Optimisation of Collaborative Spectrum Sensing with SIMO Cognitive Terminals using Genetic Algorithm

Kamran Arshad and Klaus Moessner
Centre of Communication Systems Research
University of Surrey, GU2 7XH, UK
Email:k.arshad@surrey.ac.uk

***Abstract*—Cognitive radio has been identified as a potential candidate to increase spectrum utilisation by exploiting spectrum holes on a non-interfering basis. Spectrum sensing is the key functionality to make sure that the cognitive radio is aware and will not disturb the operation of the licensed users. Collaborative spectrum sensing is needed to overcome deleterious channel effects such as fading or the hidden node problem and to increase sensing reliability and accuracy. This paper presents a novel optimisation framework for collaborative spectrum sensing in the presence of imperfect reporting channels. It is also shown in this paper that in fading channels spectrum sensing performance can be significantly improved by using multiple antennas at the cognitive radio terminal. A weighted optimised collaborative spectrum sensing scheme with multiple antenna cognitive terminals, which maximises global probability of detection at the fusion centre using genetic algorithm is presented. Based on an individual user local conditions, the algorithm assigns optimal weight to the user observation at the fusion centre. Simulation results illustrate that significant collaborative and spatial diversity gains can be achieved by the proposed spectrum sensing framework.**

I. Introduction

Communication spectrum is congested and new exploitation models exploiting temporally and spatially under-used spectrum are considered in the research community. To deal with the conflicts between spectrum congestion and spectrum under-utilisation, cognitive radio (CR) has been proposed as an intelligent technology which allows unlicensed users to use licensed bands opportunistically. To guarantee an efficient operation of CR while avoiding interference to the licensed users, CR should be able to sense spectrum reliably [1]. Among various spectrum sensing techniques, energy detection is used in this study because of its low complexity and computational power [2].

Performance of spectrum sensing under varying channel conditions such as fading and shadowing can be significantly improved by collaborative or cooperative spectrum sensing e.g. see [1] and references therein. Local observation (soft decision) or 1-bit decision (hard decision) transmits through the reporting channel and fused at the fusion centre to make a global decision about the presence of the primary user (PU). It has been argued that soft decision combining gives higher performance gains than hard decision combining [3].

Many optimisation techniques for collaborative spectrum sensing in terms of the fusion rule [2], number of users [4] and thresholds [5] have been presented in the literature. But previous studies on the optimisation of collaborative spectrum sensing considered scenarios in which primary transmitter is far away from the collaborative cognitive secondary users (CCSU) and perfect reporting channel has been assumed [1], [2]. Recently, performance of collaborative spectrum sensing with noisy reporting channel was also studied for the case of hard decision fusion in [6]. Authors assumed a simple noisy reporting channel with equal channel gains in [6] and considered hard decision fusion in which CCSU needs to send just 1-bit decision to the fusion centre. Moreover, previous research highlighted collaborative sensing techniques which combine data or decision from the CCSU with equal weights [2]. Collaborative spectrum sensing schemes with weighted user contributions have been discussed in [3] and [7]. Average signal power at a secondary user (SU) was exploited to weight different collaborating cognitive nodes in [3]. In [7] an optimal strategy for cooperative spectrum sensing was presented and optimal weights for each SU in an AWGN channel were derived analytically.

In this paper, Genetic Algorithm (GA) based weighted collaborative spectrum sensing strategy is presented to enhance collaborative spectrum sensing performance. Multiple antenna systems are widely used in wireless communication and are also considered for the future communication technologies [8]. We considered a Single Input Multiple Out (SIMO) collaborative spectrum sensing system in this study to reduce sensitivity to fading and assumed that every cognitive user may have multiple antennas. The proposed optimum spectrum sensing mechanism is based on a realistic model that takes realistic channels into account. It is shown in this paper that imperfect reporting channels have a direct impact on the performance of collaborative spectrum sensing and must be taken into account for optimum spectrum sensing performance. Global decision made at the fusion centre is based on a weighted combination of the local test statistics from individual CCSU. The weight of each secondary user at the band manager is indicative of its contribution to the global decision making. For example, if a secondary user has more antennas, generates a high SNR for the received signal, frequently makes accurate local decisions and has a good reporting channel than it is assigned a larger weight.

