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Cooperative Cognitive Wireless Communications Systems

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science in Electrical and Electronics Engineering

Submitted by

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Master of Science in Electrical and Electronics Engineering

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ABSTRACT

Cognitive wireless communications is used recently to improve the spectrum utilization. The main work of this thesis is focusing on a challenging research topic in this field which is the cooperation between different users within one cognitive network to improve spectrum sensing for the network.

Instead of targeting a certain probability of detection or a certain probability of false alarm, this thesis is presenting the network spectral efficiency rate as a new target of cooperative spectrum sensing. A constant spectral efficiency rate should yield a constant throughput rate of the network.

Targeting several spectral efficiency rates using different network sizes, window lengths, received signal-to-noise values, and different fusion rules is investigated in this thesis. The maximum probability of detection can be achieved using an optimal number of cooperated users with the highest signal-to-noise ratio less than the total network users and using a window length shorter than the total allowable sensing window.

Moreover, It is proved that modifying the previous hard decision scheme into a soft decision weighted scheme will improve the achieved maximum probability of detection of the network. The weights added to the sensing results are optimized using the optimization of the modified deflection coefficient. Although the weighted network needs to cooperate all users to reach the maximum probability of detection, an optimal sensing window length less than the total allowable sensing window could be achieved.

Dedication

To my beloved family

Acknowledgements

First of all, I would like to thank Allah the most gracious for helping me to complete this work. Then I would to thank my family, my advisor Dr. Mohab Mangoud for his support and patience, all academic and administrative staff of the department of Electrical and Electronics Engineering at the University of Bahrain and to all friends and colleagues for their support and encouragement.

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Table of Notations

AWGN	Additive White Gaussian Noise
CAF	Cyclic Autocorrelation Function
CDR	Constant Detection Rate
CER	Constant Efficiency Rate
CFAR	Constant False Alarm Rate
CR	Cognitive Radio
CSS	Cooperative Spectrum Sensing
CSD	Cyclic Spectral Density
FA	False Alarm
FC	Fusion Centre
LRT	Likelihood Rate Test
MD	Miss Detection
MDC	Modified Deflection Coefficient
PU	Primary User
ROC	Receiver Operating Characteristic
SDR	Software defined Radio
SNR	Signal to Noise Ratio
SU	Secondary User
WCER	Weighted Constant Efficiency Rate
WRAN	Wireless Regional Access Network

Chapter 1

Introduction

1.1. Definition of Cognitive Radio

1.2. Overview of Research

1.3. Contributions of This Work

1.4. Thesis Outline

Chapter 1

Introduction

The utilization of electromagnetic radio spectrum is one of the most recent challenges in modern communications. Almost the full spectrum is assigned to primary users while these users are not utilizing the assigned spectrum all the time. This situation motivates the need for a secondary user network which can operate in the non-operation time of the primary users. Software defined radios (SDRs) as discussed by Joseph Mitola III (1993) were introduced with the capability to be controlled with software. They were initially used in military applications before they were used in commercial applications. However, SDRs should be previously programmed to change functions and operations. This problem initiated the need to a cognitive system which can reconfigure itself according to the operating environment.

1.1 Definition of Cognitive Radio

In his doctoral thesis, Joseph Mitloa III (2000) defined cognitive radio technology as "the intersection of wireless technology and computational intelligence". He defined cognitive radio (CR) as " a really smart radio that would be self-aware, RF-aware, user-aware, and that would include language technology and machine vision along with a lot of high-fidelity knowledge of the radio environment".

Haykin (2005) defined the CR as "an intelligent wireless communication system that is aware of its surrounding environment, and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier frequency, and modulation strategy) in real-time, with two primary objectives in mind:

- highly reliable communications whenever and wherever needed .
- efficient utilization of the radio spectrum".

The U.S. Federal communications commission (FCC) (2005) has another definition "a cognitive radio (CR) is a radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interoperability, access secondary markets."

1.2 Overview of Research

Started with the work of Urkowitz (1967) in energy detection of unknown deterministic signals, energy detector became an effective way for spectrum sensing. with its simplicity, low cost and independence of prior knowledge of the detected signal. Kostylev (2000) discussed the performance of the energy detector over fading channels. Digham, Alouini, & Simon (2007) obtained expressions for the probability of detection over Rayleigh and Nakagami fading channels. The effect of user collaboration on the performance of sensing in fading channels was

investigated by Ghasemi & Sousa (2007). Ben Letaief & Zhang (2009) presented solutions to overcome hidden terminal problems under realistic scenarios where the reporting channels are subjects to fading and shadowing. Peh & Liang (2007) found that it is not necessary to cooperate all users in a cognitive network to achieve the optimum performance for a targeted probability of detection or a targeted probability of false alarm. Wang, Xiao, Zhou, & Wang (2007) studied the effect of the detection time on the channel efficiency.

From the knowledge of the above mentioned research efforts, the need of a new cooperative spectrum sensing method which targets a certain level of network efficiency and finding the optimal conditions to maximize the performance of the sensing network under different scenarios is realized and proposed in this thesis.

1.3 Contributions of This Work

The main contributions of this thesis are as follows:

Firstly, introduction of a novel cooperative spectrum sensing method to achieve a targeted efficiency rate which results in a constant throughput rate for a cognitive radio network. The maximum probability of detection under the new constrains can be achieved by the cooperation of a certain number of secondary users with highest received signal-to-noise levels out of total secondary network. The cooperation should be done using an optimal sensing window less than the allowable sensing window using AND & OR hard decision fusion rules. Under constraints of the constant spectral efficiency rate, the network performance was studied for different network sizes, targeted efficiency rates, total window lengths, and different received SNR levels.

Secondly, enhancement of the previously mentioned method using a soft decision weighted scheme where the weights were optimized using the optimization of the minimum deflection coefficient. The optimal sensing time for the weighted scheme was calculated. The performance of the weighted scheme was investigated using different network sizes, targeted efficiency rates, total window lengths, and received SNR levels.

1.4 Outline of Thesis

This thesis is organized as follows:

In **Chapter 1**, introduction, definition of cognitive radio, overview of the research, and contributions of the thesis are presented.

In **Chapter 2**, a survey of cooperative cognitive spectrum sensing is done. Starting with a brief introduction of the primary signal detection of a single threshold hypothesis test followed by an introduction of methods of spectrum sensing. Then, the classification of cooperative spectrum sensing topologies, cooperation models, data fusion, user selection methods, and reporting channels are discussed. Finally, spectral efficiency of the energy detector is investigated showing the direct relation between spectral efficiency and achieved throughput.

In **Chapter 3**, a brief review on the spectral efficiency of cooperative spectrum sensing is followed by the introduction of a novel cooperative spectrum sensing method. This method is providing a constant spectral efficiency rate (CER) for a network of secondary users at a total frame length. Applying multiple scenarios of different network sizes, efficiency rates, window lengths, and received signal-to-noise ratios (SNRs) is showing the optimal number of cooperating users and the

optimal sensing window length to get the maximum probability of detection of the network when AND & OR hard fusion rules are used.

In **Chapter 4**, a study of the spectral efficiency of the soft decision weighted cooperative spectrum sensing scheme is done. Then, constant efficiency constrains are applied to the same system model to get a weighted constant efficiency rate (WCER) cooperative spectrum sensing network. The optimal number of cooperative users and the optimal widow length to achieve the maximum probability of detection of the network are calculated. Followed by a comparison between WCER and hard decision CER using AND & OR fusion rules under different scenarios of network size, targeted efficiency, total window length, and received SNR levels.

In **Chapter 5**, a summary of results, conclusions and future work are presented.

Chapter 2

Survey of Cooperative Spectrum Sensing Techniques

2.1. Primary Signal Detection

2.2. Methods of Spectrum Sensing

2.3. Cooperative Spectrum Sensing

2.4. Sensing Spectral Efficiency

2.5. Conclusion

Chapter 2

Survey of Cooperative Spectrum Sensing Techniques

Spectrum sensing is one of the most important functions of cognitive radio technology. Starting with the binary hypothesis and basic definitions of spectrum sensing in section 2.1. Some spectrum sensing detectors are explained in section 2.2 with a special attention given to energy detector. In section 2.3, the classification of cooperative spectrum sensing, cooperation models, data fusion, user selection and reporting channels are briefly explained. Sensing spectral efficiency is discussed in section 2.4 showing the relation between efficiency and throughput. Finally, a conclusion of the survey is proposed in section 2.5.

2.1 Primary Signal Detection

As described by Yücek & Arslan (2009), a binary hypothesis test is performed at the SU to check the availability of the PU signal at the sample (n). This binary hypothesis can be represented as:

$$H_0(idle): x(n) = v(n) \tag{2.1}$$

$$H_1(busy): x(n) = h(n).s(n) + v(n) \tag{2.2}$$

for $n = 1,2,\dots,N$ where N is the total window length, x is the received signal by the SU, s is the PU signal, h is the channel gain and v is the sensing channel noise.

Under this binary hypothesis test, there are two types of errors. Type 1 error is named false alarm (FA) and it is defined as the declaration of an idle channel as busy which will stop the SU from transmitting even that the channel is free to use. Type 2 error is named miss detection (MD) and it is defined as the declaration of a busy channel as idle which will permit the SU to transmit while the channel is busy leading to interference between PU and SU. Probabilities of the two types of errors can be written as:

$$P_f = P(H_1|H_0) \tag{2.3}$$

$$P_m = P(H_0|H_1) \tag{2.4}$$

where P_f is the probability of false alarm and P_m is the probability of miss detection. A detection at the SU occur when a busy channel is detected. The probability of detection P_d can be written as:

$$P_d = 1 - P_m \tag{2.5}$$

The relation between all above mentioned probabilities can be summarized in a two dimension plot called the receiver operating characteristic (ROC) which is a plot of P_d versus P_f as shown in Fig. 2.1.

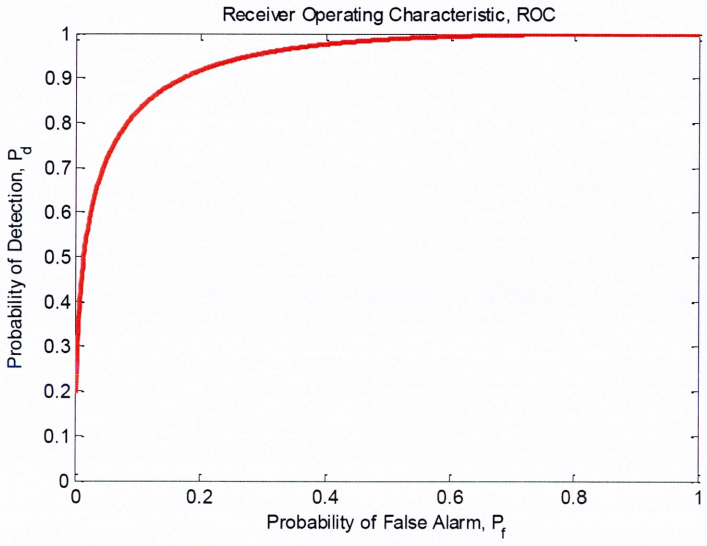


Fig. 2.1 Typical ROC P_d vs P_f for Energy Detector

2.2 Methods of Spectrum Sensing

To identify whether a PU signal is present or not, some spectrum sensing methods are used. In this section, a number of most common used detectors are discussed.

2.2.1 Energy Detector

Energy detector is the most popular detector used for spectrum sensing. Although there are some problems such as receiver uncertainty, the need of a long sensing window and poor results in detecting spread spectrum signals. The energy detector remains the first choice in spectrum sensing due to its low complexity and computational needs.

Urkowitz (1967) introduced the energy detector for unknown deterministic signals. The decision metric u of the energy detector is:

$$u = \frac{1}{N}\sum_{n=1}^{N}|x(n)|^2 \tag{2.6}$$

Where $x(n)$ is the received signal by the SU at sample n.

Under additive white Gaussian noise (AWGN) channel, the noise $v(n)$ can be considered as a zero mean Gaussian random variable with a variance of σ_v^2, and the PU is considered as a zero mean Gaussian random variable with a variance of σ_s^2. Assuming that the channel gain is time invariant, the decision metric should follow a chi-square distribution with 2N degrees of freedom (χ_{2N}^2). The decision metric is compared to a threshold λ so that the probabilities of detection and false alarm will be:

$$P_d = P(u > \lambda|H_1) \tag{2.7}$$

$$P_f = P(u > \lambda|H_0) \tag{2.8}$$

By the work of Gendenko & Kolmogorov (1954), central limit theorem states that for $N \geq 10$ The χ^2_{2N} distribution could be approximated by a Gaussian distribution with the following means under H_0 and H_1 respectively :

$$\mu_0 = \sigma_v^2 \tag{2.9}$$

$$\mu_1 = \sigma_s^2 + \sigma_v^2 \tag{2.10}$$

And the following variances under H_0 and H_1 respectively:

$$\sigma_0^2 = \frac{\sigma_v^4}{N} \tag{2.11}$$

$$\sigma_1^2 = \frac{\sigma_v^4}{N}(2\gamma + 1) \tag{2.12}$$

The probabilities of detection and false alarm will be:

$$P_d = Q\left(\left(\frac{\lambda}{\sigma_v^2} - 1\right)\sqrt{N}\right) \tag{2.13}$$

$$P_f = Q\left(\left(\frac{\lambda}{\sigma_v^2} - \gamma - 1\right)\sqrt{\frac{N}{2\gamma + 1}}\right) \tag{2.14}$$

Where $\gamma = \sigma_s^2/\sigma_v^2$ is the signal-to-noise ratio (SNR). Substituting 2.13 in 2.14 will produce a close form expression of P_f in terms of P_d, which can be written as:

$$P_f = Q\left(\sqrt{2\gamma + 1}Q^{-1}(P_d) + \gamma\sqrt{N}\right) \tag{2.15}$$

Reforming 2.15 to find P_d in terms of P_f will generate:

$$P_d = Q\left(\frac{Q^{-1}(P_f) - \gamma\sqrt{N}}{\sqrt{2\gamma + 1}}\right) \tag{2.16}$$

ROC of the energy detector can be easily generated using the previous forms, Fig. 2.3 is showing the ROC for an energy detector with

variable SNR values at a fixed window length while Fig. 2.4 is showing an ROC with variable window lengths at a fixed SNR value.

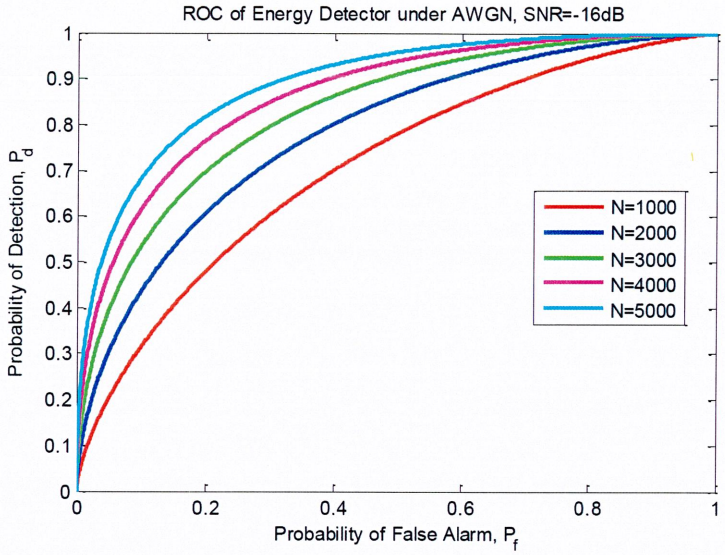


Fig. 2.2 ROC for Energy Detector under AWGN with Variable N

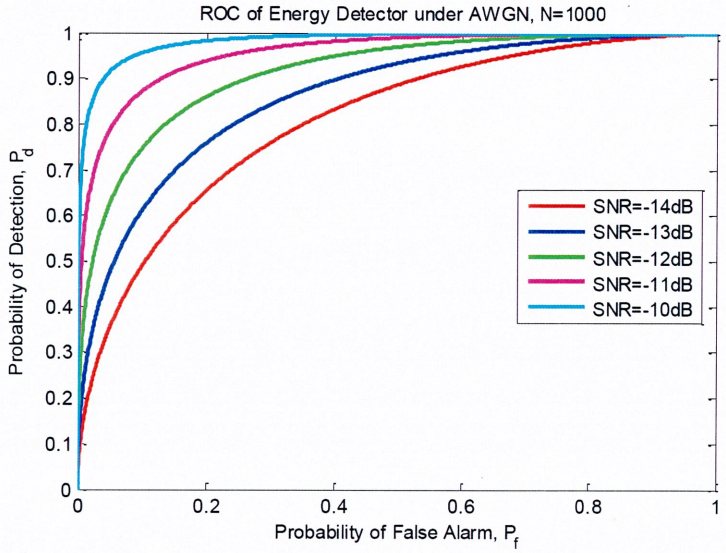


Fig. 2.3 ROC for Energy Detector under AWGN with variable SNR

Moving further with the energy detector, Kostylev (2000) discussed the performance of the energy detector over fading channels. The probabilities of detection over Rayleigh and Nakagami fading channels were introduced by Digham, Alouini, & Simon (2007). Weidling, Dalta, Petty, Krishnan, & Minden (2005) introduced an

iterative method to find the decision threshold. Sahai, Hoven, & Tandra (2004) found that a small noise power error will cause a significant performance loss and that the detection below a certain SNR level can be impossible due to the effects of noise uncertainty and quantization. Lehtomäki, Vartiainen, & Saarnisaari (2006) studied forwarding based on energy levels when the noise power assumed to be unknown and detecting primary signals over multiple frequency band was studied by Quan Z. , Cui, Sayed, & Vincent Poor (2009).

2.2.2 Cyclostationary Detector

Cabric, Mishra, & Brodersen (2004) characterize modulated signals as cyclostationary even though the transmitted data is a stationary random process because the use of cyclic prefix, sine wave carriers, pulse trains, hopping sequences or repeating spreading will give the signal its periodicity. The first works of the cyclostationary detector were introduced by Hurd (1969) and Gardner (1972).The test statistic of the cyclostationary detector was defined by Gardner (1991) as the cyclic spectral density function (CSD) which can be calculated from:

$$S(f,\alpha) = \sum_{\tau=-\infty}^{\infty} R_y^{\alpha}(\tau)\, e^{-j2\pi f\tau} \tag{2.17}$$

where $R_y^{\alpha}(\tau)$ is the cyclic autocorrelation function (CAF) and α is the cyclic frequency. The CAF could be calculated as:

$$R_y^{\alpha}(\tau) = E\left[y(n+\tau)y^*(n-\tau)e^{j2\pi\alpha n}\right] \tag{2.18}$$

The CSD function will reach its maximum value when the cyclic frequencies are equal to those from the transmitted signals. It is shown that the CSD function does not depend on noise variance, this will avoid the cyclostationary detector from having a minimum SNR for operation.

2.2.3 Matched Filter Detector

Kay (1998) and Proakis (2001) showed that the matched filter detector is the optimal detector when the transmitted primary signal is known. The test statistic for the matched filter detector is calculated as:

$$u = \frac{1}{N}\sum_{n=1}^{N} x(n)\, s^*(n) \tag{2.19}$$

The matched filter detector needs short time to achieve certain (P_d) or (P_f) compared to the energy detector as proposed by Tandra & Sahai (2005) where the required number of samples in low SNR environments is growing by a factor of $(1/SNR)$ which is much better than $(1/SNR^2)$ achieved by the energy detector.

2.2.4 Waveform Based Detector

To detect previously known primary signals, the waveform based detector was introduced by Tang (2005) showing better and faster performance than energy detector. The decision metric is calculated as:

$$u = Re\left[\sum_{n=1}^{N} x(n)\, s^*(n)\right] \tag{2.19}$$

Tang (2005) also showed that the performance of the waveform based detector will increase as the signal length increase. Cabric, Mishra, & Brodersen (2006) showed that the effect of synchronization errors on the waveform based detector is one of the challenges facing this detector even though the simulation proved that the waveform based detector required short time for detecting primary signals.

