [10] are two categories of general sensing approaches of spectrum with more number of antennas. The essential concept after the eigenvalue based sensing technique is to determine if the received signals general covariance matrix is proportional to unit matrix or not. Implicit in this concept is that the guess of the noise variances are similar at various antennas. Nevertheless, in certain situations, this assumption can be considered as invalid, e.g., as a result of heterogeneous surrounding environments or uncalibrated receivers, the noise variances cannot be exactly same at distinct antennas. By considering adequately more correlation among the antennas spatially, the sensing method founded on covariance of received signals operates well regardless of the variances of noise at different antennas. It deems mentioning that the eigenvalue based detection is typically slightly superior to the covariance based detection.

However, the eigenvalue based detection is of relatively greater complexity than the covariance based detection as a result of the eigenvalue decomposition [11]. According to random matrix theory, analysis of the expression for the threshold of the eigenvalue based detection technique has been conducted. It is mentioned in [12] and [13] that the Wishart matrices greatest and lowest eigenvalues are estimated to deterministic quantities. The greatest eigenvalue follows Tracy-Widom distribution with big sample numbers of the signal to be received. The asymptotic threshold expression is given in [14] on the basis of some theorems. The precise threshold expression is obtained in [15] by utilizing the expressions of the joint distributions of a random subclass of systematic order of eigenvalues in Wishart matrices [16]. For achieving analytical formulae of false alarm ( $P_f$ ) and detection probabilities ( $P_d$ ), the dissemination of the testing criteria for the covariance based detector is examined in this paper. The expression of  $P_d$  allows for the performance evaluation of the covariance based detection. Finally, theoretical  $P_d$ ,  $P_f$  expressions are verified with Monte-Carlo simulations.

Rest of the paper is organized as follows for ease of reading and comprehension. System model is introduced in Section 2. Expression for decision threshold is given in section 3. Section 4, gives the simulated results to verify the analysis. Finally, section 5 discusses the conclusions.

## II. SYSTEM MODEL

If Sensing the available spectrum is typically treated as a binary testing problem based on dual hypothesis, i.e., a decision required to be taken on whether licensed user signals are using the spectrum or not. Correspondingly,  $H_0$  and  $H_1$  are used to denote the hypothesis zero (spectrum is not used by the licensed user) and the other hypothesis (spectrum is used by the licensed user). Fig. 1 indicates the scenario for dynamic spectrum sharing where several incumbent users (IUs) and cognitive users (CUs) are simultaneously present. The interference caused to the IUs is negligible due to the opportunistic access of licensed bands by the CU networks. The before mentioned operating networks may be heterogeneous or homogeneous. The assumption here is that one licensed user operates in a permitted channel and a cognitive user is furnished with  $M$  number of antennas.

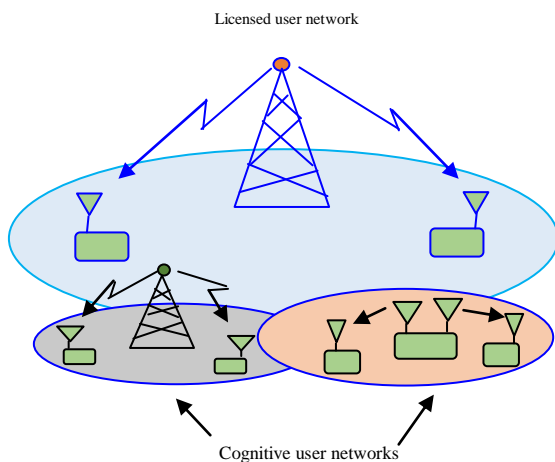


Fig. 1 Multiple licensed and cognitive user network scenario

Let  $y_m(n)$  be the received signal at discrete instants of time from the  $m^{\text{th}}$  antenna. Based on binary hypothesis, the signal received by  $M$  antennas is expressed as