978-1-4244-5213-4/09/ $26.00 ©2009 IEEE

The optimum collaborative spectrum sensing problem is formulated as a nonlinear optimisation problem in this paper. For a given probability of false alarm, structure of CR and channel conditions, optimal weights are choosen in such a way that it maximises global probability of detection at the fusion centre. With realistic channels between primary transmitter and the fusion centre it is hard to derive an analytical expression for the optimum weights hence the problem is considered to be an NP-hard optimisation problem. This paper proposes a GA based solution to calculate the optimum weight for each secondary user with the aim to maximise the global probability of detection.

The rest of the paper is organised as follows. In section II we describe the system model and use cases considered. Section III introduces the collaborative spectrum sensing framework and details the problem formulation. In order to achieve optimum spectrum sensing performance, GA is used to calculate the weights for each user in section IV. Simulation results are presented in section V and section VI concludes this paper.

II. System Model

We consider a cognitive radio network, with M users each having K antenna, and a fusion centre to sense a portion of the spectrum in order to detect PU, as shown in Fig. 1. We assume two use cases: Use case 1 refers to the case when PU is far away from the CCSU hence same mean SNR can be assume for all CCSU. In use case 2, the PU is not far away from the M secondary users and each user has a different value of mean SNR depending on its distance from the PU. It is also assumed that all CCSU have independent and indentically distributed (i.i.d.) observations. Proposed structure of a CR is also shown in Fig. 1. Signals received from multiple antenna goes through the energy detectors respectively and the local fusion centre within a CR makes local observation u_i. We also assume spatially uncorrelated Rayleigh fading at multiple antennas of a CR terminal. This assumption is based on the fact that the operating frequency range of a CR is already known in advance and antennas are suitably placed [8].

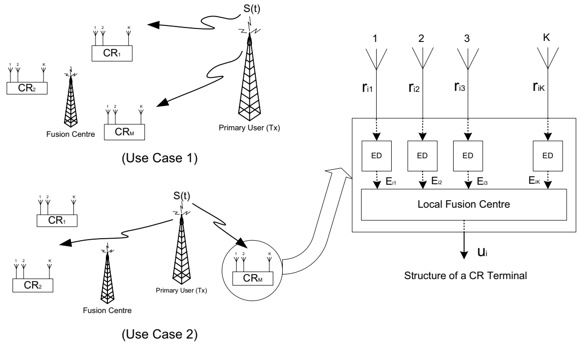

Fig. 1. Use Cases considered in Simulations

III. Problem Formulation

A. Local Spectrum Sensing

In this section, the local spectrum sensing problem is formulated as a binary hypothesis testing problem [9]:

$$r_{ij}(p) = \begin{cases} \upsilon_{ij}(p) & ;\mathcal{H}_0 \\ h_{ij}s(p) + \upsilon_{ij}(p) & ;\mathcal{H}_1 \end{cases} \tag{1}$$

where $p = 1, 2, 3, ..., N$, $i = 1, 2, 3, ..., M$ and $j = 1, 2, 3, ...K$ and N is the total number of samples observed by a CR in the given observation time. Primary user signal is denoted by $s(t)$, h_{ij} is the channel gain between jth antenna of ith CR and the PU, and $\upsilon_i = \upsilon_{ij}$ is additive white gaussian noise and is defined as $\upsilon_{ij} \sim \mathcal{N}(0, \sigma_{ij}^2)$. Without loss of generality, $s(p)$ and $\upsilon_i(p)$ are assumed to be independent of each other. So energy collected by the ith user at jth antenna is,

$$E_{ij} = \sum_{p=1}^{N} |r_{ij}(p)|^2 \tag{2}$$

Since E_{ij} is the sum of squares of N gaussian random variables, for a large value of N (e.g. $N > 10$ [10]), test statistics of E_{ij} is,