2.2.5 Wavelet Detector

The idea of the wavelet detector introduced by Tian & Giannakis (2006) is to divide the entire desired sensing range into sub-bands and perform wavelet transform on each sub-band. The power spectral density of each sub-band is searched to find edges representing the transmission between idle and busy channels. However, the wavelet detector may require high sampling rates since it is aiming to detect wideband signals.

2.2.6 Eigenvalue based detector

Zeng & Liang (2007) showed that the eigenvalues of the covariance matrix of the received signal is used to detect the presence of the primary signal by using the ratio of the maximum eigenvalue to the minimum eigenvalue. The quantization of the ratio is used to find the threshold using random matrix theory (RMT) explained by Tulino & Verdú (2004) which is also used to find (P_f). The eigenvalue based detector can overcome the noise uncertainty problem and does not need a previous knowledge of the primary signal. Maximum eigenvalue detection was proposed by Zeng, Koh, & Liang (2008) and condition number detection was introduced by Zeng & Liang (2009).

2.2.7 Statistical Covariance Based Detector

The sample covariance matrix generated from a number of received signal samples was used to detect the presence of the primary signal by Zeng & Liang (2009) where two test statistics are generated from the sample covariance matrix and the decision is made by comparing them. The statistical covariance based detector does not need previous knowledge of the primary signal or synchronization.

2.2.8 Radio Identification Based Detector

Using a previous information of the primary signal, a radio identification based detector was introduced by Yücek & Arslan (2006) where matching the received signals with the primary signal information is used to identify the presence of the primary signal.

2.2.9 Multiple Antenna Detector

Pandharipande & Linnartz (2007) proved that a significant improvement in the performance of the energy detector is achieved when multiple antennas are used in the SU. Liang, Pan, & Zeng (2010) discussed the performance of multiple antenna spectrum on eigenvalue based sensing. Furthermore, generalized likelihood ratio detector with multiple antenna introduced by Taherpour, Nasiri-Kenari, & Gazor (2009) outperforms energy detector. Mahapatra & Krusheel (2008) showed that the maximum rate combining based cyclostationary detector performance improved when multi receivers are used. Improvement using multiple decision result fusion method and comparison detection method along with maximum rate combining are done by Zhang, Yu, & Sun (2009).

2.3 Cooperative Spectrum Sensing

Cooperative spectrum sensing is targeting the improvement of sensing performance by sharing sensing information to make a combined decision which is more accurate than individual decisions. This improvement caused by spatial diversity is called cooperative gain. Ghasemi & Sousa (2005) proved that cooperation is improving the sensing performance significantly when the SU network is operating in

fading or shadowing environments. Mishra, Sahai, & Brodersen (2006) showed that even a few number of cooperative users facing independent fades are able to achieve practical threshold levels. It was also proved that cooperative gain is sensitive to failing radios and this can be compensated by ignoring their results.

Fig. 2.5 is showing how cooperative gain increases the individual threshold to get better sensing performance. Cabric, Mishra, & Brodersen (2004) had three questions regarding cooperative spectrum sensing:

- How much can be gained from cooperation?
- How can cognitive radio cooperate?
- What is the overhead associated with cooperation?

The topics surrounded by the above mentioned questions (cooperation method, gain, and overhead) are the key topics in cooperative spectrum sensing and they are involved in any cooperative sensing scheme.

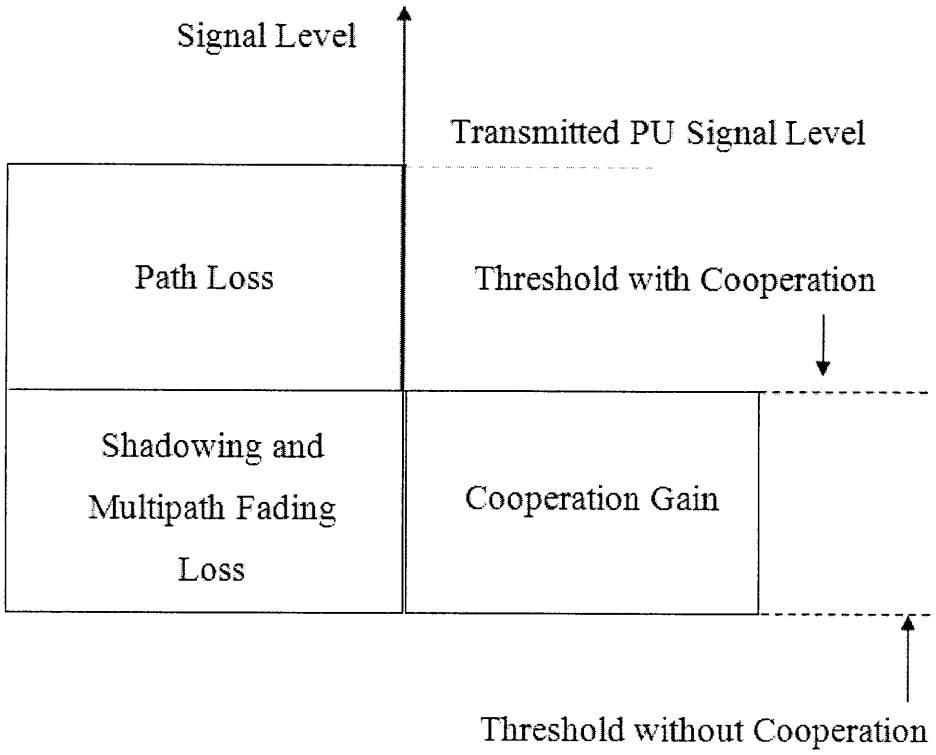


Fig. 2.4 Threshold Improvement with Cooperative Sensing

2.3.1 Classification of Cooperative Spectrum Sensing

Akyildiz, Lo, & Balakrishnan (2011) showed that cooperative spectrum sensing can be classified based on how the SU are sensing data in the cognitive network. Each type will be discussed briefly.

2.3.1.1 Centralized Cooperative Sensing

In centralized sensing as shown in Fig. 2.6, the fusion centre (FC) assign a frequency band for all users to perform sensing individually. The FC receives the individual sensing results via the reporting channel then orders all SU to perform the task based on the sensing decision made in it as proposed by Visotsky, Kuffner, & Peterson (2005) and Unnikrishnan & Veeravalli (2008).

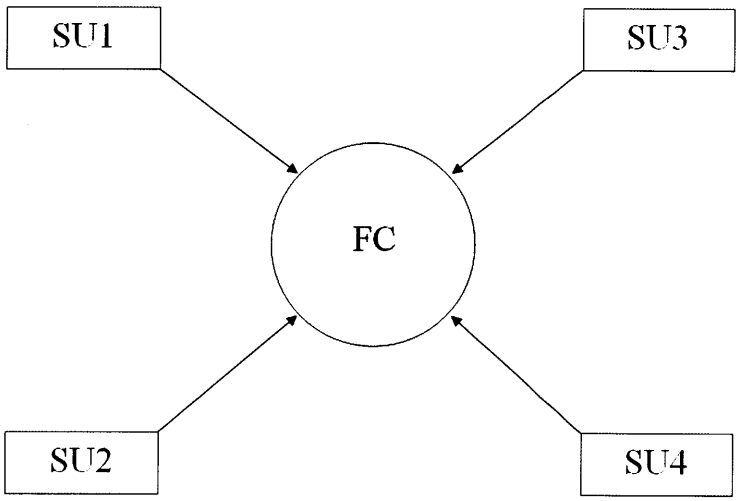


Fig. 2.5 Centralized Cooperative Spectrum Sensing

2.3.1.2 Distributed Cooperative Sensing

In distributed cooperative sensing as proposed by Li, Yu, & Huang (2009), SU network share the local sensing results and decide whether the primary signal is present or not. As shown in Fig. 2.7, no FC is needed in distributed cooperative sensing. Until the sensing criteria is met, several

iteration may be necessary to achieve a network decision which can slow down the sensing process.

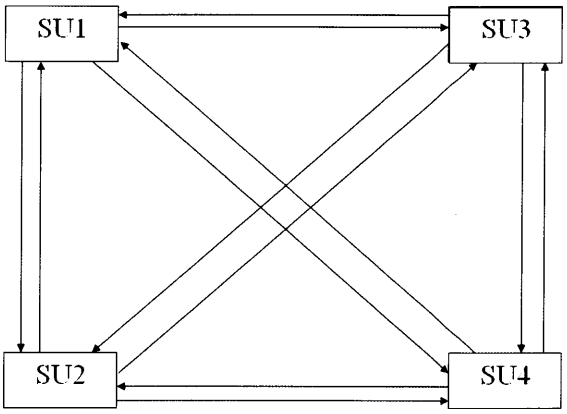


Fig. 2.6 Distributed Cooperative Sensing

2.3.1.3 Relay-Assisted Cooperative Sensing

Relay-assisted cooperative sensing as proposed by Ben Letaief & Zhang (2009) is useful when some SUs have weak reporting channels, they can send their sensing results through other SUs having strong reporting channels as shown in Fig. 2.8 where SU2 and SU3 have weak reporting channels. Both are sending their sensing results to SU4 which forwards both relayed sensing results along with its own result to the FC.

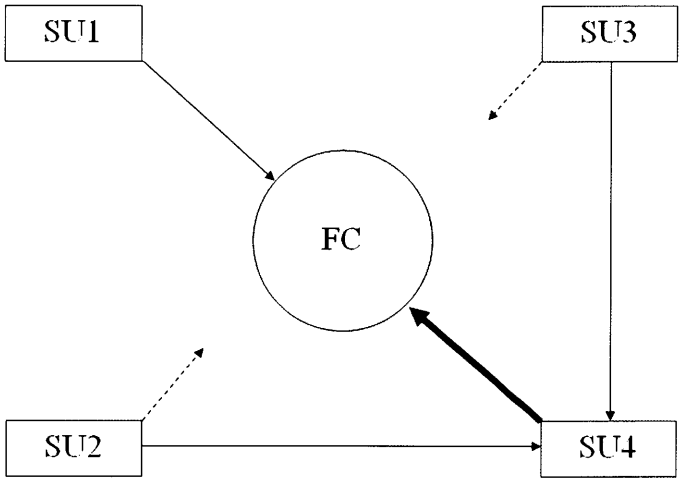


Fig. 2.7 Relay-Assisted Cooperative Sensing

2.3.2 Cooperation Models

Cooperative spectrum sensing is achieved by cooperation of SUs to achieve optimal performance. The most popular models of cooperation are the parallel model and the game theoretical model.

2.3.2.1 Parallel Model

Viswanathan & Varshney (1997) defined the parallel cooperation model as a cooperation model formed from a group of sensors observing a physical phenomenon, then reporting their observations individually to the FC which issues the cooperative decision to all sensors. Parallel cooperation model as shown in Fig 2.9 can be considered as the most popular model used in cooperative spectrum sensing as proposed by Visser, Janssen, & Paweczak (2008) and Zhang, K. Mallik, & Ben Letaief (2008).

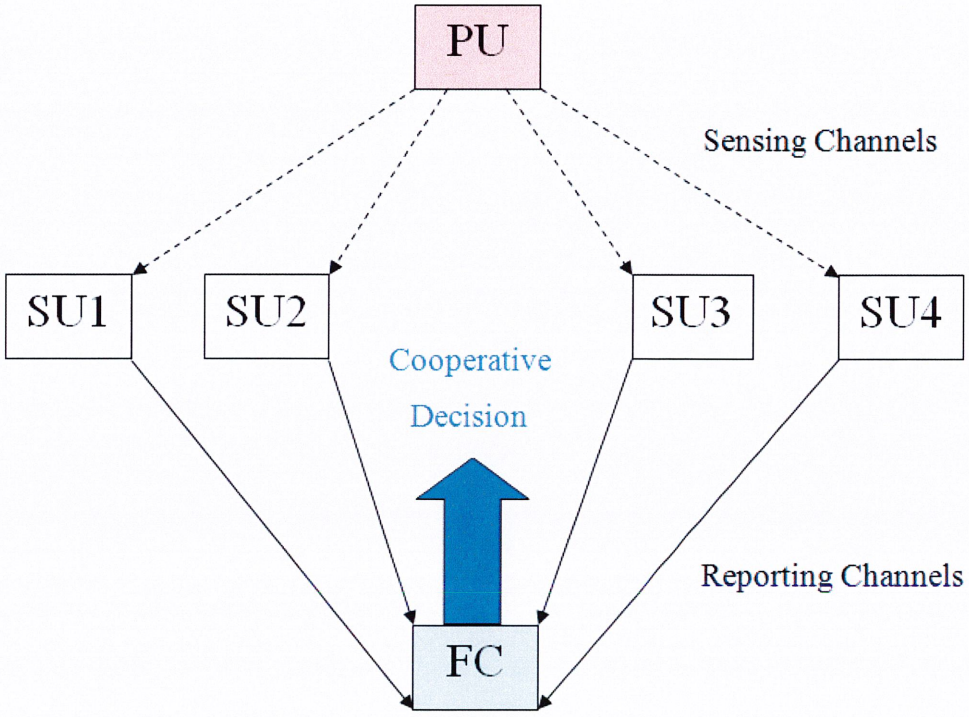


Fig. 2.8 Parallel Model

2.3.2.2 Game Theoretical Model

Based on game theory introduced by Myerson (1991), cooperative sensing is modelled as game with a set of players (SUs). Games can be classified into two major types. The first type is called evolutionary game as proposed by Wang, Ray Liu, & Clancy (2010) where the SU can select freely between working individually or cooperating with other users. The second type is called coalitional game where the SUs form groups called coalitions so that the coalition head (CH) will receive the sensing results from the coalition SUs as discussed by Saad, Han, Debbah, Hjorungnes, & Basar (2009) and shown in Fig. 2.10.

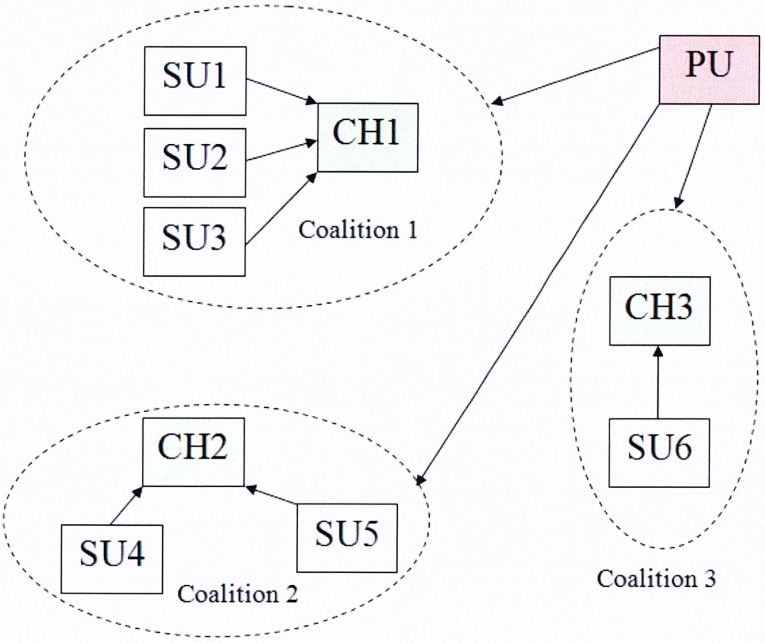


Fig. 2.9 Coalitional Game Theoretical Model

2.3.3 Data Fusion

Akyildiz, Lo, & Balakrishnan (2011) defined data fusion as the process of combining local sensing data for hypothesis testing. and classified it into three types: hard combining, soft combining, and quantized soft combining.

2.3.3.1 Hard Combining

In hard combining, SUs send their one-bit sensing decisions to the FC. There are several types of hard combining fusion rules. The general equation to find (P_d) and (P_f) for the cooperation of (k) SUs in a network with size (M) is given by:

$$P_d = \sum_{i=k}^{M} \binom{M}{i} P_{d,i}^{i} \left(1 - P_{d,i}\right)^{M-i} \tag{2.20}$$

$$P_f = \sum_{i=k}^{M} \binom{M}{i} P_{f,i}^{i} \left(1 - P_{f,i}\right)^{M-i} \tag{2.21}$$

Where $P_{d,i}$ is the probability of detection at the ith user, and $P_{f,i}$ is the probability of false alarm at the ith user. In AND fusion rule, the FC will decide the PU signal is present when all users are deciding that the channel is busy $(i = 1)$. In OR fusion rule, the FC will decide that the PU signal is present when any SU decides that the channel is busy $(i = M)$.

2.3.3.2 Soft Combining

In soft combining fusion rules, the complete individual sensing samples are sent to the FC. A good example on soft decision was introduced by Quan, Cui, & Sayed (2008) as a weighted scheme. Based on the targeted (P_d) or (P_f), the optimized weights are applied to the local test statistics to improve the SU network performance. Xiao, Liu, & Ma (2010) introduced a weighted scheme where the weights were calculated from the received SNRs.

2.3.3.3 Quantized Soft Combining

In this type of fusion, SUs send the quantized data from the sensing results to the FC. Ma, Zhao, & Li (2008) divided the test statistic region into four regions using three thresholds. The quantized two-bit data is sent from each SU to the FC. Other examples for quantized soft decision were proposed by Mustonen, Matinmikko, & Mammela (2009) and Tani & Saba (2010).

2.3.4 User Selection

Cooperative gain is affected by the selection of cooperative users since the sensing results are varying. A good selection of cooperative users will results in a better network performance. User selection methods can be summarized in centralized selection and cluster-based selection.

2.3.4.1 Centralized User Selection

This type of user selection is mainly done in the FC. Peh & Liang (2007) assumed that the FC is selecting an optimal number of users with best received SNR values to maximize the network performance. Selen, Tullberg, & Kronander (2008) proposed three selection methods based on shadow correlation among SUs.

2.3.4.2 Cluster-Based Selection

Malady & da Silva (2008) proposed several methods of clustering as follows:

- Random clustering: SUs are clustered in equal-sized clusters randomly.

- Reference-based clustering: SUs are clustered in reference to the distance to a given point.
- Statistical clustering: SUs are clustered using their statistical information and proximities.
- Distance-based clustering: SUs are clustered based on their distance to the PU signal source.

Wei & Zhang (2010) showed that the proposed cluster-and-forward scheme has an optimal number of clusters for each cluster size.

2.3.5 Reporting Channel

As discussed by Lo, Akyildiz, & Al-Dhelaan (2010), the FC receives sensing results from the SUs through a control channel which can be also used to share the sensing results between SUs in distributed or relay-assisted networks. The reporting channel is subject to different fading scenarios such as AWGN studied by Quan, Cui, & Sayed (2008), correlated log-normal shadowing studied by Di Renzo, Imbriglio, Graziosi, & Santucci (2009), Rayleigh fading investigated by Zhou, Li, Li, Wang, & Soong (2010), and multipath fading investigated by Zhang & Ben Letaief (2008).

2.4 Sensing Spectral Efficiency

From the work of Wang, Xiao, Zhou, & Wang (2007), Kattepur, Hoang, Liang, & Er (2007) and as discussed by Wyglinski, Nekovee, & Hou (2010), the spectral efficiency of spectrum sensing at the window length (n) could be defined as:

$$\eta(n) = \frac{N-n}{N}(1-P_f) \tag{2.22}$$

So that: $1 \leq n \leq N$; $0 \leq P_f \leq 1$; $0 \leq \eta \leq 1$. Substituting equation 2.15 into equation 2.22 to get a closed form for the efficiency of the energy detector in terms of (P_d) will generate:

$$\eta(n) = \frac{N-n}{N}\left(1 - \left(Q\left(\sqrt{2\gamma+1}Q^{-1}(P_d) + \gamma\sqrt{n}\right)\right)\right) \tag{2.23}$$

Fig. 2.11 and Fig 2.12 are showing the changing of the (η) with the variation in SNR, sensing window length (n), and the targeted (P_d). Using the SNR values of -20dB, -15dB, -10dB, -5dB, 0dB and 5dB, targeting 0.9 and 0.99 detection rates on a sensing window up to 10000 samples is showing that a higher SNR will cause a higher (η) at a lower (n) and targeting a higher (P_d) will require a larger (n) and will result in a lower (η) at the same SNR value.