$$y(n) = \begin{cases} q(n), & H_0 \\ p(n) + q(n), & H_1 \end{cases} \quad (1)$$

If the licensed user is not present then the received signal vector  $y(n) = [y_1(n), y_2(n), \dots, y_M(n)]^T$  contains only additive white Gaussian noise samples which are independent and identically distributed (IID) complex Gaussian with zero  $q(n) = [q_1(n), q_2(n), \dots, q_M(n)]^T$ ,  $q(n) : \mathcal{CN}(0, \sigma_q^2 I_M)$  with  $\sigma_q^2$  and  $I_M$  are the noise power and unit matrix of dimension  $M$ , respectively. The results provided in this paper can be simply extended to complex signal case also.  $H_1$  indicates the presence of licensed users, i.e., the received signal  $y(n)$  consists of licensed user signal combines with noise.  $p(n) = [p_1(n), p_2(n), \dots, p_M(n)]^T$  is the vector of licensed user signals. It is assumed that  $p(n)$  is IID in time domain and  $p(n) : \mathcal{CN}(0, R_p)$  with  $R_p(u, v) = \rho_{uv} \sigma_p^2$  being the  $(u, v)^{\text{th}}$  element of  $R_p$ .  $\sigma_p^2$  is the licensed user signal power on every receiving antenna,  $\rho_{uv}$  is cross correlation coefficient among the licensed user signals from the  $u^{\text{th}}$  and the  $v^{\text{th}}$  antennas. Assumed that  $p(n)$  is not dependent on  $q(n)$ . The received signal statistical covariance matrix is defined as

$$R_y = E[y(n)y^T(n)] \quad (2)$$

Then

$$R_y = \begin{cases} \sigma_q^2 I_M, & H_0 \\ R_p + \sigma_q^2 I_M, & H_1 \end{cases} \quad (3)$$

Hence,  $y(n)$  is a random vector with different variances for two hypothesis and the general properties are

$$y(n) : \begin{cases} \mathcal{CN}(0, \sigma_q^2 I_M), & H_0 \\ \mathcal{CN}(0, R_p + \sigma_q^2 I_M), & H_1 \end{cases} \quad (4)$$

If the licensed user is absent, then  $R_p = 0$ . Hence, the non-diagonal entries of  $R_y$  are all zeros. Else, due to the similarities among licensed user signals,  $R_y$  is non-diagonal matrix. For the detection of incumbent user presence, the ratio of the off-diagonal entries to the diagonal entries of  $R_y$  is considered for test statistic. With these observations, the testing criteria of covariance based detector is given by,

$$TS = \frac{TS_1}{TS_2} \quad (5)$$

where

$$TS_1 = \sum_{u \neq v; u, v=1}^M |R_y(u, v)| \quad (6)$$

and

$$TS_2 = \sum_{u=1}^M |R_y(u, u)| \quad (7)$$

Practically, the statistical covariance matrix  $R_y$  is predictable through a model covariance matrix. Let  $N$  be the number of samples considered at every receiver through the sensing duration. Then the model covariance matrix of dimension  $M \times M$  is given by

$$R_y = \frac{1}{N} \sum_{n=1}^N y(n)y^T(n) \quad (8)$$

Therefore, the testing criteria for covariance based detection method can be expressed as

$$T_S = \frac{T_{S1}}{T_{S2}} \quad (9)$$

where

$$T_{S1} = \sum_{u \neq v; u, v=1}^M |R_y(u, v)| \quad (10)$$

and

$$T_{S2} = \sum_{u=1}^M |R_y(u, u)| \quad (11)$$

The decision threshold of covariance based detector is denoted with  $\Gamma$ . Depending on the value of  $\Gamma$ , the decision can be made as

$$\text{decision} = \begin{cases} H_0, & T_S < \Gamma \\ H_1, & T_S > \Gamma \end{cases} \quad (12)$$

The detection ( $p_d$ ) and false alarm ( $p_f$ ) probabilities are given by

$$p_f = \Pr(T_S > \Gamma / H_0) \quad (13)$$

and

$$p_d = \Pr(T_S > \Gamma / H_1) \quad (14)$$

respectively. The detection and false alarm probability depends on dissemination of test statistics under both the hypothesis. Thus (13) and (14) can be formulated as

$$p_f = 1 - F_{T_S/H_0}(\Gamma) \quad (15)$$

and

$$p_d = 1 - F_{T_S/H_1}(\Gamma) \quad (16)$$

where  $F_{T_S/H_0}$  and  $F_{T_S/H_1}$  are cumulative distribution functions of new test statistics under  $H_0$  and  $H_1$  hypothesis, respectively. The detection performance can be evaluated easily by obtaining the CDFs of  $T_S$  with mathematical expressions and then setting the decision threshold for any fixed  $P_f$ . Detection performance and threshold for decision are obtained based on the distribution of  $T_S$ .