$$E_{ij} \sim \begin{cases} \mathcal{N}\big(N\sigma_{ij}^2, 2N\sigma_{ij}^4\big) & ;\mathcal{H}_0 \\ \mathcal{N}\big(\overline{N+\gamma_i\sigma_{ij}^2}, \overline{2N+2\gamma_i\sigma_{ij}^4}\big) & ;\mathcal{H}_1 \end{cases} \tag{3}$$

where γ_i is the mean SNR detected by the ith secondary user and it is assumed that mean SNR is the same at all K_i antennas of a CR. The statistics of local soft decision for ith CR, by assuming that noise variance at all antennas for an ith CR is same (i.e. $\sigma_{ij}^2 = \sigma_i^2$) is expressed as,

$$u_i \sim \begin{cases} \mathcal{N}\left(\sum_{j=1}^{K_i} N\sigma_{ij}^2, \sum_{j=1}^{K_i} 2N\sigma_{ij}^4\right) & ;\mathcal{H}_0 \\ \mathcal{N}\left(\sum_{j=1}^{K_i} \overline{N+\gamma_i\sigma_{ij}^2}, \sum_{j=1}^{K_i} \overline{2N+2\gamma_i\sigma_{ij}^4}\right) & ;\mathcal{H}_1 \end{cases}$$

$$u_i \sim \begin{cases} \mathcal{N}\big(NK_i\sigma_i^2, 2NK_i\sigma_i^4\big) & ;\mathcal{H}_0 \\ \mathcal{N}\big(\overline{N+\gamma_i}K_i\sigma_i^2, \overline{2N+2\gamma_i}K_i\sigma_i^4\big) & ;\mathcal{H}_1 \end{cases} \tag{4}$$

If the decision threshold at the ith secondary user is λ_i than probability of false alarm and probability of detection for ith users is defined as,

$$P_f^i = Q\left(\frac{\lambda_i - NK_i\sigma_i^2}{\sqrt{2NK_i}\sigma_i^2}\right) \tag{5}$$

$$P_d^i = Q\left(\frac{\lambda_i - \overline{N+\gamma_i}K_i\sigma_i^2}{\sqrt{2\overline{N+2\gamma_i}K_i}\sigma_i^2}\right) \tag{6}$$

B. Collaborative Spectrum Sensing

The summary statistics at local secondary nodes $\{u\}$ as defined in (4) is then transmitted to the fusion centre through reporting channels. In this paper realistic reporting channels with noise, $n_i \sim \mathcal{N}(0, \delta_i^2)$ and variable channel gains $\{g\}$ are considered, as shown in Fig. 2. Statistics of local observations

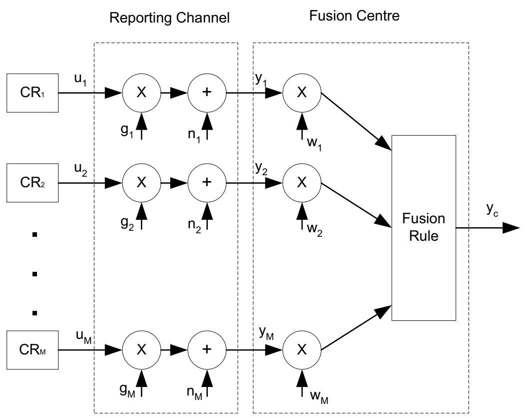

Fig. 2. Schematic diagram of weighted collaboration at fusion centre

after passing through the reporting channel is,

$$y_i \sim \begin{cases} \mathcal{N}\Big(NK_ig_i\sigma_i^2, 2NK_ig_i^2\sigma_i^4+\delta_i^2\Big) & ;\mathcal{H}_0 \\ \mathcal{N}\Big(\overline{N+\gamma_i}K_ig_i\sigma_i^2, 2\overline{N+2\gamma_i}K_ig_i^2\sigma_i^4+\delta_i^2\Big) & ;\mathcal{H}_1 \end{cases} \tag{7}$$