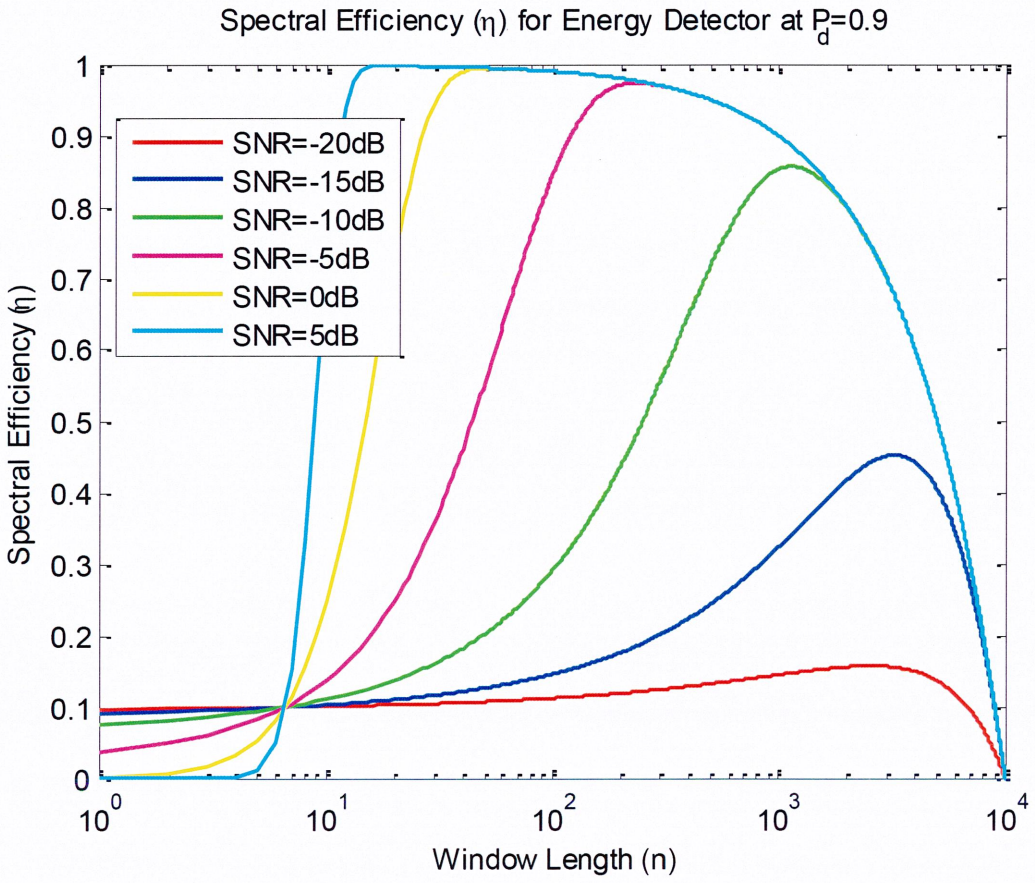


Fig. 2.10 Spectral Efficiency for Energy Detector at P_d =0.9

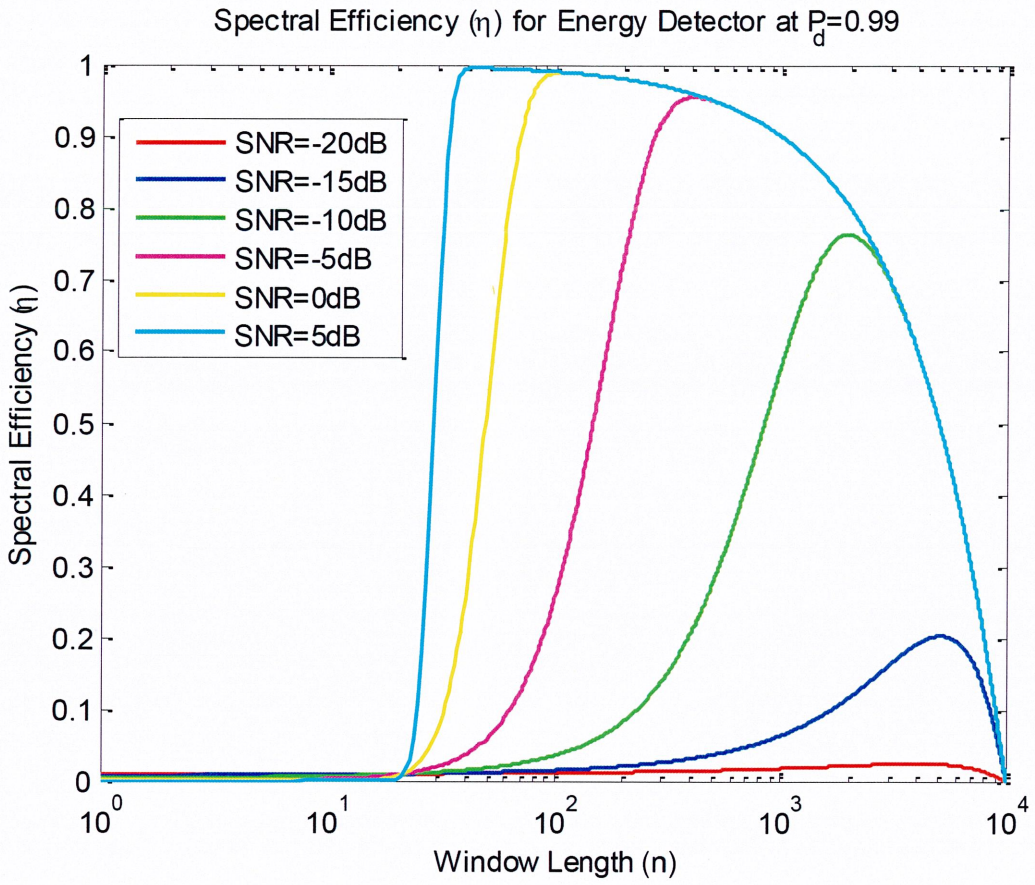


Fig. 2.11 Spectral Efficiency for Energy Detector at P_d =0.99

Spectral efficiency is directly related to the throughput in a total frame time (T_f) by the sampling time (T_s).

$$T_f = NT_s \tag{2.23}$$

In time domain, the achieved throughput using a sensing time (t) out of a total frame time (T_f) can be written as:

$$R(t) = \frac{T_f - t}{T_f}(1 - P_f) \tag{2.24}$$

2.5 Conclusion

The chapter starts with a brief explanation on the primary signal detection using a single threshold binary hypothesis followed by a brief survey about different types of detectors used in spectrum sensing.

Moving to the cooperative spectrum sensing (CSS) which can be classified into centralized, distributed and relay assisted. It was also explained that the most popular CSS models are parallel and game theoretical model while data fusion can be classified into hard, soft and quantized soft combining fusion rules. User selection in CSS can be centralized or clustered and the reporting channel could be affected with several types of noise. Focusing on the popular energy detector, spectral efficiency which is directly related to the achieved throughput is studied in section 2.4.

Chapter 3

Constant Efficiency Rate Cooperative Spectrum Sensing

3.1. System Model

3.2. Cooperative Efficiency using Hard Fusion Rules

3.3. Constant Efficiency Rate using Hard Fusion Rules

3.4. Numerical Results and Analysis

3.5. Conclusion

Chapter 3

Constant Spectral Efficiency Rate Cooperative Spectrum Sensing

Cooperative spectrum sensing is used to overcome many problems facing the individual sensing as discussed in the previous chapter. Peh & Liang (2007) showed that there is an optimal number of cooperated users less than the total network size which gives the best performance of a secondary network using AND & OR hard decision fusion rules. Wang, Xiao, Zhou, & Wang (2007) showed that there is an optimal detection window less than the total window to achieve maximum network efficiency. This chapter starts with a brief view of the used system model in section 3.1. Works of both above mentioned papers are merged targeting a previously defined detection rate in section 3.2. In section 3.3, changing the target from the achievement of a certain detection rate to the achievement of a certain efficiency rate will result in a new optimization problem which has its new constrains. The novel cooperative spectrum sensing method used to solve this problem will be named constant efficiency rate (CER). Finding the optimal numbers of cooperative users and window length for the network will be discussed in section 3.4 along with the investigation of the effect of some key parameters in spectrum sensing on the detection performance of the SU network including network size, targeted efficiency rate, total window length, received SNR levels. Finally, the chapter will be summarized and concluded in section 3.5.

3.1 System Model

Based on IEEE 802.22 WRAN (2014), and as illustrated in Fig. 3.1 where (M) SUs are randomly distributed around the FC of the SU network. All distances between the SUs and the PU should be known for the FC. The received power at each SU can be calculated by:

$$P_{r,i} = \frac{P_{pu}}{d_i^{\alpha}}\beta \tag{3.1}$$

where $P_{r,i}$ is the received power by the ith SU, P_{pu} is the transmitted power by the PU, d_i is the distance between the PU and the ith SU, α is the path loss exponent and β is a scalar. The received SNR at the ith SU can be obtained from:

$$\gamma_i = 10\log\frac{P_{r,i}}{\sigma_i} \tag{3.2}$$

for $1 \leq i \leq M$. Where σ_i is the sensing channel noise for the ith SU.

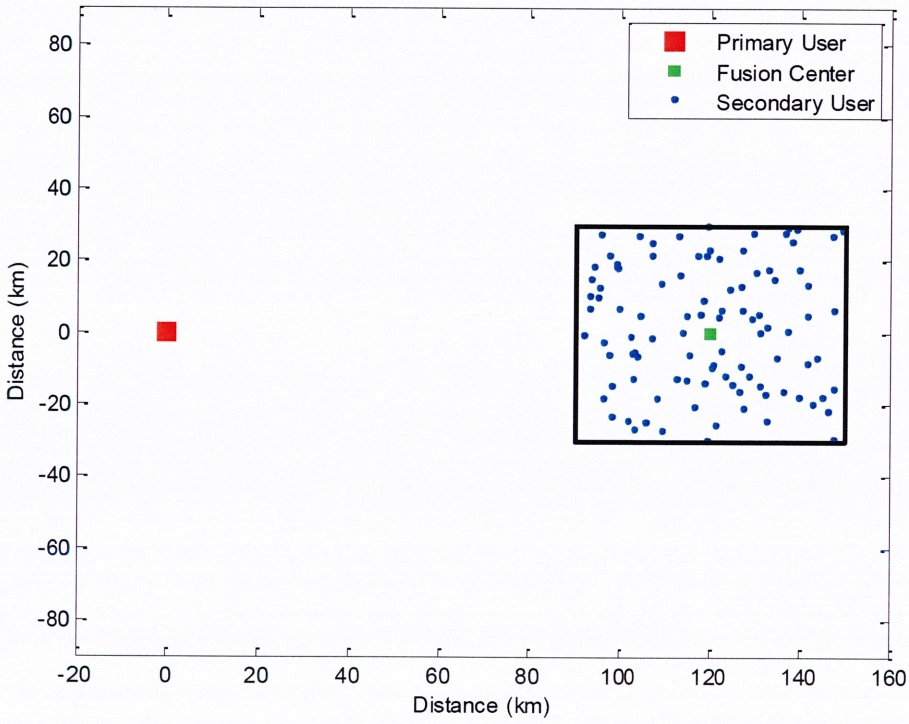


Fig. 3.1 Simulation scenario for M=100

3.2 Cooperative Spectral Efficiency Using Hard Fusion Rules

In CSS, the spectral efficiency has optimal values of number of cooperative users (k) and sensing window length (n) when the SU network is targeting a certain P_d as proposed by Rashid, et al. (2012) and Sun, et al. (2013). In this section, the spectral efficiency of cooperative SU networks using AND & OR fusion rules will be discussed.

3.2.1 Network Spectral Efficiency Using AND Fusion Rule

AND fusion rule states that when all network users detects the primary signal, the FC will state that the PU is present. Mathematically, the probabilities of detection and false alarm for AND networks can be written as:

$$P_{d,AND} = \prod_{i=1}^{k} P_{d,i} \tag{3.3}$$

$$P_{f,AND} = \prod_{i=1}^{k} P_{f,i} \tag{3.4}$$

The P_d of the AND network can be approximated as:

$$P_{d,AND} = P_{d,i}^{k} \tag{3.5}$$

So that the individual detection rate will be approximated as:

$$P_{d,i,AND} = \sqrt[k]{P_{d,AND}} \tag{3.6}$$

When AND hard fusion rule is used in a network of size (M) and a sensing window length of (n), the probability of false alarm for each SU $P_{f,i}$ at the cooperation of k SUs can be calculated as:

$$P_{f,i,AND}(k,n) = Q\left(\sqrt{2\gamma_i + 1}Q^{-1}\left(\sqrt[k]{P_{d,AND}}\right) + \gamma_i\sqrt{n}\right) \tag{3.7}$$

And the network P_f is calculated by:

$$P_{f,AND}(k,n) = \prod_{i=1}^{k} Q\left(\sqrt{2\gamma_i + 1}\,Q^{-1}\left(\sqrt[k]{P_{d,AND}}\right) + \gamma_i\sqrt{n}\right) \tag{3.8}$$

For $1 \leq n \leq N; 1 \leq k \leq M$. Substituting 3.8 into 2.22 will generate a closed form for η of AND network in terms of k and n as the following:

$$\eta_{AND}(k,n) = \frac{N-n}{N}\left(1 - \prod_{i=1}^{k}\left(Q\left(\sqrt{2\gamma_i + 1}\,Q^{-1}\left(\sqrt[k]{P_d}\right) + \gamma_i\sqrt{n}\right)\right)\right) \tag{3.9}$$

Fig. 3.2 is showing that the maximum efficiency of AND network could be achieved by the cooperation of an optimal number of SUs at an optimal sensing window length. Fig. 3.3 is showing that the maximum performance of the AND network could be achieved by the cooperation of an optimal number of SUs using the maximum sensing window. Comparing Fig. 3.2 and Fig 3.3 is showing that the optimal number of cooperative users is not necessarily the same in both cases.

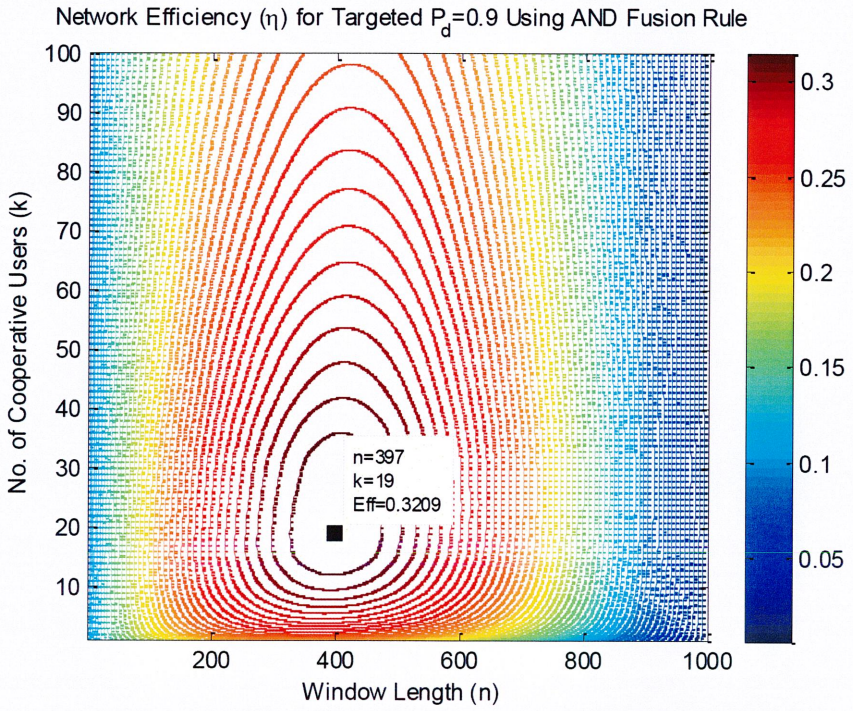


Fig. 3.2 AND η for P_d=0.9, M=100, N=1000, $P_{f\_opt\eta}$= 0.468

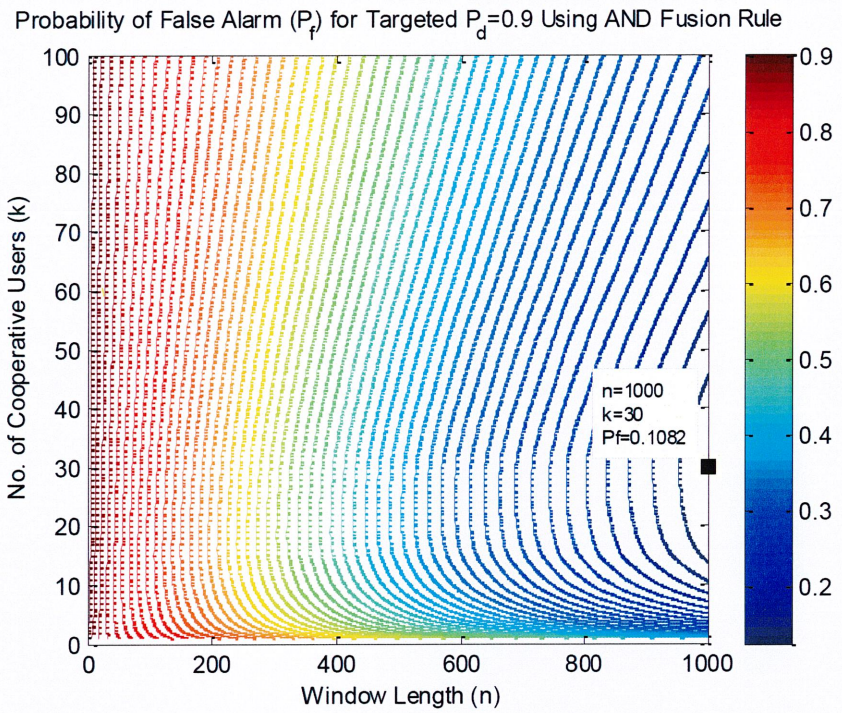


Fig. 3.3 AND P_f for P_d=0.9, M=100, N=1000, η=0

3.2.2 Network Spectral Efficiency Using OR Fusion Rule

OR fusion rule states that when at least one of the network users detects the primary signal, the FC will state that the PU is present. The (P_d) and (P_f) for OR networks can be written as:

$$P_{d,OR} = 1 - \prod_{i=1}^{k}(1 - P_{d,i}) \tag{3.10}$$

$$P_{f,OR} = 1 - \prod_{i=1}^{k}(1 - P_{f,i}) \tag{3.11}$$

The (P_d) of the OR network is approximated as:

$$P_{d,OR} = 1 - (1 - P_{d,i})^k \tag{3.12}$$

So that the individual detection rate can be approximated as:

$$P_{d,i,OR} = 1 - \sqrt[k]{(1 - P_{d,OR})} \tag{3.13}$$

When OR fusion rule is used, the P_f of the ith user in a cooperation of (k) SUs at a window length (n) of can be calculated by:

$$P_{f,i,OR}(k,n) = Q\left(\sqrt{2\gamma_i + 1}Q^{-1}\left(1 - \sqrt[k]{1 - P_d}\right) + \gamma_i\sqrt{n}\right) \quad (3.14)$$

And the network P_f is calculated by:

$$P_{f,OR}(k,n) = 1 - \prod_{i=1}^{k}\left(1 - Q\left(\sqrt{2\gamma_i + 1}Q^{-1}\left(1 - \sqrt[k]{1 - P_d}\right) + \gamma_i\sqrt{n}\right)\right) \quad (3.15)$$

For $1 \leq n \leq N; 1 \leq k \leq M$. Substituting equation 3.15 into equation 2.22 will generate the closed form of spectral efficiency

$$\eta_{OR}(k,n) = \frac{N-n}{N}\left(\prod_{i=1}^{k}\left(1 - Q\left(\sqrt{2\gamma_i + 1}Q^{-1}\left(1 - \sqrt[k]{1 - P_{d,OR}}\right) + \gamma_i\sqrt{n}\right)\right)\right) \quad (3.16)$$

The maximum efficiency of OR network is achieved by cooperating an optimal number of users at an optimal window length as shown in Fig. 3.4. Under the same conditions, the maximum efficiency of OR network is better than the maximum efficiency of AND network. Fig. 3.5 is showing the performance of the OR network under the variation of number of cooperative users and window length. The maximum performance is achieved through cooperating an optimal number of users at the maximum window length. Outperforming AND network under same simulation parameters, it is also not necessary to a unique optimal number of users for maximizing performance and efficiency.