### III. DECISION THRESHOLD

Based on the dissemination of the test-statistic, the threshold decision expression can be derived for any given  $P_f$ . The decision threshold is given by

$$\Gamma = \frac{-B + \sqrt{B^2 - 4AC}}{2A} \quad (17)$$

for  $p_f \leq 0.5$  and

$$\Gamma = \frac{-B - \sqrt{B^2 - 4AC}}{2A} \quad (18)$$

for  $p_f > 0.5$

$$\text{where, } A = M^2 - \frac{2M}{N} (\phi^{-1}(p_f))^2 \quad (19)$$

$$\phi^{-1}(\cdot) \text{ is inverse function of } \phi(\cdot) \text{ and } \phi(t) = \frac{1}{\sqrt{2\pi}} \int_t^{+\infty} e^{-\frac{1}{2}t^2} dt \quad (20)$$

$$B = 2(M^3 - M^2) \left( \frac{2\sqrt{2}}{N\pi} e^{-\frac{N}{4}} + \sqrt{\frac{2}{N\pi}} \left( \phi\left(-\sqrt{\frac{N}{2}}\right) - \phi\left(\sqrt{\frac{N}{2}}\right) - 1 \right) \right) \quad (21)$$

$$\left( (\phi^{-1}(p_f))^2 - 2(M^3 - M^2) \sqrt{\frac{2}{N\pi}} \right)$$

and

$$C = (M^2 - M)^2 \frac{2}{N\pi} - \frac{1 - \rho_{T_{S1}T_{S2}}^2 + 2\rho_{T_{S1}T_{S2}}^4}{1 + \rho_{T_{S1}T_{S2}}^2} \quad (22)$$

$$\left( \frac{1}{N} (M^2 - M) \left( 2 - \frac{4}{\pi} \right) \right)$$

$\rho_{T_{S1}T_{S2}}$  is cross-correlation coefficient between  $T_{S1}$  and  $T_{S2}$ . From above expressions, it can be observed that decision threshold is not dependent on noise power  $\sigma_q^2$ . Therefore, the covariance based detector is insensitive to noise ambiguity.

### IV. RESULTS

The mathematical formulae of decision threshold  $\Gamma$ , probability of false alarm  $p_f$ , and detection probability  $p_d$  are checked by comparing them with simulated outcomes that are acquired from Monte-Carlo simulations with  $10^5$  trails are discussed in this section.

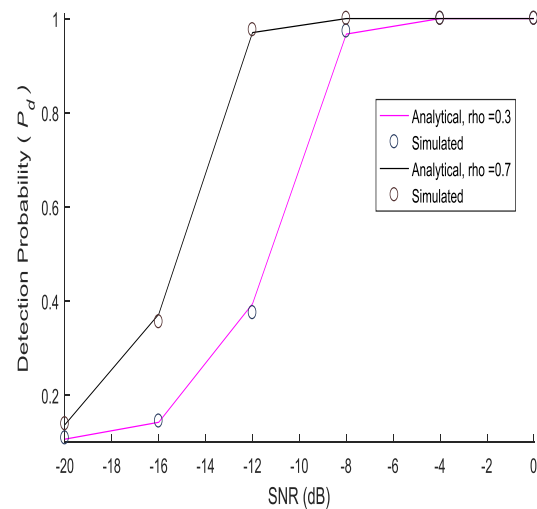


Fig. 2 Detection probability of for  $M = 5$  and  $N=1500$

The threshold expression  $\Gamma$  is obtained with (17) and (18),  $P_f$  and  $P_d$  are calculated with (15) and (16) respectively. For simplicity, the cross correlation coefficients of primary signals among receiving antennas are all expected to be equal, i.e.,  $\rho_{uv} = \rho$ . For the various values of signal-to-noise ratio (SNR) and different  $\rho$ , the probability of detection is investigated. The SNR can

be expressed as  $\frac{\sigma_p^2}{\sigma_q^2}$ .



The  $M$  and  $N$  are set to 5 and 1500 individually. The  $p_f$  is fixed to 0.1 and the decision threshold then observed for specified  $p_f$ . Fig. 2 represents the detection probability for  $\rho = 0.3$  and  $\rho = 0.7$ . From the figure, it can be observed that the probability of detecting the presence of primary is more in case of  $\rho = 0.7$  compared to  $\rho = 0.3$ . With  $\rho = 0.3$  and at SNR = -12dB, the detection probability is 0.3746; with  $\rho = 0.7$  and at SNR = -12dB, the probability of detection is 0.9758. Increasing the  $M$  to 10, the results are presented in Fig. 3. Also in this instance, the analytical curves are well fitted with the simulated data. Additionally, as the antenna correlation and antenna number increases, the detection performance shows an improvement as can be seen in Fig. 2 & 3.