A global test statistics is calculated at the fusion centre by assigning weights $\{w\}$ to the received observations $\{y\}$ by,

$$y_c = \sum_{i=1}^{M} w_i \cdot y_i = \mathbf{w}^T\mathbf{y} \tag{8}$$

where the weight vector $\mathbf{w}$ is defined as $\mathbf{w} = \{w_1, w_2, ..., w_M\}^T$ and the received decision vector at the fusion centre is defined as $\mathbf{y} = \{y_1, y_2, ..., y_M\}^T$. Weight vector $\mathbf{w}$ at the fusion centre satisfies $||w||_2^2 = 1$ where $||.||_2^2$ denotes the Euclidean norm. From (7) and (8) the distribution of y_c can be derived and is given as,

$$\mathcal{N}\left(\sum_{i=1}^{M} NK_ig_i\sigma_i^2w_i, \sum_{i=1}^{M}\Big(2NK_ig_i^2\sigma_i^4w_i^2+\delta_i^2w_i^2\Big)\right); \mathcal{H}_0$$

$$\mathcal{N}\left(\sum_{i=1}^{M}\overline{N+\gamma_i}K_ig_i\sigma_i^2w_i, \cdots \right.$$
$$\left. \sum_{i=1}^{M}\Big(2\overline{N+2\gamma_i}K_ig_i^2\sigma_i^4w_i^2+\delta_i^2w_i^2\Big)\right); \mathcal{H}_1$$

If we assume $\mathbf{h} = \{h_1, h_2, ..., h_M\}^T$, $\mathbf{g} = \{g_1, g_2, ..., g_M\}^T$, $\mathbf{K} = \{K_1, K_2, ..., K_M\}^T$, $\boldsymbol{\gamma} = \{\gamma_1, \gamma_2, ..., \gamma_M\}^T$, $\boldsymbol{\sigma} = \{\sigma_1^2, \sigma_2^2, ..., \sigma_M^2\}^T$ and $\boldsymbol{\delta} = \{\delta_1^2, \delta_2^2, ..., \delta_M^2\}^T$, than statistics of y_c under $\mathcal{H}_0$ and $\mathcal{H}_1$ can be written as,

$$\begin{aligned} \mathrm{E}[y_c/\mathcal{H}_0] &= N\mathbf{g}^T\mathrm{diag}(\boldsymbol{\sigma})\mathrm{diag}(\mathbf{K})\mathbf{w} \\ \mathrm{Var}[y_c/\mathcal{H}_0] &= \mathbf{w}^T[2N\mathrm{diag}^2(\mathbf{g})\mathrm{diag}^2(\boldsymbol{\sigma})\mathrm{diag}(\mathbf{K}) + \mathrm{diag}(\boldsymbol{\delta})]\mathbf{w} \\ \mathrm{E}[y_c/\mathcal{H}_1] &= N\mathbf{g}^T\mathrm{diag}(\boldsymbol{\sigma})\mathrm{diag}(\mathbf{K})\mathbf{w} + \mathbf{g}^T\mathrm{diag}(\boldsymbol{\gamma})\cdots \\ &\quad \mathrm{diag}(\boldsymbol{\sigma})\mathrm{diag}(\mathbf{K})\mathbf{w} \\ \mathrm{Var}[y_c/\mathcal{H}_1] &= \mathbf{w}^T[2N\mathrm{diag}^2(\mathbf{g})\mathrm{diag}^2(\boldsymbol{\sigma})\mathrm{diag}(\mathbf{K}) + 4\mathbf{g}^T\cdots \\ &\quad \mathrm{diag}^2(\boldsymbol{\sigma})\mathrm{diag}(\boldsymbol{\gamma})\mathrm{diag}(\mathbf{K}) + \mathrm{diag}(\boldsymbol{\delta})]\mathbf{w} \end{aligned}$$

where diag(.) is a diagonal matrix with elements of the given vector on its diagonal and Var(.) denote the variance operator.