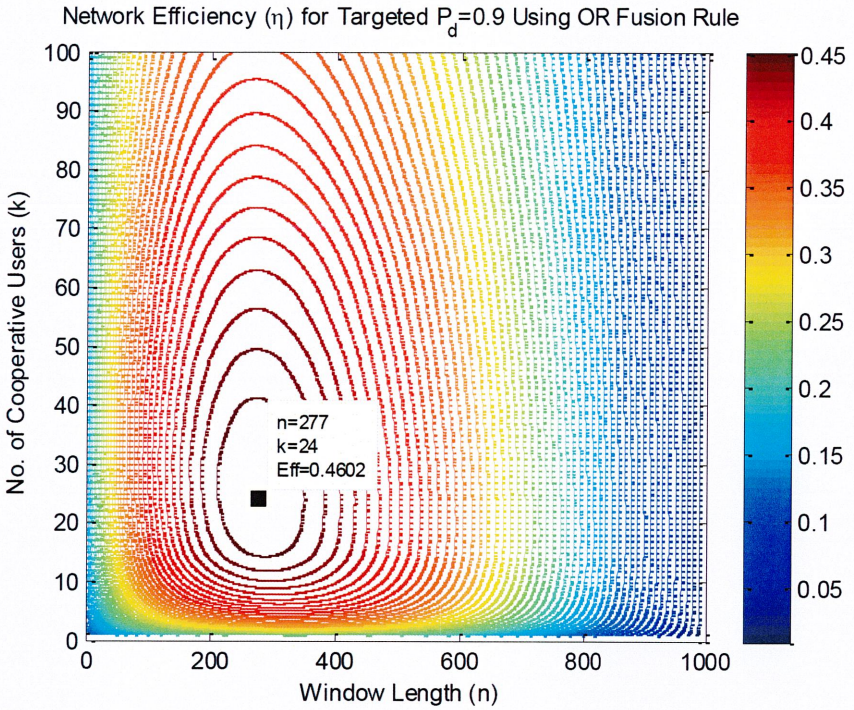


Fig. 3.4 OR η for P_d=0.9, M=100, N=1000, $P_{f\_opt}\eta$= 0.363

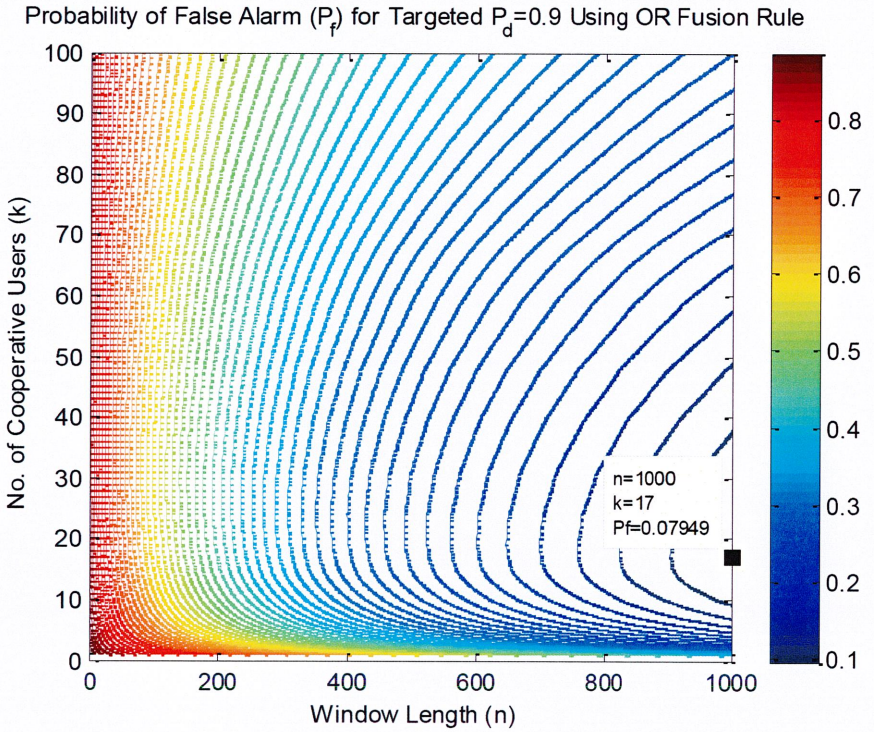


Fig. 3.5 OR P_f for P_d=0.9, M=100, N=1000, η =0

What can be concluded from the previous simulations is that the maximum performance of the network needs an optimal number of highest SNR users (k_{opt,P_f}) and the full window (N) to perform sensing. To achieve the maximum network efficiency, an optimal number of cooperative users ($k_{opt,eff}$) and an optimal window length (n_{opt}) should be used. The optimal conditions are changing as the network size, received SNRs values, targeted (P_d), fusion rule, and window length are changing. This will cause a sensing-throughput tradeoff as explained by Peh, Liang, Guan, & Zeng (2009).

3.3 Constant Efficiency Rate Cooperative Spectrum Sensing

Assumed that the new constraint of sensing will be fixing the efficiency/throughput of the networks, targeting a constant efficiency will reform equation 2.22 into :

$$P_f(\eta, n) = 1 - \frac{N\eta}{N - n} \tag{3.17}$$

Since equation 3.17 have two constrains: $0 \leq P_f \leq 1$ and $0 \leq \eta \leq 1$, These constrains will create a new higher bound of (n) which is the highest allowable window length to achieve the targeted efficiency rate $N_{det}(\eta)$ and it can be calculated by:

$$N_{det}(\eta) = N(1 - \eta) \tag{3.18}$$

3.3.1 Constant Efficiency Rate using AND fusion Rule

The probabilities of false alarms in the AND network can be approximated as:

$$P_{f,AND}(\eta, n) = P_{f,i}^{k} = 1 - \frac{N\eta}{N-n} \tag{3.19}$$

$$P_{f,i}(\eta, k, n) = \sqrt[k]{P_{f,AND}(\eta, n)} = \sqrt[k]{1 - \frac{N\eta}{N-n}} \tag{3.20}$$

The (P_d) for ith SU within an AND cooperation of (k) SUs can be calculated by:

$$P_{d,i,AND}(\eta, k, n) = Q\left(\frac{Q^{-1}\left(\sqrt[k]{1 - \frac{N\eta}{N-n}}\right) - \gamma_i\sqrt{n}}{\sqrt{2\gamma_i + 1}}\right) \tag{3.21}$$

And the probability of detection for the AND-cooperation of (k) users will be:

$$P_{d,AND}(\eta, k, n) = \prod_{i=1}^{k} Q\left(\frac{Q^{-1}\left(\sqrt[k]{1 - \frac{N\eta}{N-n}}\right) - \gamma_i\sqrt{n}}{\sqrt{2\gamma_i + 1}}\right) \tag{3.22}$$

Where $1 \leq i \leq k; 1 \leq k \leq M; 1 \leq n \leq N_{det}$.

3.3.2 Constant Efficiency Rate using OR Fusion Rule

The probabilities of false alarm in the OR network are:

$$P_{f,OR}(\eta, n) = 1 - \left(1 - P_{f,i}\right)^{k} = 1 - \frac{N\eta}{N-n} \tag{3.23}$$

$$P_{f,i,OR}(\eta, k, n) = 1 - \sqrt[k]{\left(1 - P_{f,OR}(\eta, n)\right)} = 1 - \sqrt[k]{\frac{N\eta}{N-n}} \tag{3.24}$$

The (P_d) for the ith SU in a cooperation of (k) SUs at a frame length (n) using OR fusion rule can be written as:

$$P_{d,i,OR}(\eta,k,n) = Q\left(\frac{Q^{-1}\left(1-\sqrt[k]{\frac{N\eta}{N-n}}\right)-\gamma_i\sqrt{n}}{\sqrt{2\gamma_i+1}}\right) \tag{3.25}$$

And the (P_d) for the OR cooperation of k users is:

$$P_{d,OR}(\eta,k,n) = 1-\prod_{i=1}^{k} Q\left(\frac{Q^{-1}\left(1-\sqrt[k]{\frac{N\eta}{N-n}}\right)-\gamma_i\sqrt{n}}{\sqrt{2\gamma_i+1}}\right) \tag{3.26}$$

Where $1 \le i \le k; 1 \le k \le M; 1 \le n \le N_{det}$.

3.4 Numerical Results and Analysis

The simulation scenario is assuming that the received SNR at the location of FC is -10dB, the PU is 120 km away from the FC which considered to be placed at the center of the SU network. The SU network is randomly distributed in a 900 km² square around the FC, the path loss exponent is 3.2, the total window length is set to be 1000 and the targeted efficiency rate is assumed to be 0.9. The results shows the average of 20 random network distributions.

3.4.1 Constant Efficiency Rate Using AND Fusion Rule

Starting with AND fusion rule to optimize the network performance under CER constrains. It should be known that AND fusion rule states that the SU network will declare the PU as present when all SUs agree to do so. The sensing results will be affected significantly and negatively by SUs receiving low SNRs.

Fig. 3.6, Fig. 3.7, Fig. 3.8, Fig 3.9, Fig. 3.10, Fig. 3.11, Fig. 3.12, and Fig. 3.13 are showing the performance of the SU network when AND rule is used in the FC and the network size (M) is varying from 25 to 200. All figures are showing that for each (M) an optimal number of cooperative users (k_{opt}) which is less than the (M) should cooperate at an optimal window length (n_{opt}) which is less than the allowable detection window under constant efficiency constrains (N_{det}) to achieve the maximum performance. both optimal values are increasing as (M) increases as well as the SU network performance.

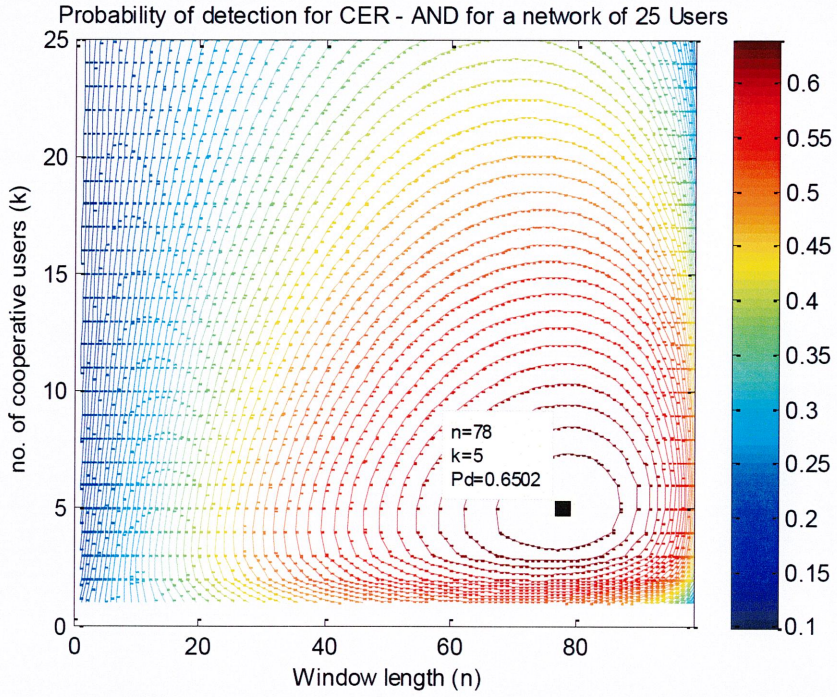


Fig. 3.6 P_d for CER-AND, M=25, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt\eta}$= 0.024

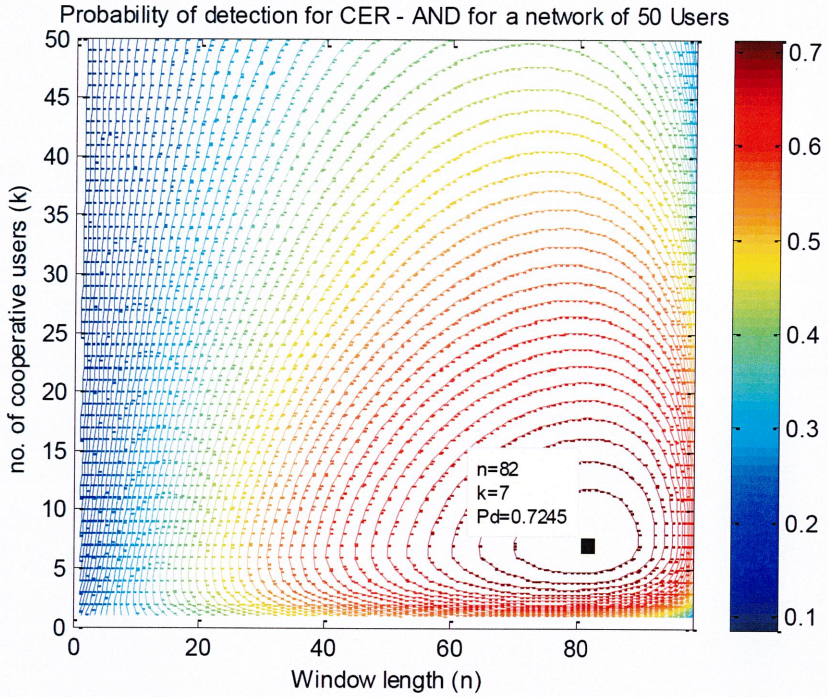


Fig. 3.7 P_d for CER-AND, M=50, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.02

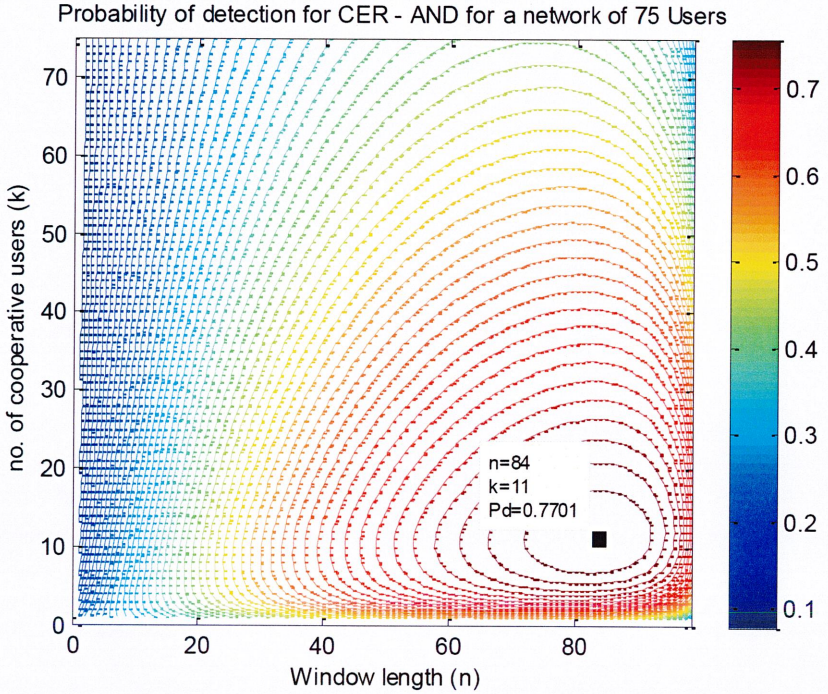


Fig. 3.8 P_d for CER-AND, M=75, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.017

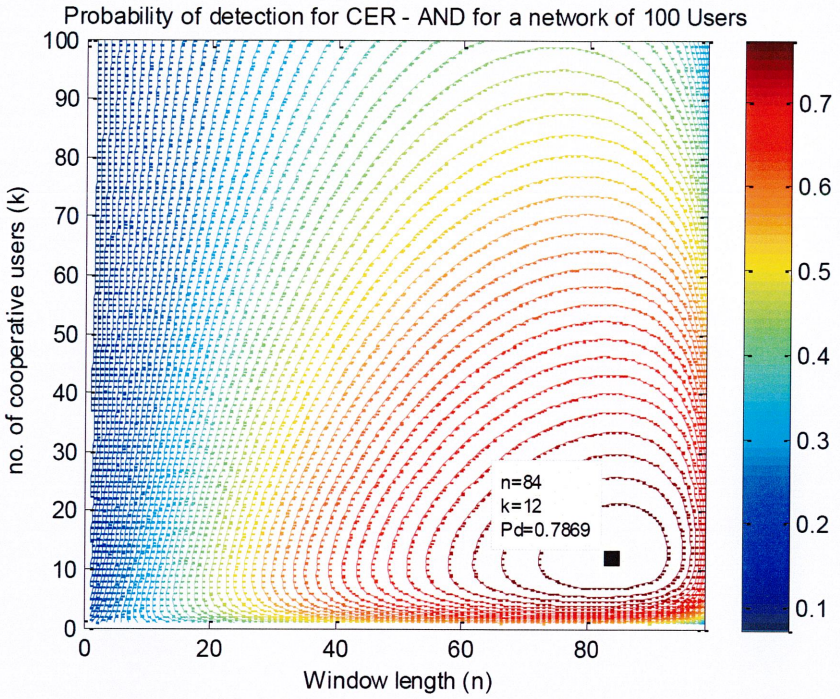


Fig. 3.9 P_d for CER-AND, M=100, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.017

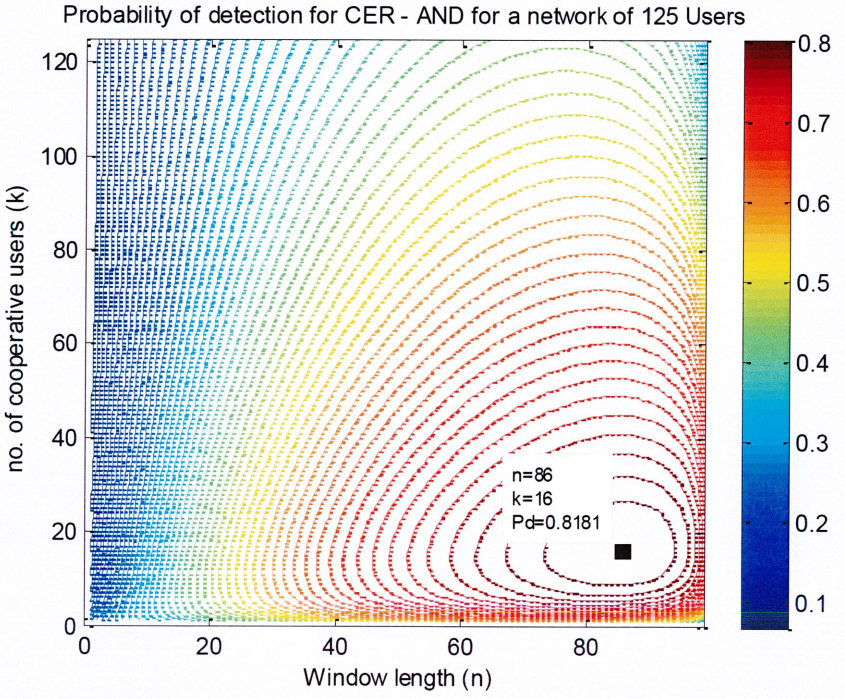


Fig. 3.10 P_d for CER-AND, M=125, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.015