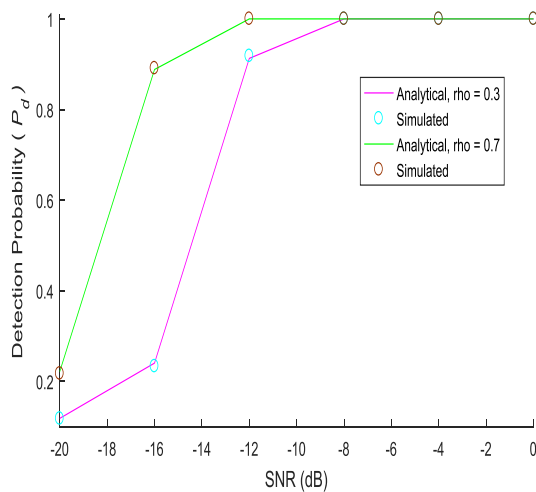


Fig. 3 Detection probability for  $M = 15$  and  $N=1500$

The receiver operating characteristics (ROC) curves of the covariance based detector is shown in Fig. 4. The curves in Fig. 4 are obtained with  $M = 5$  and  $N = 1500$ , SNR = -20dB for different  $\rho$  values. The probability of detection increases with the probability of false alarm. With  $\rho = 0.3$  and at  $p_f = 0.1$ , the probability of detection is 0.124; with  $\rho = 0.7$  and at  $p_f = 0.1$ , the detection probability is 0.1728.

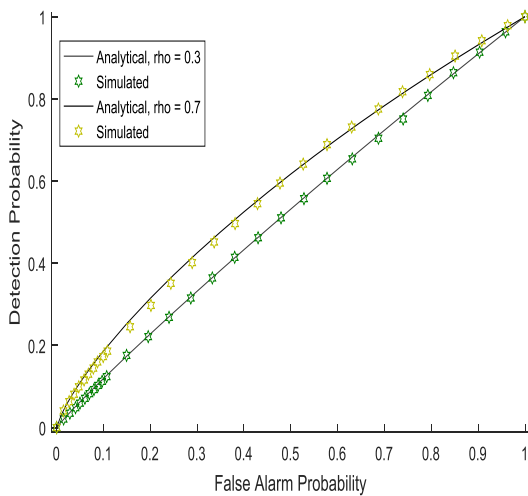


Fig. 4 Receiver operating characteristics,  $M = 5$  and  $N=1500$ , SNR = -20dB

Fig. 5 shows the ROC plots of the covariance based detector with  $M = 15$  and  $N = 1500$ , SNR = -12dB for two different cross-correlation coefficient values. From the figure, it can be found that the probability of detecting the presence of primary user is more in case of  $\rho = 0.7$  compared to  $\rho = 0.3$  for a given probability of false alarm. With  $\rho = 0.3$  and at  $p_f = 0.1$ , detection probability is 0.2781; with  $\rho = 0.7$  and at  $p_f = 0.1$ , the detection probability is 0.8647.

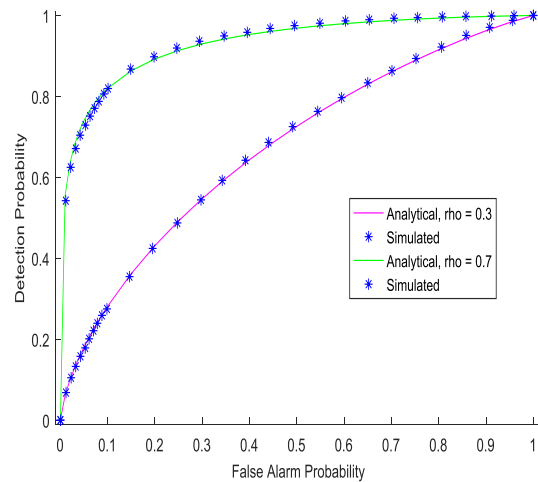


Fig. 5 Receiver operating characteristics,  $M = 15$  and  $N=1500$ , SNR = -12dB

V. CONCLUSION

This paper finds mathematical expressions for the dissemination of the testing criteria for the covariance based detector. The sensing performance of the covariance based detector is analyzed for various correlation coefficient values. It can be found that the detection performance of the detector is improved with increased number of antennas. The detector at a given probability of error and with correlation coefficient  $\rho = 0.3$ , number of antennas,  $M = 5$ , the obtained detection probability is 0.3898. While taking into account the same constraints and with increased number of antennas ( $M = 15$ ), the detection probability acquired is 0.7021. It is concluded that, the performance of the detector is poor under low SNR values.