For decision threshold λ_c, global probability of false alarm and detection at the fusion centre is,

$$Q_f = Q\left(\frac{\lambda_c - \mathrm{E}[y_c/\mathcal{H}_0]}{\sqrt{\mathrm{Var}[y_c/\mathcal{H}_0]}}\right) \tag{9}$$

$$Q_d = Q\left(\frac{\lambda_c - \mathrm{E}[y_c/\mathcal{H}_1]}{\sqrt{\mathrm{Var}[y_c/\mathcal{H}_1]}}\right) \tag{10}$$

C. Spectrum Sensing under Fading

When the channel between primary transmitter and secondary user is varying due to fading or shadowing, (6) and (10) gives the probability of detection conditioned on instantaneous SNR γ_i. On the other hand, probability of false alarm as defined in (5) and (9) remains the same, as it is independent of γ_i. Average probability of detection may be derived by averaging instantaneous probability over the fading statistics.

$$P_d^i = \int_{\gamma} Q\left(\frac{\lambda_i - \mathrm{E}[u_i/\mathcal{H}_1]}{\sqrt{\mathrm{Var}[u_i/\mathcal{H}_1]}}\right) f_{\gamma}(x)\, dx \tag{11}$$

$$Q_d = \int_{\gamma} Q\left(\frac{\lambda_i - \mathrm{E}[y_c/\mathcal{H}_1]}{\sqrt{\mathrm{Var}[y_c/\mathcal{H}_1]}}\right) f_{\gamma}(x)\, dx \tag{12}$$

where distributions of u_i and y_c are defined in (4) and (9) respectively (by replacing γ_i by the independent variable x) and $f_\gamma(x)$ is PDF of SNR under fading.

IV. GA based Optimum Collaborative Spectrum Sensing

In this paper, our goal is to maximise the global probability of detection for a given value of probability of false alarm, number of antennas, number of users and given channel conditions. From equations (9) and (10),

$$Q_d = Q\left(\frac{\sqrt{\mathrm{Var}[y_c/\mathcal{H}_0]}Q^{-1}(Q_f) + \mathrm{E}[y_c/\mathcal{H}_0] - \mathrm{E}[y_c/\mathcal{H}_1]}{\sqrt{\mathrm{Var}[y_c/\mathcal{H}_1]}}\right)$$

Maximising Q_d is equivalent to minimise $f(\mathbf{w})$ as $Q(x)$ is a decreasing function of x, where $f(\mathbf{w})$ is given by,

$$\begin{aligned} f(\mathbf{w}) &= \frac{\sqrt{Q^{-1}(Q_f)\mathrm{Var}[y_c/\mathcal{H}_0]} + \mathrm{E}[y_c/\mathcal{H}_0] - \mathrm{E}[y_c/\mathcal{H}_1]}{\sqrt{\mathrm{Var}[y_c/\mathcal{H}_1]}} \\ &= \frac{Q^{-1}(Q_f)\sqrt{\mathbf{w}^T\mathbf{A}\mathbf{w}} - \mathbf{w}^T[\mathrm{diag}(\mathbf{g})\mathrm{diag}(\boldsymbol{\sigma})\mathrm{diag}(\mathbf{K})]\boldsymbol{\gamma}}{\sqrt{\mathbf{w}^T\mathbf{B}\mathbf{w}}} \end{aligned} \tag{13}$$

where,

$$\mathbf{A} = 2N\mathrm{diag}^2(\mathbf{g})\mathrm{diag}^2(\boldsymbol{\sigma})\mathrm{diag}(\mathbf{K}) + \mathrm{diag}(\boldsymbol{\delta})$$

$$\mathbf{B} = 2\Big(NI_M + 2\mathrm{diag}(\boldsymbol{\gamma})\Big)\mathrm{diag}^2(\mathbf{g})\mathrm{diag}^2(\boldsymbol{\sigma})\mathrm{diag}(\mathbf{K}) + \mathrm{diag}(\boldsymbol{\delta})$$