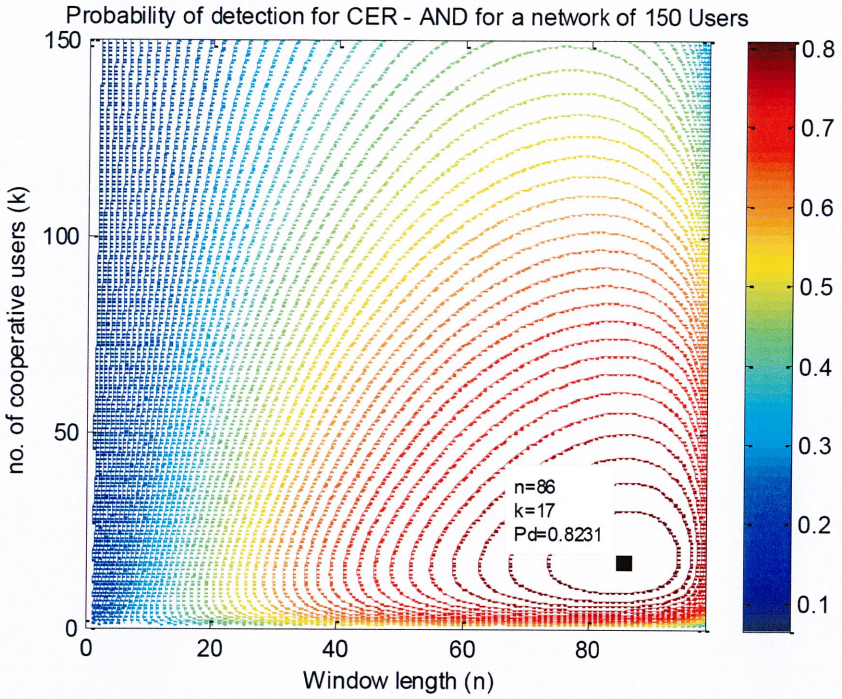


Fig. 3.11 P_d for CER-AND, M=150, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.015

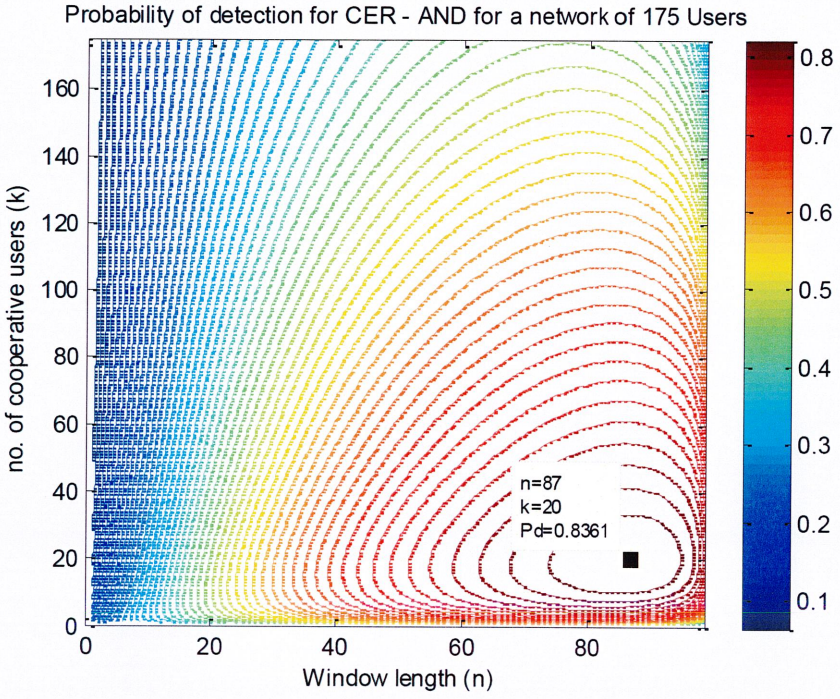


Fig. 3.12 P_d for CER-AND, M=175, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.014

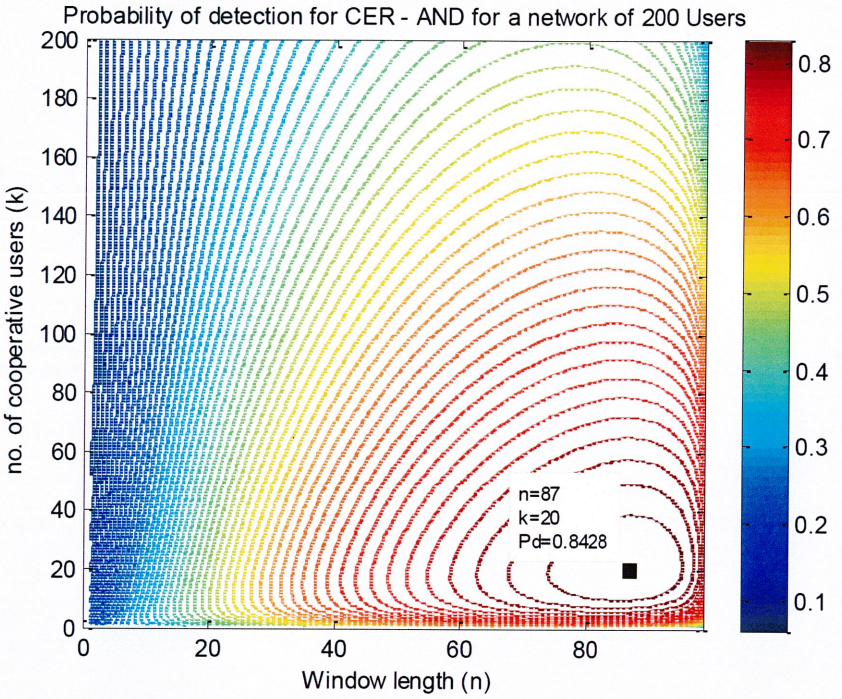


Fig. 3.13 P_d for CER-AND, M=200, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.014

3.4.2 Constant Efficiency Rate Using OR Fusion Rule

Applying the same conditions used previously on CER-AND network to the CER-OR network. It should be known that OR fusion rule states that the SU network will declare a the channel as busy when only one SU is detecting the PU signal. Thus, the SU network performance will be rapidly improving in high SNR environments. Fig. 3.14, Fig. 3.15, Fig. 3.16, Fig. 3.17, Fig. 3.18, Fig. 3.19, Fig. 3.20, and Fig. 3.21 are showing that there is a certain optimal number of SUs (k_{opt}) which is less than (M) and a certain optimal window length (n_{opt}) which is less than the allowable detection window length (N_{det}). Under both optimal values, the P_d of the SU network is maximized. This behavior is not changing when (M) is changed. Under the conditions of the simulation, (n_{opt}) and (k_{opt}) are increasing as (M) increases so as the SU network

performance. Focusing on contours behaviors, it is clear that all CER-OR networks have wide contour areas near top values while CER-AND networks contours have narrow areas near top values. These areas are increasing as (M) increases and the rate of increment shows clearly the improvement of CER-OR network performance when the number of SUs having relatively high SNR levels is increasing. The contour lines is marking the possible solutions in terms of (k, n) pairs to achieve a certain level of detection. Finally, it is shown that the maximum (P_d) achieved by optimizing CER-OR network is higher than the (P_d) achieved by optimizing CER-AND network.

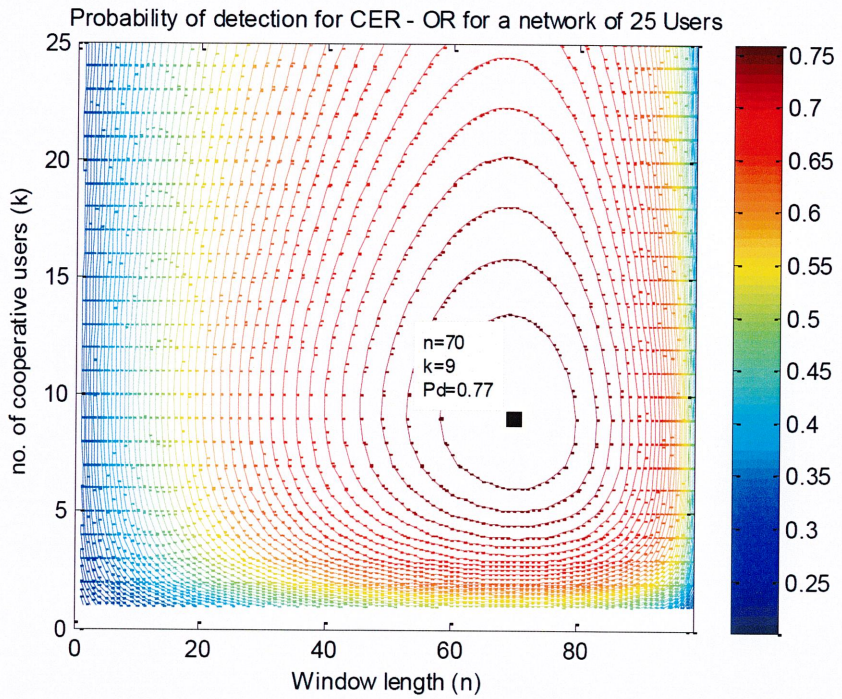


Fig. 3.14 P_d for CER-OR, M=25, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt\eta}$= 0.032

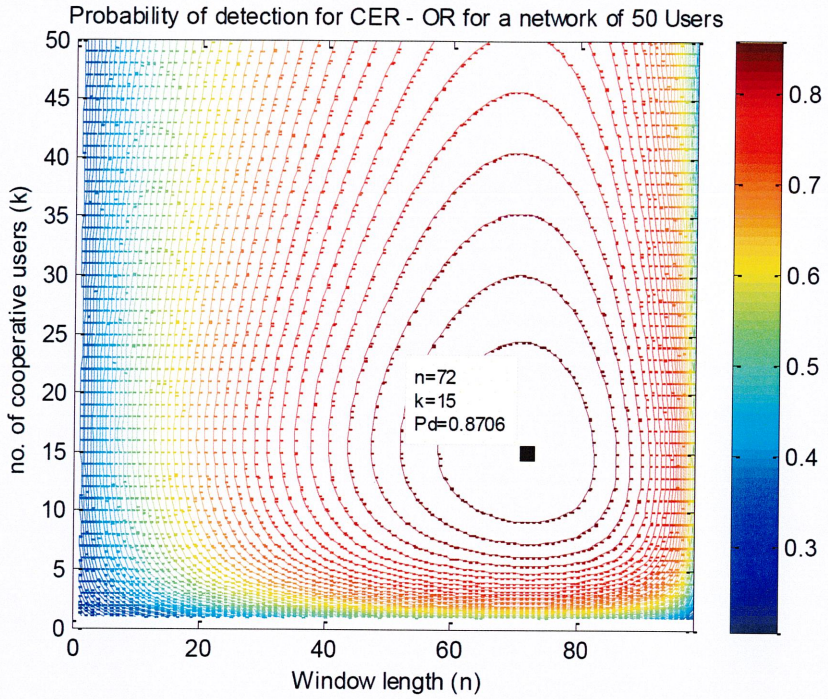


Fig. 3.15 P_d for CER-OR, M=50, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.03

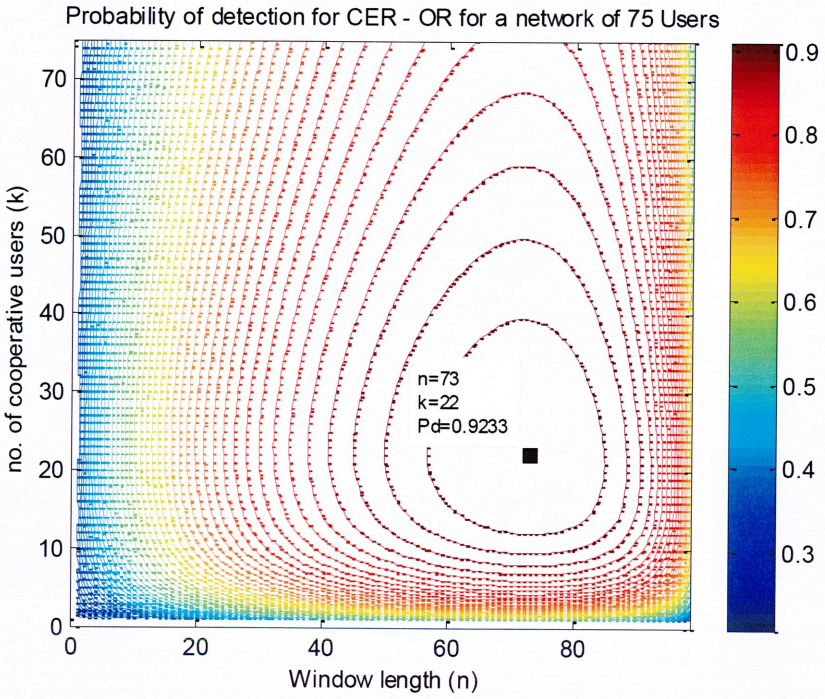


Fig. 3.16 P_d for CER-OR, M=75, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.029

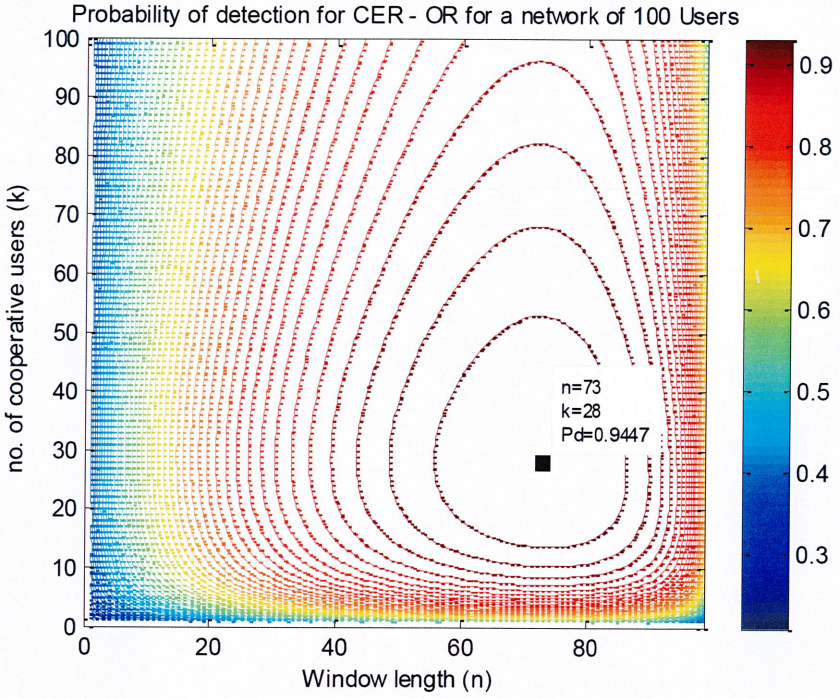


Fig. 3.17 P_d for CER-OR, M=100, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.029

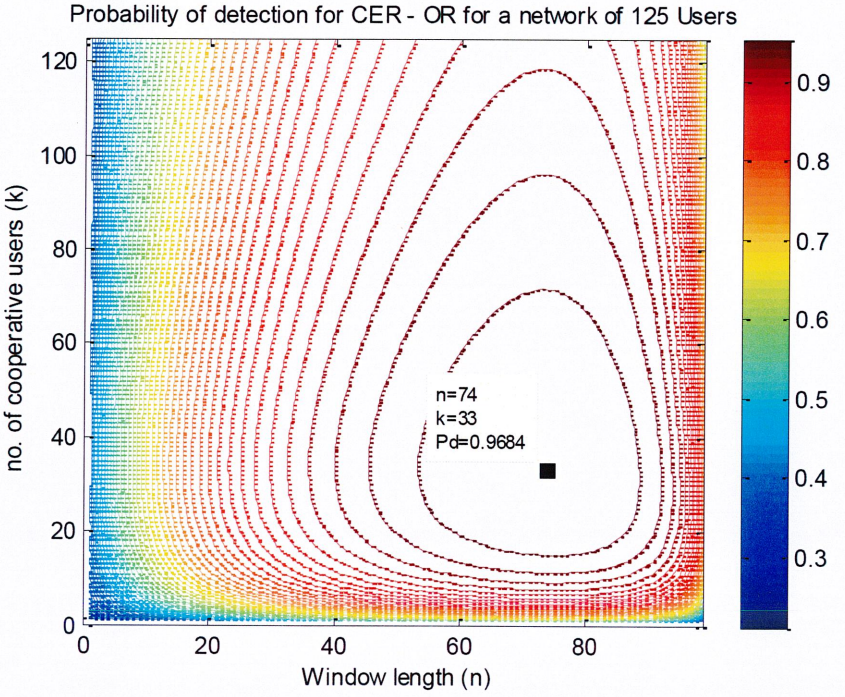


Fig. 3.18 P_d for CER-OR, M=125, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.028

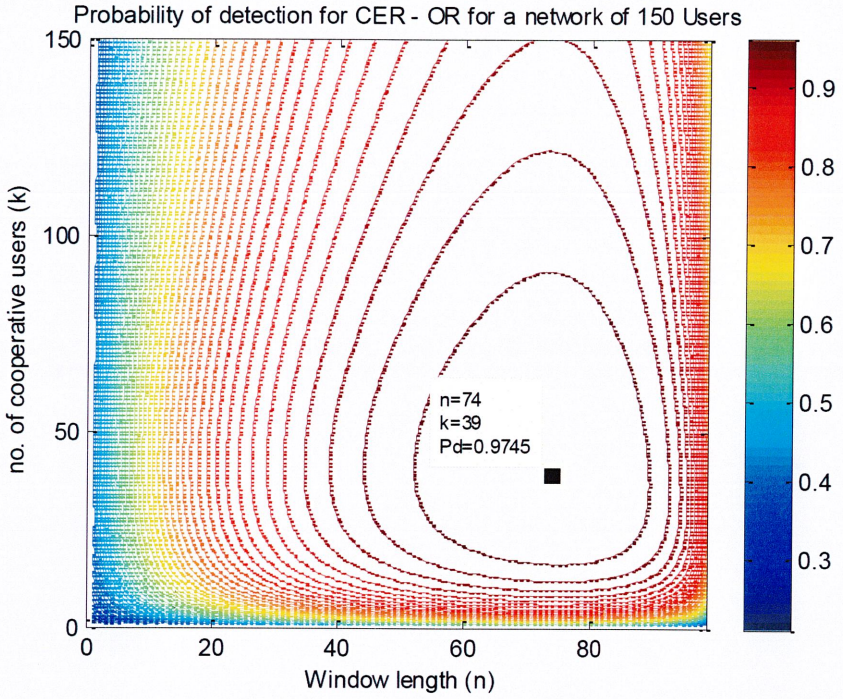


Fig. 3.19 P_d for CER-OR, M=150, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.028

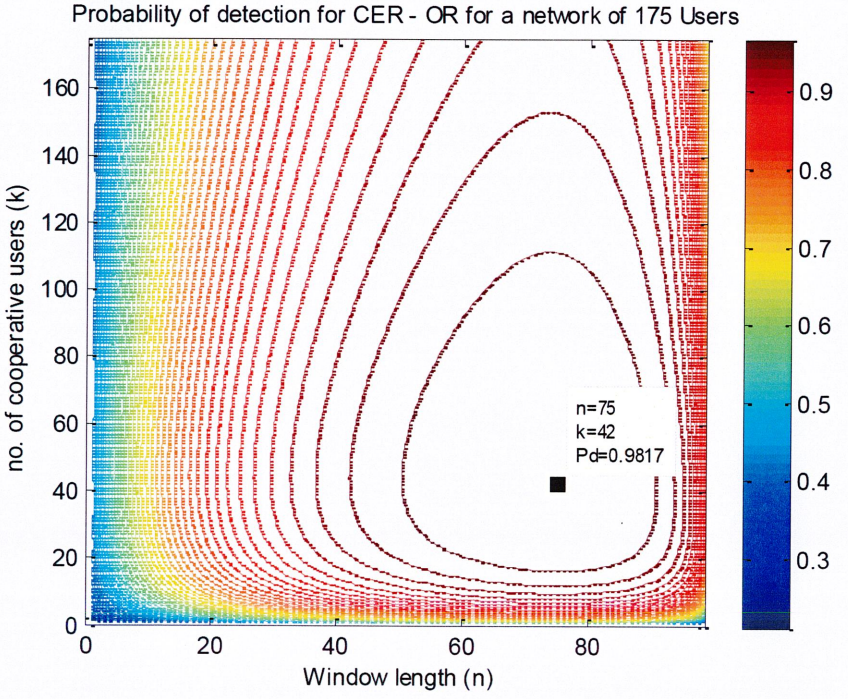


Fig. 3.20 P_d for CER-OR, M=175, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.027

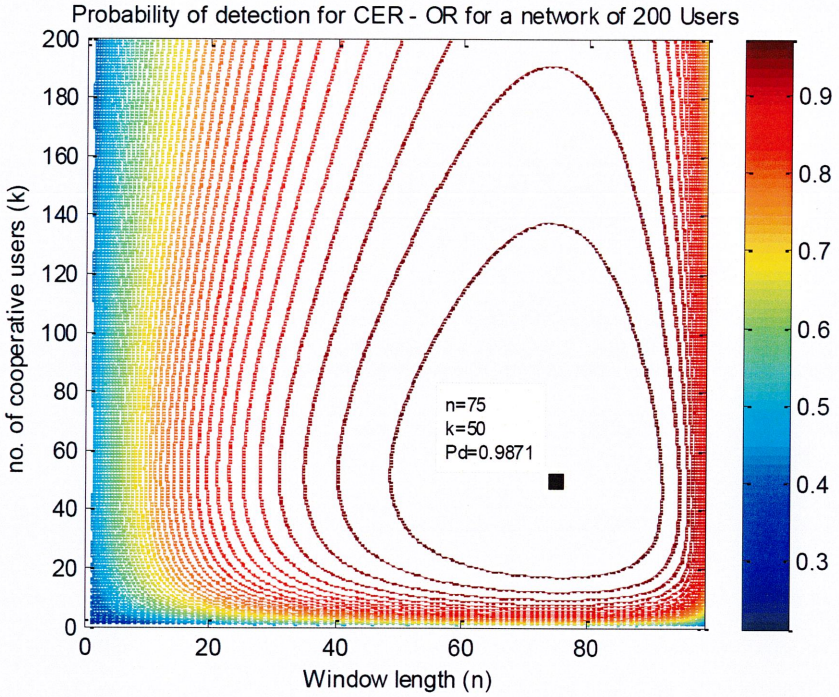


Fig. 3.21 P_d for CER-OR, M=200, N=1000, η=0.9, SNR at FC=-10 dB, $P_{f\_opt}\eta$= 0.027

All previous simulations can be summarized in Fig. 3.22 which shows that CER-OR has a better performance than CER-AND under the simulation conditions for both optimized and non-optimized schemes and the improvement done by using (k_{opt}) and (n_{opt}) instead of (M) and (N_{det}) respectevily with all network sizes tested in the simulation. Random SNR values used in the simulation will cause some differences in the steps between successive network sizes but the general behaviour of the graph is showing that the performance will improve as the network size increases since the number of SUs recieving relatively high SNR levels is increasing. It is also shown that CER-OR reaches it maximum performance using a shorter (n_{opt}) than CER-AND which means that it will have a larger (P_f) while CER-AND needs to cooperate less users than CER-OR to reach its maximum performance.