REFERENCES

1. Panwar N, Sharma S, Kumar Singh A, "A survey on 5G: the next generation of mobile communication," Elsevier Phys Commun 18(2), 2016 pp. 64–84.
2. Andrews JG, "What will 5G be?," IEEE J Sel Areas Commun 32(6), 2014, pp.1065–1082.
3. Mitola J, Maguire GQ, "Cognitive radio: making software radio more personal," IEEE Pers Commun 6(4), 1999, pp. 13-18.
4. Yucek T, Arslan H, "A survey of spectrum sensing algorithms for cognitive radio applications," IEEE Commun Surv Tutorials 11(1), 2009, pp. 116–130.
5. Ali A, Hamouda W, "Advances on spectrum sensing for cognitive radio networks: theory and applications," IEEE Commun Surv Tutorials, 2016, PP(99):1
6. A. Sonneschein & P. M. Fishman, "Radiometric detection of spread spectrum signals in noise of uncertain power," IEEE Trans. Aerosp. Electron. Syst., 1992, vol. 28, no. 3, pp. 654–660.



7. A. Mariani, A. Giorgetti, & M. Chiani, "Effects of noise power estimation on energy detection for cognitive radio applications," *IEEE Trans. Commun.*, 2011, vol. 59, no. 12, pp. 3410–3420.
8. V. Rakovic, D. Denkovski, V. Atanasovski, P. Mähönen, & L. Gavrilovska, "Capacity-aware cooperative spectrum sensing based on noise power estimation," *IEEE Trans. Commun.*, 2015, vol. 63, no. 7, pp. 2428–2441.
9. A. Taherpour, M. Nasiri-Kenari, & S. Gazor, "Multiple antenna spectrum sensing in cognitive radios," *IEEE Transactions on Wireless Communications*, 2010, vol. 9, no. 2, pp. 814–823.
10. Y. Zeng, & Y. C. Liang, "Spectrum sensing algorithms for cognitive radio based on statistical covariance," *IEEE Trans. Veh. Technol.*, 2009, vol. 58, no. 4, pp. 1804–1815.
11. Y. Zeng, Y. Laing, E. Peh, & A. T. Hoang, "Cooperative Covariance and Eigenvalue Based Detections for Robust Sensing," in *IEEE Global Telecommunications Conference(GLOBECOM)*, IEEE, 2009, pp. 1–6.
12. Z. D. Bai, "On the distribution of largest eigenvalue in principle components analysis," *Anal. Statist.*, 2001, vol. 29, no. 2, pp. 295–327.
13. Z.D. Bai, "Methodologies in spectral analysis of large dimensional random matrices, a review," *Statist. Sinica*, 1999, vol. 9, pp. 611–677.
14. Y. Zeng and Y.C. Liang, "Eigenvalue-based spectrum sensing algorithms for cognitive radio," *IEEE Trans. Commun.*, 2009, vol. 57, no. 6, pp. 1784–1793.
15. F. Penna, R. Garello, D. Figliloli, & M. A. Spirito, "Exact nonasymptotic threshold for eigenvalue based spectrum sensing," in *Proc. 4th Int. Conf. Cognitive Radio Oriented Wireless Netw. Commun.*, Hannover, Germany, 2009.
16. M. Chaini & A. Zanella, "Joint distribution of an arbitrary subset of the ordered eigenvalues of Wishart matrices," in *IEEE 19th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, 2008, pp.1–6.

## AUTHORS PROFILE



**Babji Prasad Chapa** received the B.Tech degree in Electronics and Communication Engineering from JNT University in 2007. He obtained M.Tech. degree in systems and Signal Processing from JNT University, Hyderabad, in 2010. He has a teaching experience of 8 years. He was project guide for several

UG and PG students. He has published more than 5 papers in journals and around 10 papers in national/ international conferences. He is recipient of best teacher award. He is currently carrying out research in Cognitive Radio Networks.



**Gottapu Sasibhushana Rao** has total 32 years of experience which includes 17 years of teaching and 15 years of industrial experience. He is currently a Senior Professor and Head, in Department of ECE, AU college of Engineering, Andhra University. His research interests include GPS, Image Processing,

Cognitive Radio, Massive MIMO, and Energy Efficient Communications. He has published more than 500 papers in various reputed journals and conferences. He has authored five textbooks. He has guided more than 30 Ph.D.'s and 130 post graduates. He is recipient of Best Researcher Award and Dr. Sarvepalli Radhakrishnan award for best academician. He is also Editorial Board Member for reputed scientific publications.



**Suresh Dannana** received his B.Tech degree in Electronics and Communication Engineering from JNT University, in 2005. He obtained the M.Tech. degree in Systems and Signal Processing from JNT University College of Engineering, Hyderabad, in 2010. Later he joined as Asst. Prof. in GMR Institute of Technology, Rajam in 2010. He has a teaching

experience of 12 years. He has guided several UG and PG projects. He has published more than 10 papers in journals and around 7 papers in national/ international conferences. He is currently carrying out research in Spectrum sensing techniques in Cognitive Radio.