Similarly for fading channel, average probability of detection can be obtained by averaging Q_d over fading statistics as described in section III-C. The optimisation problem can be formulated as,

$$\begin{aligned} &\text{minimise} \quad f(\mathbf{w}) \\ \text{st.} \quad &||\mathbf{w}||_2^2 = 1 \quad \text{and} \quad w_i > 0\ \forall i \in \{1, 2, 3, ..., M\} \end{aligned} \tag{14}$$

Genetic algorithm is used as a solution approach to minimise $f(\mathbf{w})$ as defined in (13) for a given value of Q_f. The GA has been proposed as a computational analogy of adaptive systems by Holland [11]. They are modelled based on the principles of natural evolution and selection. The algorithm starts by randomly generating an initial population and then computing and saving the fitness of each chromosome in the current population using (13), which serves as a fitness function. Next, using a selective algorithm, chromosomes are picked up probabilistically from a mating pool to produce off-springs via crossover and mutation operations. This process is repeated until a satisfied solution is obtained or the maximum generation number is reached. Details of the GA can be found in any standard text e.g. [12].

As the proposed scheme is based on the GA, proper selection of GA parameters is crucial for better results. There are several parameters that are important which include population size, choice of selection method, crossover and mutation probabilities as well as the suitable termination criteria. Based on a number of test experiments, the best suited GA parameter configuration was set-up for the optimisation problem and parameters are listed in Table I.

TABLE I
GA PARAMETER CONFIGURATION

Parameter	Value
Population Size	100
Number of Generations	100
Elitism	2%
Mutation Probability	2%
Crossover Probability	80%
Initialisation Method	Random
Crossover operation	Single point
Selection Method	Roulette wheel

V. SIMULATION RESULT

In this section, proposed optimised collaborative spectrum sensing scheme is evaluated numerically and compared with an Equal Gain Combining (EGC) scheme, in which the same weight is assigned to each SU. Results are obtained from simulations over $1,000,000$ noise realisations for the given set of noise variances. Noise variance of all collaborating users for the primary channel (i.e. channel between primary transmitter and secondary users) is assumed to be $\sigma^2 = 1$ and noise variance of the reporting channel is assumed to be $\delta^2 = 1$, until stated otherwise. Value of N is assumed to be 10 in all simulations.

The ROC curves under use case 1 when all collaborating secondary users have $\gamma_i = 10$dB for $\forall i \in \{1, 2, ..., M\}$ is shown in Fig. 3. Perfect reporting channel is assumed in Fig. 3 and the channel between CCSU and the PU is considered to be Rayleigh fading channel. Fig. 3 shows that with an increase in the number of collaborating users and number of antennas, sensing performance improves. For example, at $Q_f = 10^{-2}$, collaboration and spatial diversity gain of about 50% can be achieved as shown in Fig. 3. Similarly, in use case 1 with a perfect reporting channel, by increasing number of collaborating users with multiple antennas in a Rayleigh fading channel, a SNR of 6.38dB can be detected with 4 users having 4 antennas for $Q_f = Q_m = 10^{-1}$, while with one user having one antenna minimum detected SNR is about 18.8dB, as shown in Fig. 4.