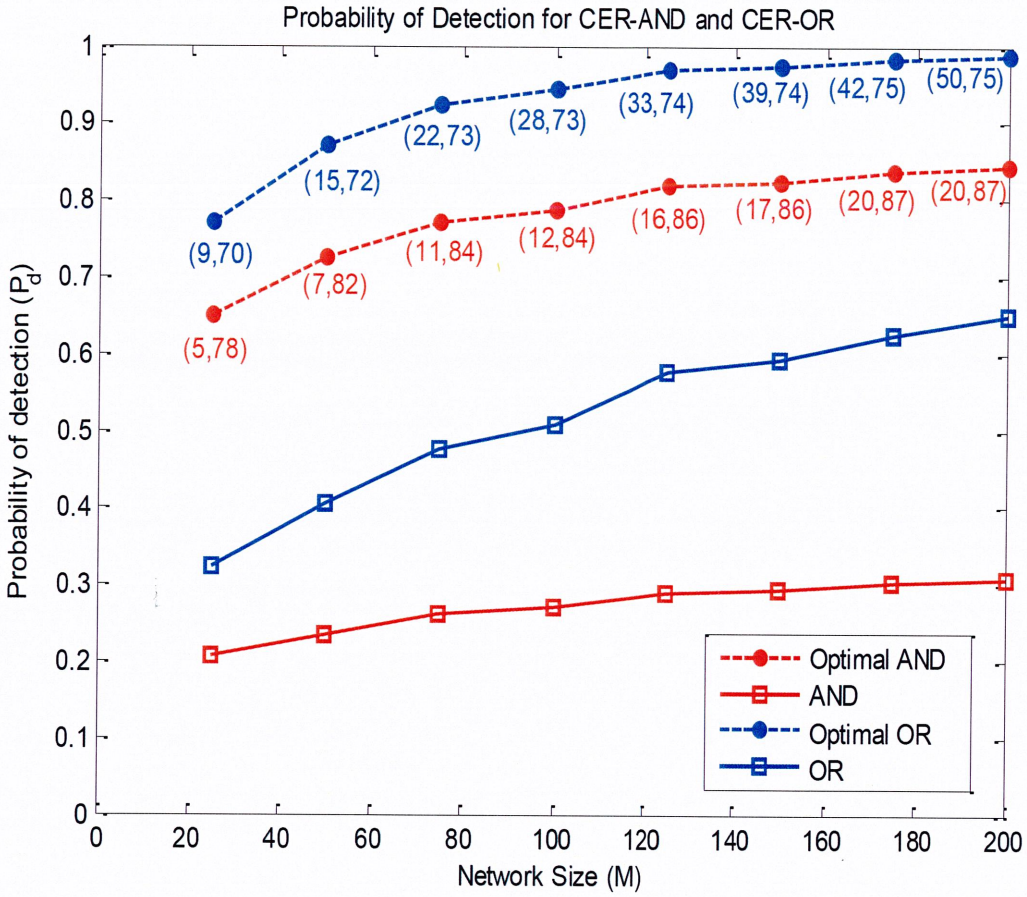


Fig. 3.22 P_d vs. M, N=1000, η=0.9, SNR at FC=-10 dB

Fixing the size of the SU network at 100, Fig. 3.23 is showing the two major effects of changing the targeted efficiency rate from 0.85 to 0.95 in steps of 0.01 for both CER-AND and CER-OR networks with full and optimal values of both window length and number of users. Firstly, targeting a lower efficiency rate will increase the performance of the SU network since (N_{det}) is increasing. Secondly, the improvement achieved by using (k_{opt}) and (n_{opt}) instead of (M) and (N_{det}) for all efficiency rates tested under the simulation conditions.

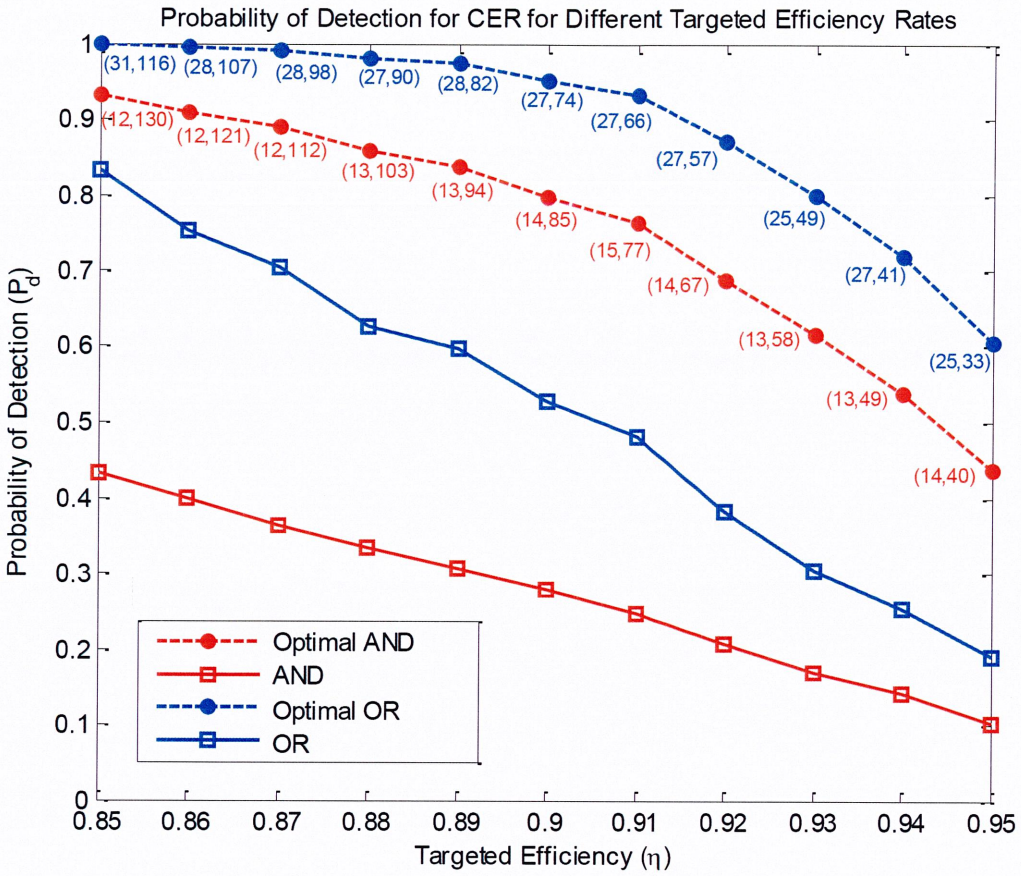


Fig. 3.23 P_d vs. η, M=100, N=1000, SNR at FC=-10 dB

Increasing the total window length (N) will increase (N_{det}) in the same rate since they are related by the targeted efficiency rate. This will directly affect the performance of the SU network in a positive way. Optimized CER-OR network still behave better and faster than optimized CER-AND network even it needs a larger number of cooperative users. The performance of CER-OR network under the conditions of full window usage and the cooperation of all SUs will improve rapidly when (N) have relatively large values since the individual sensing results are improving. (k_{opt}) is almost stable for both fusion rules under the tested values for (N) since (M) is fixed and the received SNRs by SUs are varying within the same range for all 20 trials averaged to get the results shown in Fig. 3.24.

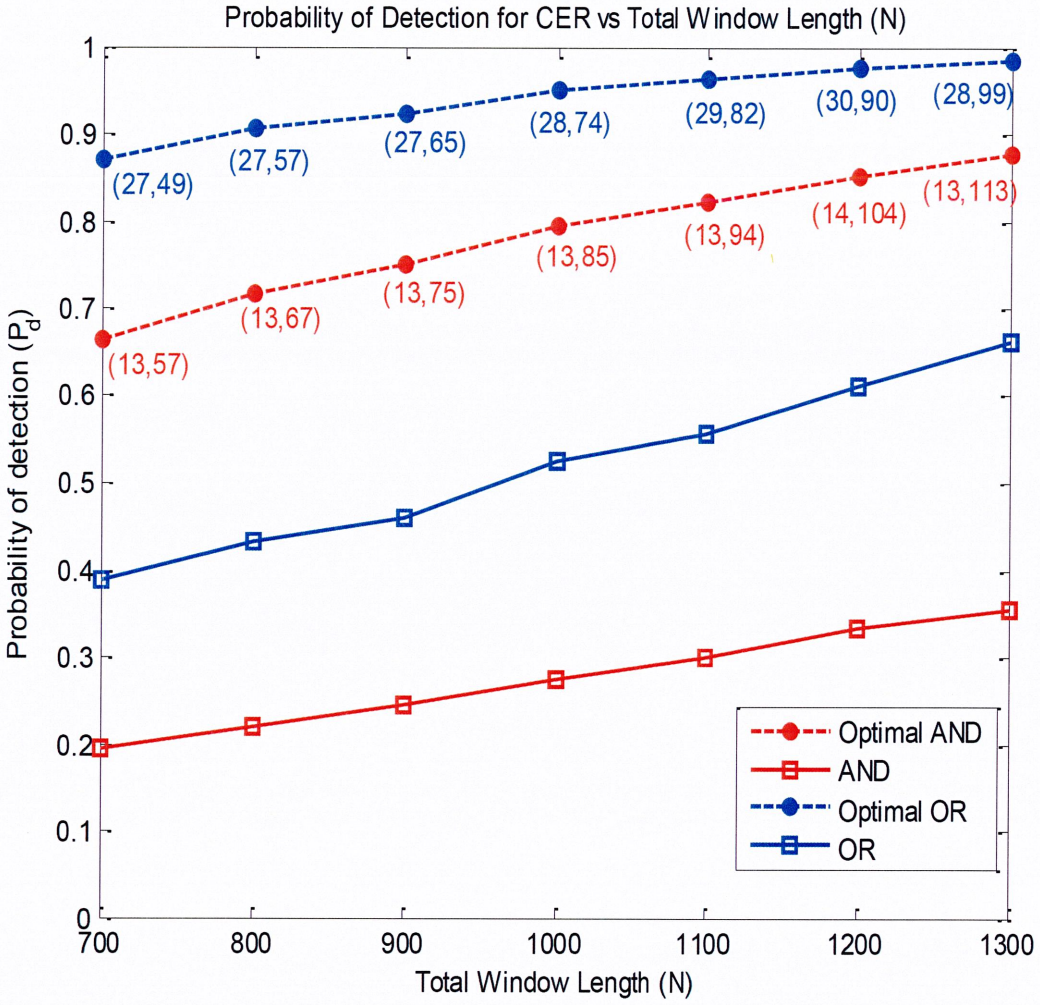


Fig. 3.24 P_d vs N, M=100, η=0.9, SNR at FC=-10 dB

The network performances of both CER-AND and CER-OR is generally improving in higher SNR environments as shown in Fig. 3.25. CER-OR network performance will start to increase rapidly under the full conditions at relatively high received SNR levels since the individual sensing results are improving. Also at relatively high SNR environments, (k_{opt}) of CER-OR network is increasing while it could be considered as stable in CER-AND networks under the same SNR levels tested in the simulation. (n_{opt}) is increasing as the SNR levels are increasing for both CER-AND and CER-OR networks which will generate lower (P_f).

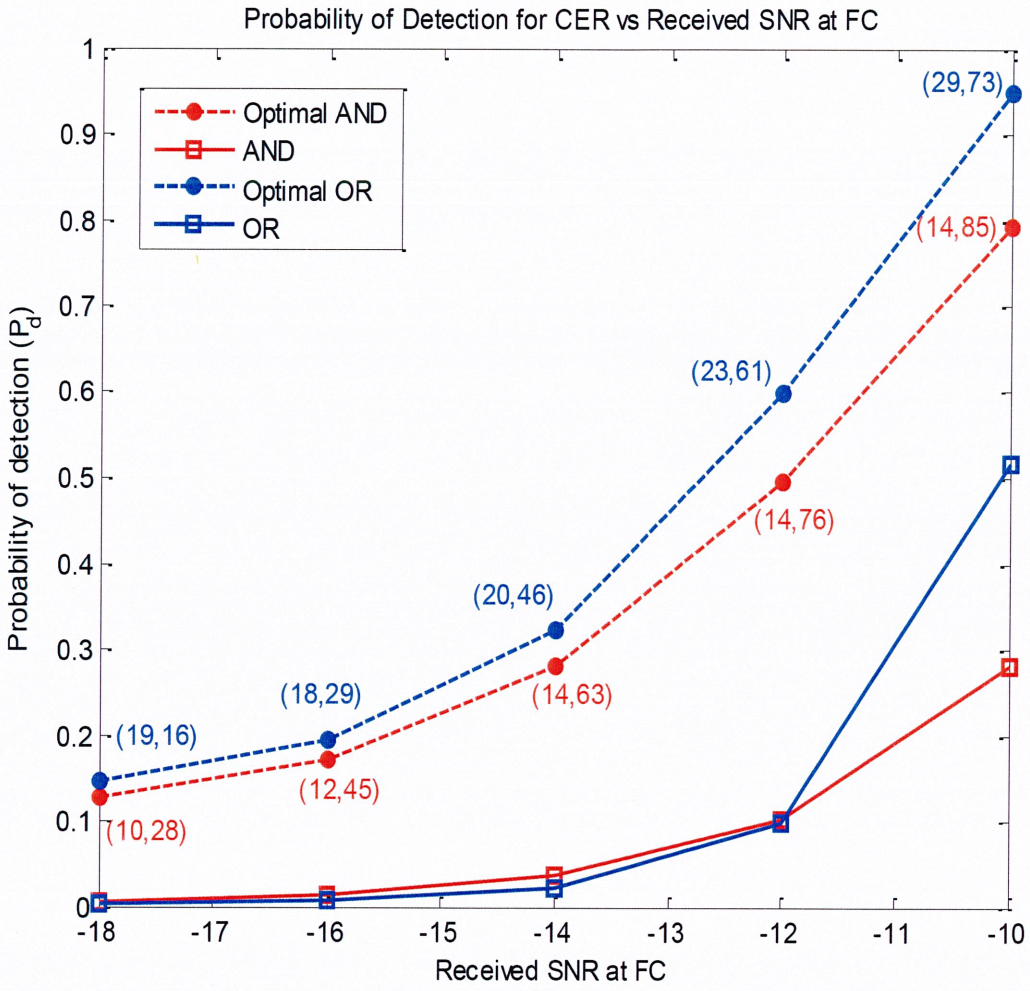


Fig. 3.25 P_d vs Received SNR at FC, M=100, N=1000, η=0.9

3.5 Conclusion

Firstly, to achieve maximum efficiency in CSS, an optimal number of SUs receiving highest SNR levels (k_{opt}) should cooperate at an optimal window length (n_{opt}). Optimal solutions in terms of (k, n) for maximum performance and maximum efficiency or throughput are not necessarily the same.

Then, constant efficiency rate cooperative spectrum sensing was introduced as a novel method which can insure a constant efficiency rate. CER was simulated using both AND & OR hard decision fusion rules. Firstly, The maximum performance of a SU network of size (M) could be achieved by the cooperation of ($k_{opt} < M$) users and using an optimal window of ($n_{opt} < N_{det}$) samples. Secondly, the maximum (P_d) achieved by optimizing CER-OR is higher than the maximum (P_d) achieved by optimizing CER-AND. From the contour behavior of CER-AND and CER-OR networks it was proved that CER-OR have wider top contour areas which mean a larger range of (k, n) pairs with performance close to the maximum performance achieved by (k_{opt}, n_{opt}). It was also shown that CER-AND has to cooperate less users than CER-OR to reach its maximum performance and CER-OR needs a shorter window length to reach its maximum performance than CER-AND.

The effect of different parameters on CER was also studied in this chapter. Starting with the study of changing (N_{det}) which can be controlled by controlling (N) or (η). The performance of the SU network is improving significantly as (N_{det}) increases. Followed by the study of SU performance as the received SNR levels change where it was proved that the network will perform better as the SNR values become higher since the individual (P_d) is increasing.

Chapter 4

Soft Decision Weighted Constant Efficiency Rate Cooperative Spectrum Sensing

4.1. System Model

4.2. Cooperative Efficiency using MDC Weighted Scheme

4.3. Constant Efficiency Rate using MDC Weighted Scheme

4.4. Numerical Results and Analysis

4.5. Conclusion

Chapter 4

Soft Decision Weighted Constant Efficiency Rate Cooperative Spectrum Sensing

In CSS using hard fusion rules, all SUs have the same weight in making the final decision. Soft decision weighted CSS methods were introduced to improve the sensing results significantly since granting SUs with higher SNRs levels larger weights will increase their effect in the final SU network decision. A weighted scheme will be used in this chapter to improve the CER method introduced in chapter 3.

4.1 System Model

Quan, Cui, & Sayed (2008) introduced a linear detector as shown in Fig. 4.1 with a modified deflection coefficient (MDC) that characterize the probability distribution of the global test statistics at the FC. Compared to quadratic detectors such as the LRT-based optimal detector introduced by Kay (1998), this linear detector has a number of advantages including:

- Less computational complexity which is more significant when the secondary network has more users.
- Closed form solutions for the probability of detection and probability of false alarm lead to improve the adaptation with changing network parameters during operation.
- The linear detector has a fixed complexity for chosen probabilities of detection and false alarm.

- The performance of the linear detector is comparable to the quadratic detection detectors.