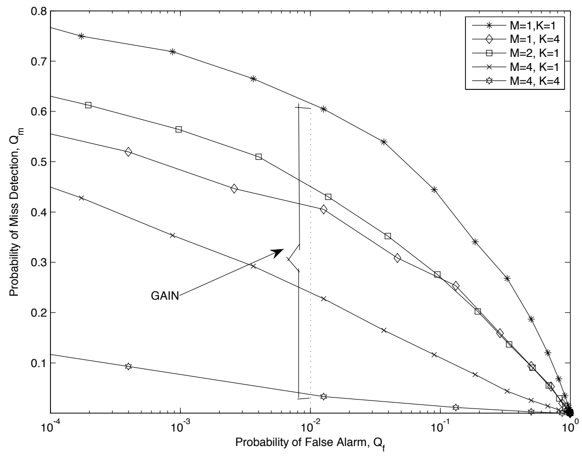

Fig. 3. ROC curves in Rayleigh fading channel (case 1), $\gamma_{dB} = 10$

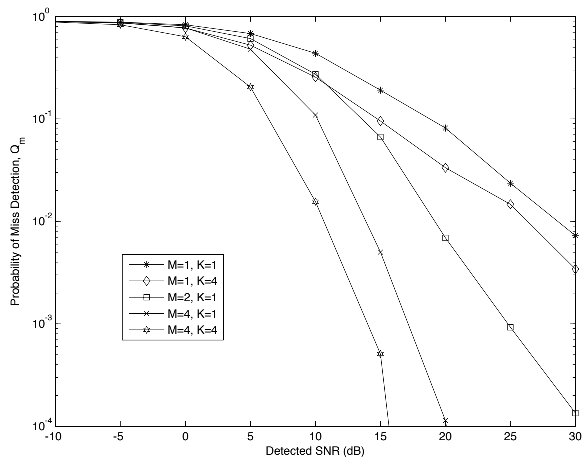

Fig. 4. Q_m versus Minimum detectable SNR in Rayleigh fading channel (case 1), $Q_f = 10^{-1}$

Fig. 5 gives the ROC curve for 6 collaborating users under use case 2. CCSU have different mean SNR values and the reporting channel is imperfect in this case i.e. noisy channels exists between CCSU and the fusion centre with variable channel gains. Value of channel gain is dependent on the location of the fusion centre and the CR and varying with time, depending on the mobility of CR and the fusion centre. It can be seen from Fig. 5 that reporting channel gain degrades the performance of spectrum sensing in the presence of Rayleigh fading channel. However, by exploiting spatial diversity at each cognitive terminal, spectrum sensing performance can be improved.

Fig. 6 compares the performance of EGC and proposed GA based Optimisation combining (GAOPT) of secondary users observations under use case 1 and use case 2 in Rayleigh fading channel to makes a final spectrum occupancy decision. In use case 1, all collaborating users have the same mean SNR $\left(\gamma_i = 10\text{dB for } \forall i \in \{1, 2, ..., M\}\right)$ and have similar reporting channel conditions with different numbers of antennas and noise variances. While in case 2, all collaborating users have different mean SNR values and we assume two users have high mean SNR compared to others. High SNR users have much better reporting channel conditions and more number of antennas than other users. Under such conditions an analytical expression for the probability of detection is derived and optimum weights are calculated by using GA. Proposed GA based optimum weighted collaborative spectrum sensing gives better performance than EGC as shown in Fig. 6 for both considered cases.

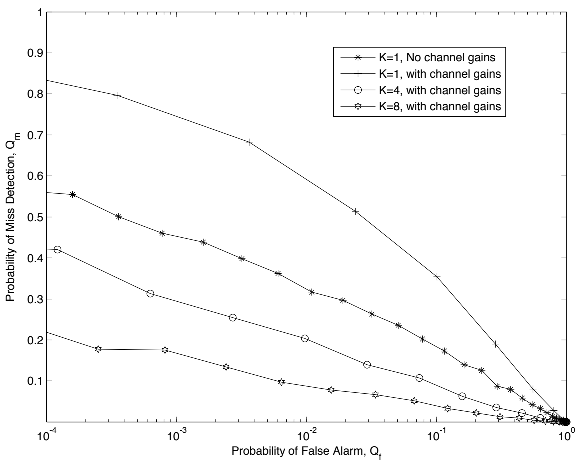

Fig. 5. ROC curves in Rayleigh fading channel with im-perfect reporting channels with $M = 6$ (use case 2)

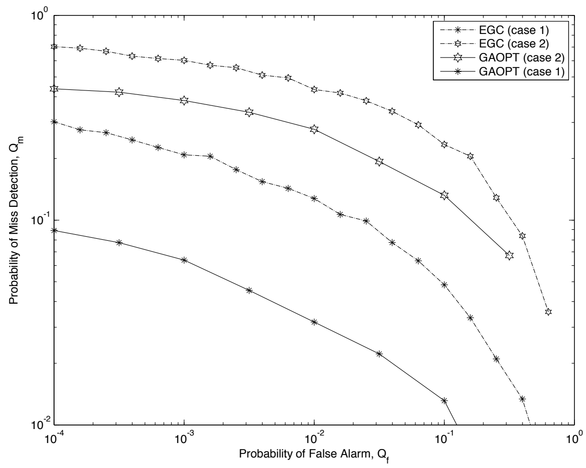

Fig. 6. Q_m vs Q_f with M=6 in Rayleigh fading channel with im-perfect reporting channel

VI. Conclusions

In this paper we propose GA based optimisation of weighted collaborative spectrum sensing in which weights are assigned to the information provided by the collaborative users to improve collaborative spectrum sensing performance in terms of receiver operating characteristics. The optimum weight vector is obtained by maximising global probability of detection using GA, which maximise the probability of detection for the given probability of false alarm, channel conditions and number of CR antennas. In this paper, realistic noisy channels are considered between collaborative users and the fusion centre with variable channel gains. It has been shown in this paper that observation fusion with optimum weights always outperform other weighting schemes considered in the literature. Proposed GA based optimisation scheme requires knowledge about local mean SNR of all secondary users, number of CR antennas and reporting channel conditions. In practical situations with a large number of collaborative users, the reporting channel bandwidth utilisation can be high. Our future research will investigate mechanisms to optimise bandwidth utilisation for the collaborative framework presented in this paper.

Acknowledgment

This work was performed in the EU FP7 project E3 and contributions of colleagues from the E3 consortium are hereby acknowledged.

References

[1] A. Ghasemi and E. S. Sousa, "Opportunistic spectrum access in fading channels through collaborative sensing," *Journal of Communications*, vol. 2, no. 2, pp. 71–81, March 2007.

[2] W. Zhang, R. Mallik, and K. Ben Letaief, "Cooperative spectrum sensing optimization in cognitive radio networks," in *IEEE International Conference on Communications, ICC'08*, May 2008, pp. 3411–3415.

[3] F. Visser, G. Janssen, and P. Pawelczak, "Multinode spectrum sensing based on energy detection for dynamic spectrum access," in *IEEE Vehicular Technology Conference, VTC Spring'08*, May 2008, pp. 1394–1398.

[4] K. Arshad and K. Moessner, "Collaborative spectrum sensing for cognitive radio," in *2009 Joint Workshop Cognitive Wireless Networks and Systems (Accepted for Publication)*, 2009.

[5] D. J. Kadhim, S. Gong, W. Liu, and W. Cheng, "Optimization of cooperation sensing spectrum performance," in *WRI International Conference on Communications and Mobile Computing, CMC'09*, vol. 1, Jan. 2009, pp. 78–82.

[6] T. Aysal, S. Kandeepan, and R. Piesiewicz, "Cooperative spectrum sensing over imperfect channels," in *IEEE Global Telecommunications Conference, GLOBECOM'08*, Dec. 2008, pp. 1–5.

[7] Z. Quan, S. Cui, and A. Sayed, "Optimal linear cooperation for spectrum sensing in cognitive radio networks," *IEEE Journal of Selected Topics in Signal Processing*, vol. 2, no. 1, pp. 28–40, Feb. 2008.

[8] C. Oestges and B. Clerckx, *MIMO Wireless Communications: From Real-World Propagation to Space-Time Code Design*. Orlando, FL, USA: Academic Press, Inc., 2007.

[9] H. Urkowitz, "Energy detection of unknown deterministic signals," *IEEE Proceedings*, vol. 55, no. 4, pp. 523–531, April 1967.

[10] P. K. Varshney, *Distributed Detection and Data Fusion*. Secaucus, NJ, USA: Springer-Verlag New York, Inc., 1996.

[11] J. H. Holland, *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*. The MIT Press, April.

[12] M. Gen and R. Cheng, *Genetic algorithms and engineering design*. Wiley, 1997.