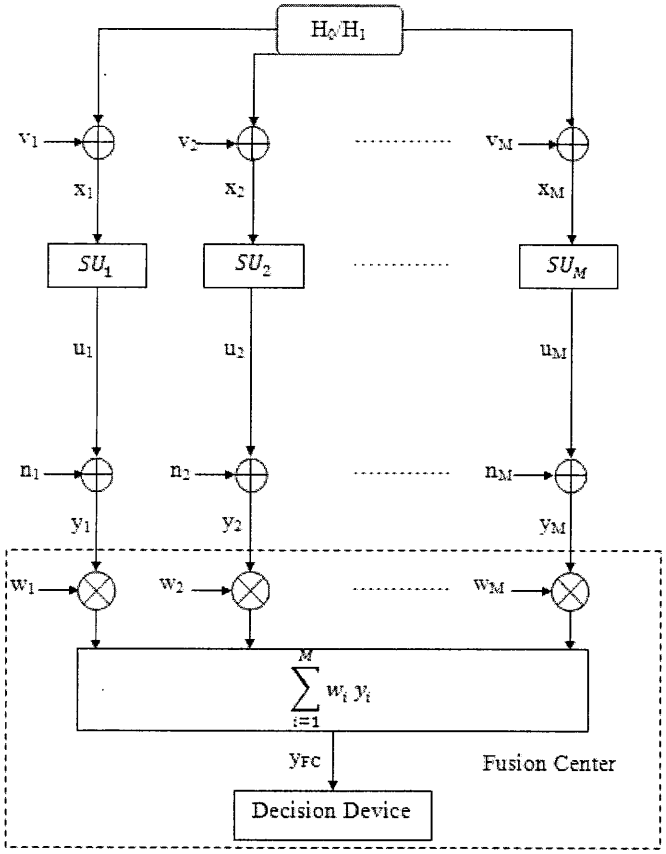


Fig. 4.1 System Model for Weighted Cooperative Spectrum Sensing

The SU network is composed of (M) SUs. The binary hypothesis for spectrum sensing at the nth sample is:

$$H_0: x_i(n) = v_i(n) \tag{4.1}$$

$$H_1: x_i(n) = h_i\, s(n) + v_i(n) \tag{4.2}$$

where x_i is the received signal by the ith SU, s is the signal transmitted by the PU, h_i is the channel gain between the PU signal source and the ith SU which assumed to be constant at the detection interval and v_i is the sensing channel noise for the ith SU which assumed to be zero-mean

additive white Gaussian noise (AWGN) with variances σ_i^2 and all variances are collected into a vector $\boldsymbol{\sigma} = [\sigma_1^2, \sigma_2^2, \cdots, \sigma_M^2]$. At each SU using energy detector, the summary statistic u_i is generated by summation of the received signal energy over the detection interval N_{det} as follows:

$$u_i = \sum_{n=1}^{N_{det}} |x_i(n)|^2 \tag{4.3}$$

for $i = 1,2,\cdots,M$. The summary statistics from all users are transmitted to the FC through the reporting channel, the received signals at the FC is represented by:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_M \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_M \end{bmatrix} \tag{4.4}$$

where n_i is the reporting channel noise for the ith SU which assumed to be a zero-mean AWGN with variance δ_i^2. The variances of the reporting channels are collected into a vector $\boldsymbol{\delta} = [\delta_1^2, \delta_2^2, \cdots, \delta_M^2]$. After adding weights to the received signals at the FC, the final test statistic is:

$$y_{FC} = \sum_{i=1}^{M} w_i y_i = \boldsymbol{w}^T \boldsymbol{y} \tag{4.5}$$

where $\boldsymbol{w} = [w_1^2, \delta_2^2, \cdots, w_M^2]^T$, $w_i \geq 0$. From the work of Quan, Cui, & Sayed (2008), the means of the test statistic at the FC under different hypothesis are:

$$\bar{y}_{FC} = E(y_{FC}) = \begin{cases} N\boldsymbol{\sigma}^T \boldsymbol{w}, & H_0 \\ (N\boldsymbol{\sigma} + E_s \boldsymbol{h})^T \boldsymbol{w}, & H_1 \end{cases} \tag{4.6}$$

where $E_s = \frac{\gamma_i \sigma_i^2}{|\boldsymbol{h}_i|^2} = \sum_{n=1}^{N_{det}} s(n)$. And the variances are:

$$\sigma_{y_{FC}}^2 = \begin{cases} \boldsymbol{w}^T \boldsymbol{A} \boldsymbol{w}, & H_0 \\ \boldsymbol{w}^T \boldsymbol{B} \boldsymbol{w}, & H_1 \end{cases} \tag{4.7}$$

where $\boldsymbol{A} = 2N diag^2(\boldsymbol{\sigma}) + diag(\boldsymbol{\delta})$ and $\boldsymbol{B} = \boldsymbol{A} + 4E_s diag(\boldsymbol{\sigma}) diag(\boldsymbol{\delta})$. At the FC, the (P_f) is calculated as:

$$P_f = Q\left(\frac{\lambda_{FC} - N\boldsymbol{\sigma}^t \boldsymbol{w}}{\sqrt{\boldsymbol{w}^T \boldsymbol{A} \boldsymbol{w}}}\right) \tag{4.8}$$

And the P_d will be:

$$P_d = Q\left(\frac{\lambda_{FC} - (N\boldsymbol{\sigma} + E_s \boldsymbol{h})^T \boldsymbol{w}}{\sqrt{\boldsymbol{w}^T \boldsymbol{B} \boldsymbol{w}}}\right) \tag{4.9}$$

Where λ_{FC} is the FC threshold. Substituting eq.(4.7) into eq.(4.8), the (P_d) of the weighted SU network can be represented as a function of (P_f) as :

$$P_d = Q\left(\frac{Q^{-1}(P_f)\sqrt{\boldsymbol{w}^T \boldsymbol{A} \boldsymbol{w}} - E_s \boldsymbol{h}^t \boldsymbol{w}}{\sqrt{\boldsymbol{w}^T \boldsymbol{B} \boldsymbol{w}}}\right) \tag{4.10}$$

Since the weight vector is an important parameter affecting the (P_d), a modified deflection coefficient (MDC) was presented as:

$$d_m^2(w) = \frac{[E(y_{FC}|H_1) - E(y_{FC}|H_0)]^2}{Var(y_{FC}|H_1)} = \frac{(E_s \boldsymbol{h}^T \boldsymbol{w})^2}{\boldsymbol{w}^T \boldsymbol{B} \boldsymbol{w}} \tag{4.11}$$

The optimization problem of the MDC is $\max_{\boldsymbol{w}} d_m^2(\boldsymbol{w})$ so that $\|\boldsymbol{w}\|_2^2 = 1$ which will lead to the optimal solution:

$$\boldsymbol{w}_{opt} = \frac{\boldsymbol{B}^{-1/2} \boldsymbol{B}^{-T/2} \boldsymbol{h}}{\|\boldsymbol{B}^{-1/2} \boldsymbol{B}^{-T/2} \boldsymbol{h}\|_2} \tag{4.12}$$

Zheng, Lou, & Yang (2010) introduced a particle swarm optimization (PSO) solution for the previously mentioned optimization problem. However, a wrong use of the matrix **B** is causing the improvement achieved by PSO over MDC. When the right values are used, both optimization methods have almost the same performance.

4.2 Cooperative Efficiency using MDC Weighted Scheme

To calculate the spectral efficiency of the SU network model shown in section 4.1 when a (P_d) is targeted, equation 4.10 can be reformed to get P_f in terms of (P_d) so that:

$$P_f(k,n) = Q\left(\frac{Q^{-1}(P_d)\sqrt{\boldsymbol{w}^T\boldsymbol{B}\boldsymbol{w}} + E_s\boldsymbol{h}^t\boldsymbol{w}}{\sqrt{\boldsymbol{w}^T\boldsymbol{A}\boldsymbol{w}}}\right) \tag{4.13}$$

Then substituting equation 4.13 in equation 2.22 to get the efficiency:

$$\eta(k,n) = \left(\frac{N-n}{N}\right)\left(1 - Q\left(\frac{Q^{-1}(P_d)\sqrt{\boldsymbol{w}^T\boldsymbol{B}\boldsymbol{w}} + E_s\boldsymbol{h}^t\boldsymbol{w}}{\sqrt{\boldsymbol{w}^T\boldsymbol{A}\boldsymbol{w}}}\right)\right) \tag{4.14}$$

For $1 \leq n \leq N$ and $1 \leq k \leq M$. Where vector lengths are (k) and the size of matrices **A** and **B** is $(k \times k)$. To reach its maximum efficiency, the weighted soft decision scheme needs to cooperate all users in the SU at an optimal window length (n_{opt}) as shown in Fig. 4.2. When the same simulation conditions in section 3.2 are used, the results will show that the weighted scheme has a larger spectral efficiency than the normal hard fusion schemes.

In Fig. 4.3, it is shown that the weighted soft decision scheme needs the full window length (N) and all SUs (M) to cooperate to achieve its maximum performance. To reach its maximum efficiency, the weighted soft decision scheme needs an optimal window length (n_{opt}). The large area made by the highest contour line is showing that the weighted scheme can reach to a performance close to the maximum performance (98% in the previous simulation) by cooperating SUs with highest received SNR levels at shorter window lengths compared to SU networks using hard fusion rules.

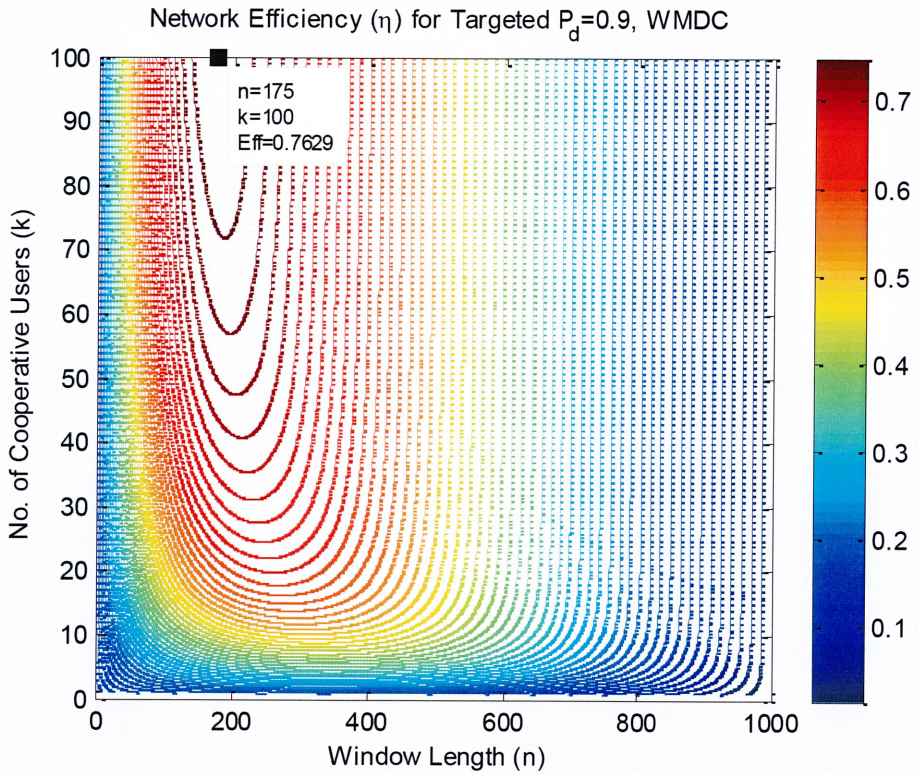


Fig. 4.2 WCER η for P_d=0.9, M=100, N=1000, $P_{f\_opt}\eta$=0.075

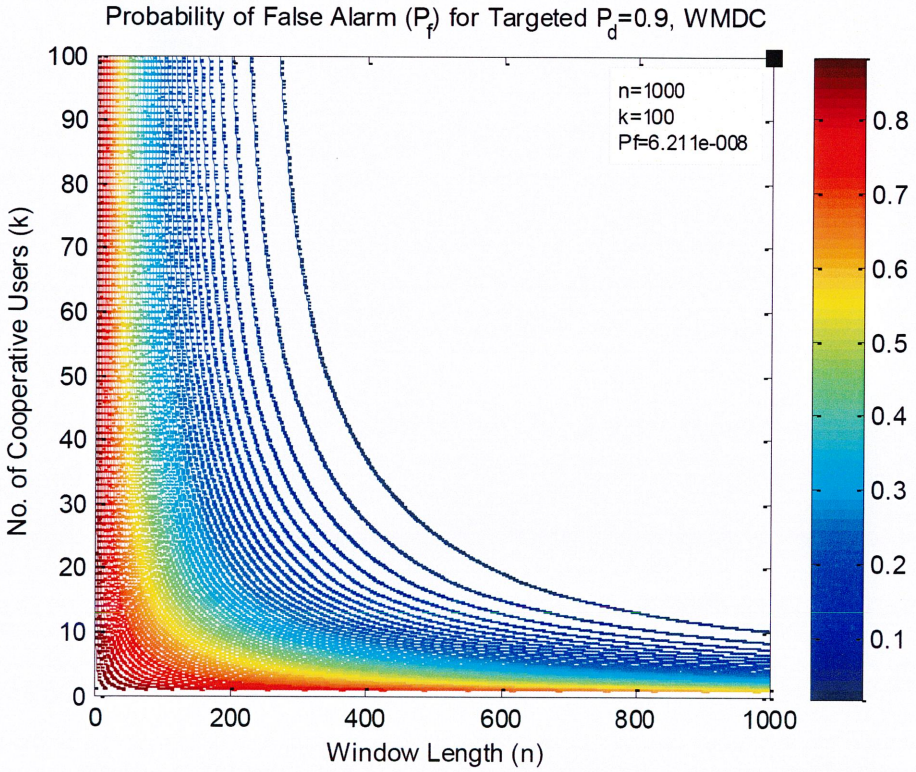


Fig. 4.3 WCER P_f for P_d=0.9, M=100, N=1000, η=0

4.3 Constant Efficiency Rate Using MDC Weighted Scheme

Targeting a fixed efficiency rate for the sensing networks will generate the same sensing boundaries as discussed in chapter 3. To Calculate the network performance when the previously mentioned weighted scheme is used, modifying (4.10) by writing (P_f) in the form of (n) and (η) will generate the following equation:

$$P_d(\eta, k, n) = Q\left(\frac{Q^{-1}(1-\frac{N\eta}{N-n})\sqrt{\boldsymbol{w}^T\boldsymbol{A}\boldsymbol{w}} - E_s\boldsymbol{h}^t\boldsymbol{w}}{\sqrt{\boldsymbol{w}^T\boldsymbol{B}\boldsymbol{w}}}\right) \tag{4.15}$$

For $1 \leq n \leq N$ and $1 \leq k \leq M$. Where vector lengths are (k) and the size of matrices **A** and **B** is $(k \times k)$.

4.4 Numerical Results and Analysis

Using the same network topology of the simulation shown in chapter 3 with changing the received SNR at the FC to -14dB. Total window length (N) is assumed to be 1000, targeted efficiency rate (η) is fixed at 0.9, and the path loss exponent (α) is considered to be 3.2. The SU network is distributed randomly in a 900 km^2 square centred at the FC which is 120 km away from the PU signal source. The simulation is getting the results of the averaging of 20 different SU distributions in the same area. The added weights at the FC are optimized using the optimization of the MDC. Both noise variance vectors of sensing and reporting channels are assumed to be unity as well as the PU signal $s(k)$.

The performance of WCER networks of size 25, 50, 75, 100, 125, 150, 175, and 200 SUs are shown in Fig. 4.4, Fig. 4.5, Fig. 4.6, Fig. 4.7, Fig. 4.8, Fig. 4.9, Fig. 4.10, and Fig. 4.11 respectively. It is shown that

the WCER sensing will need to cooperate all users in the SU network to achieve the maximum performance. From the view of window length, an optimal widow length (n_{opt}) which is less than (N_{det}) is obtained and (n_{opt}) is increasing as the network size (M) increases. It is also shown that optimizing sensing window length is more significant when (M) is relatively small. When (M) is increasing, the area made by the top contour is becoming larger showing that a larger number of SUs receiving relatively high SNRs will increase the number of (k, n) pairs with performance near to the maximum performance achieved by (M, n_{opt}).

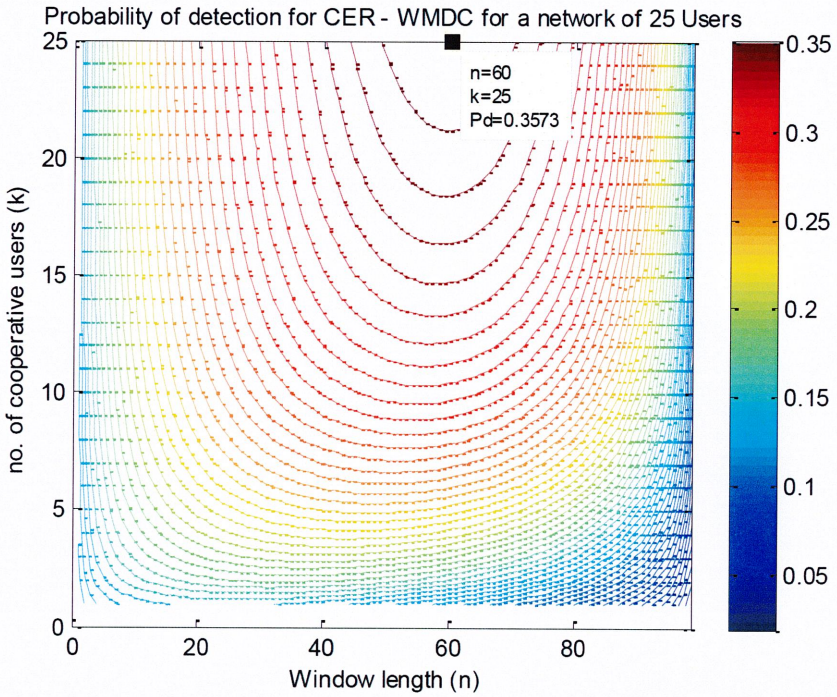


Fig. 4.4 P_d for WCER, M=25, N=1000, η=0.9, SNR at FC=-13 dB, $P_{f\_opt\eta}$= 0.043

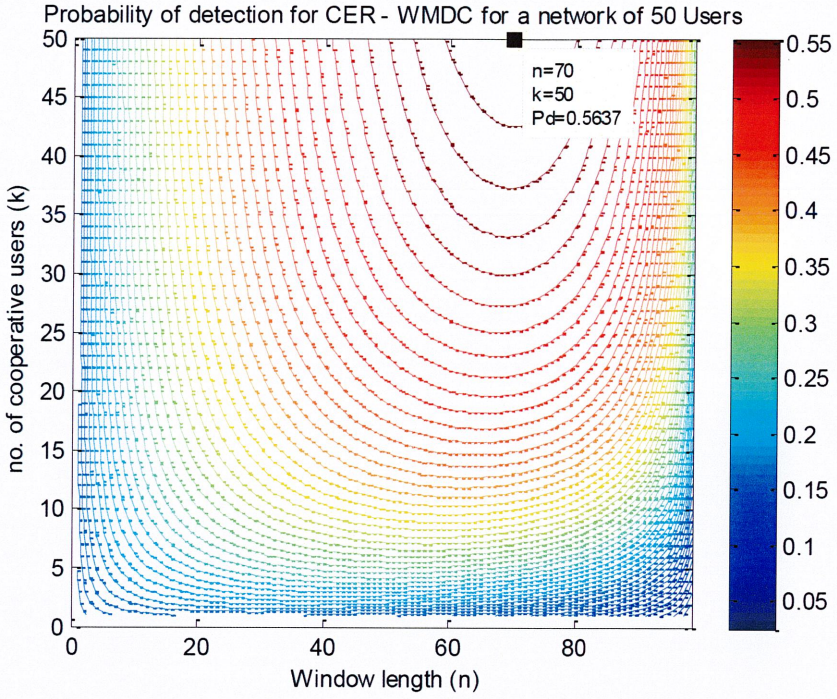


Fig. 4.5 P_d for WCER, M=50, N=1000, η=0.9, SNR at FC=-13 dB, $P_{f\_opt}\eta$= 0.033

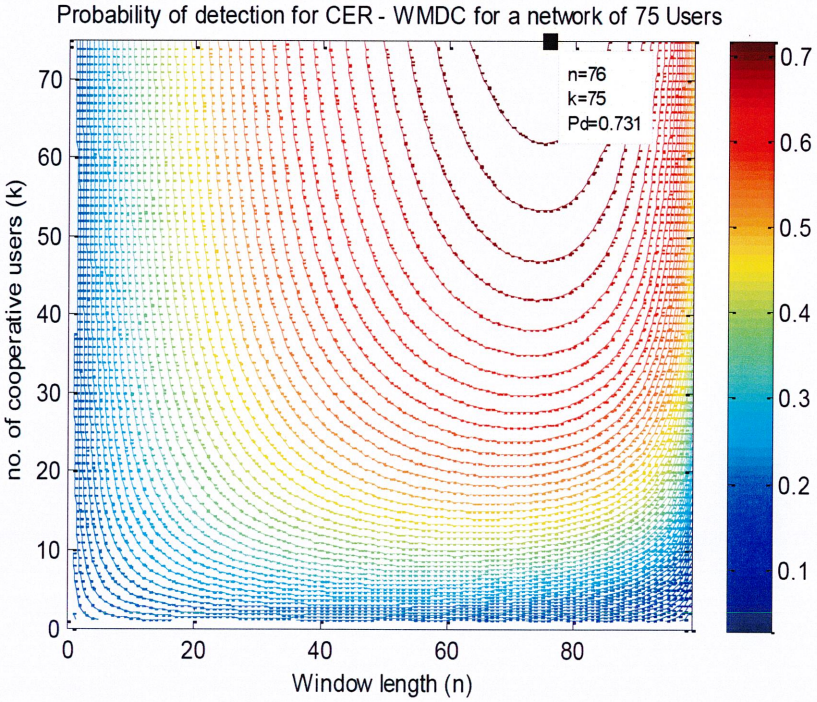


Fig. 4.6 P_d for WCER, M=75, N=1000, η=0.9, SNR at FC=-13 dB, $P_{f\_opt}\eta$= 0.026

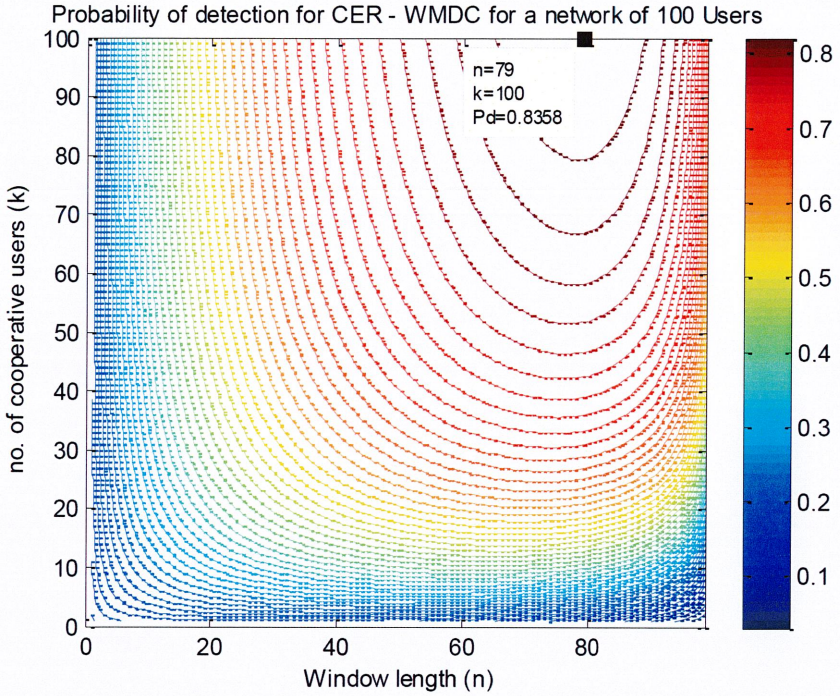


Fig. 4.7 P_d for WCER, M=100, N=1000, η=0.9, SNR at FC=-13 dB, $P_{f\_opt}\eta$= 0.023

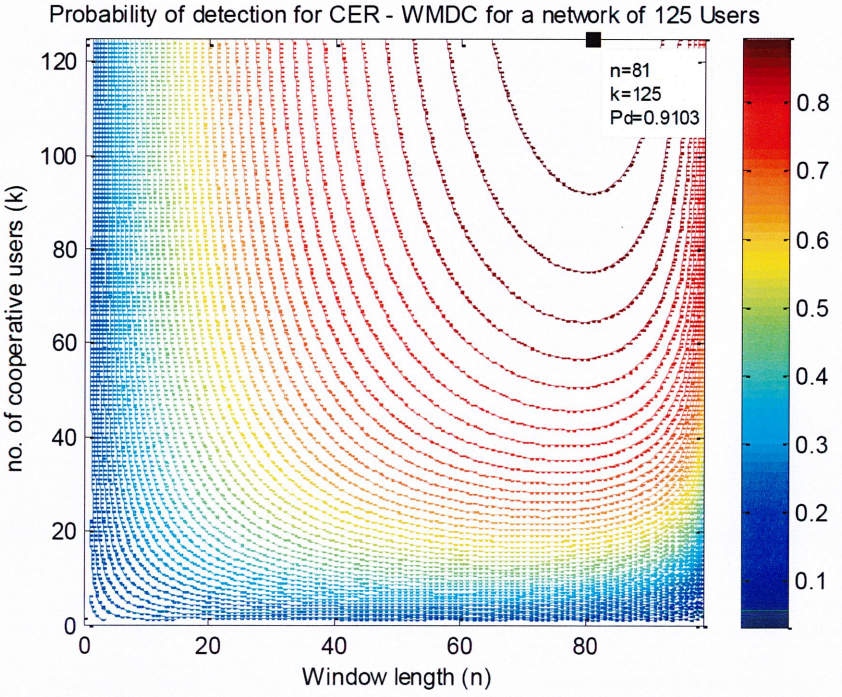


Fig. 4.8 P_d for WCER, M=125, N=1000, η=0.9, SNR at FC=-13 dB, $P_{f\_opt}\eta$= 0.021

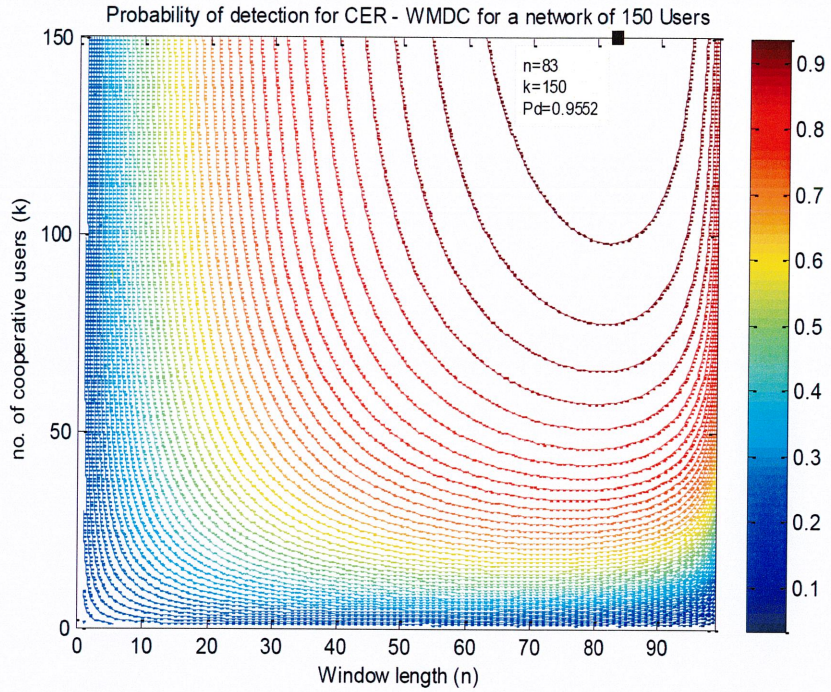


Fig. 4.9 P_d for WCER, M=150, N=1000, η=0.9, SNR at FC=-13 dB, $P_{f\_opt}\eta$= 0.019

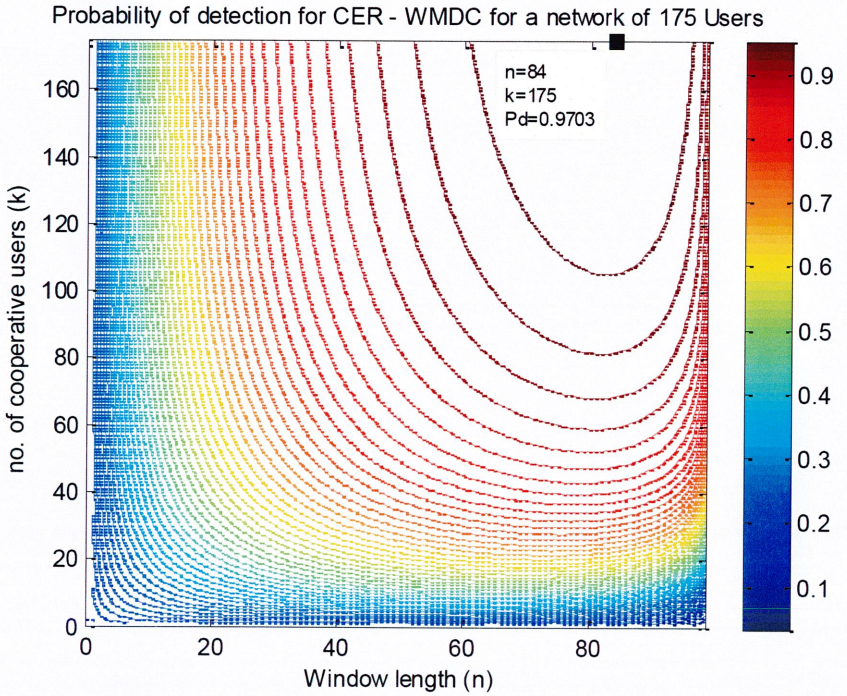


Fig. 4.10 P_d for WCER, M=175, N=1000, η=0.9, SNR at FC=-13 dB, $P_{f\_opt}\eta$= 0.017

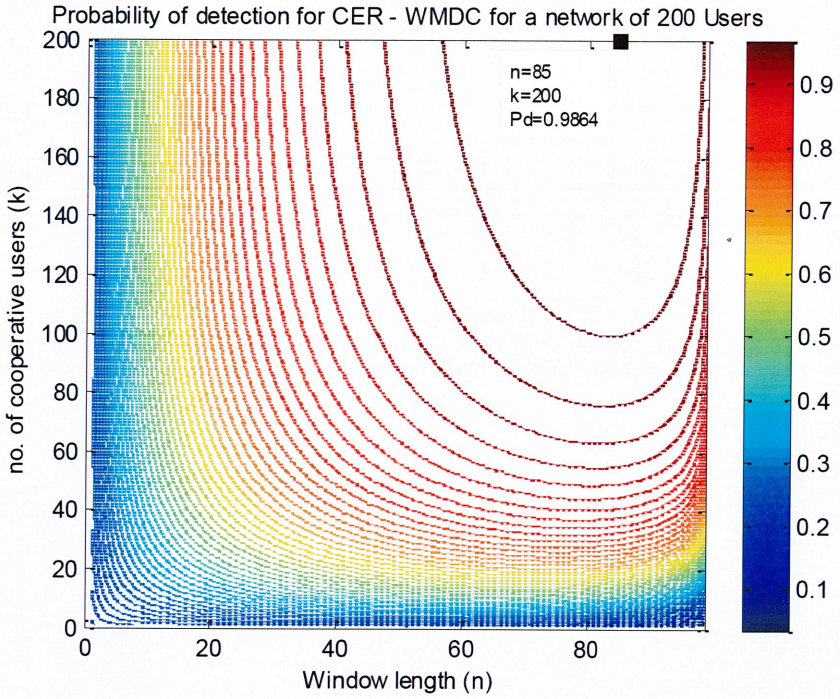


Fig. 4.11 P_d for WCER, M=200, N=1000, η=0.9, SNR at FC=-13 dB, $P_{f\_opt}\eta$= 0.016

The relation between the performance of the SU network and the network size (M) is shown in Fig. 4.12. Averaging a sufficient number of SUs networks distributions will show that the performance of the SU network will increase as (M) increases. However, the increment between the successive network sizes is varying because of the variation of SNR values in each of the 20 trials averaged in the simulation. It is also proved that the optimization of window length is necessary to insure that the WCER will perform better than optimized CER-AND and optimized CER-OR. Increasing the network size will increase the number of SUs with high SNR values and this will reduce the gap between optimized window length and full window sensing in WCER. Comparing the optimal conditions shows clearly that WCER is requiring longer sensing window and more cooperative SUs to achieve its optimal performance than CER-AND and CER-OR.

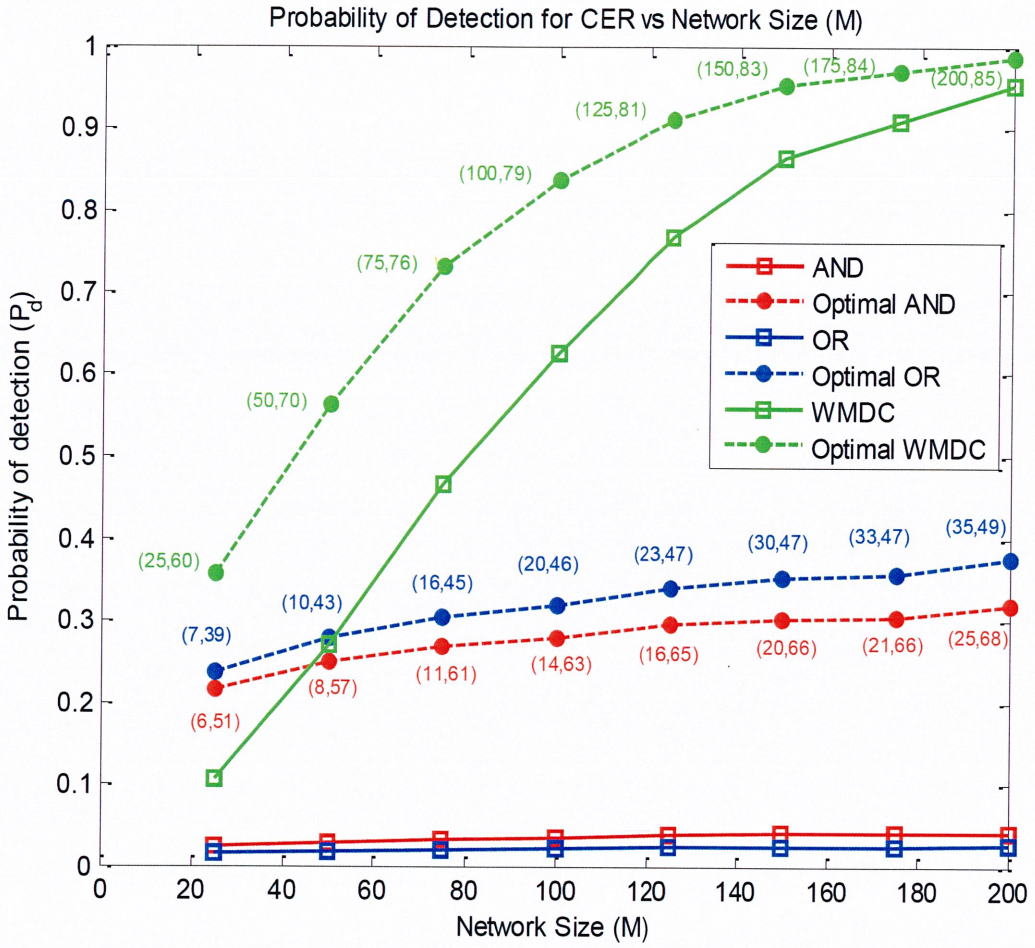


Fig. 4.12 P_d vs. M, N=1000, η=0.9, SNR at FC=-13 dB

Fig 4.13 is showing the sensing performance of WCER network of 100 SUs, using the same initial conditions of SU network distribution area, path loss exponent, total window length, and SNR at FC. The sensing network performance is tested by targeting different efficiency rates. Under the simulation conditions, WCER is performing better than hard fusion CER even without optimizing the sensing window. Fig 4.13 is also showing that the performance of WCER is improving as the targeted efficiency is decreasing since (N_{det}) will increase.

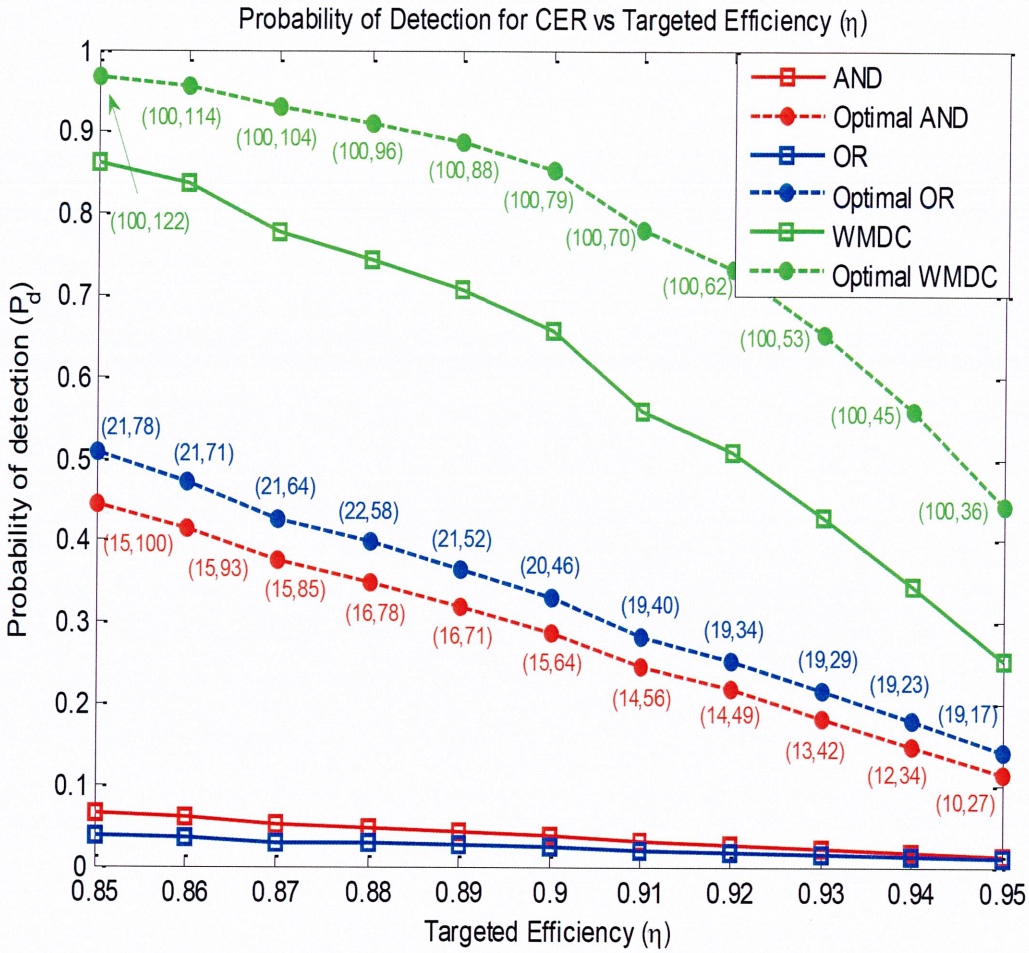


Fig. 4.13 P_d vs. η, M=100, N=1000, SNR at FC=-13 dB

The effect of changing the total window length (N) on a SU network composed of 100 SUs with the same initial conditions of distribution area, path loss exponent, SNR at FC, and targeted efficiency rate is shown in Fig. 4.14. Increasing (N) will affect the WCER network performance positively as well as the hard fusion CER schemes since (N_{det}) will increase in the same rate of the increment of (N). Fig. 4.14 is also showing that the optimizing sensing time for WCER will be less significant as the total window length is increasing since the individual sensing results are improving.

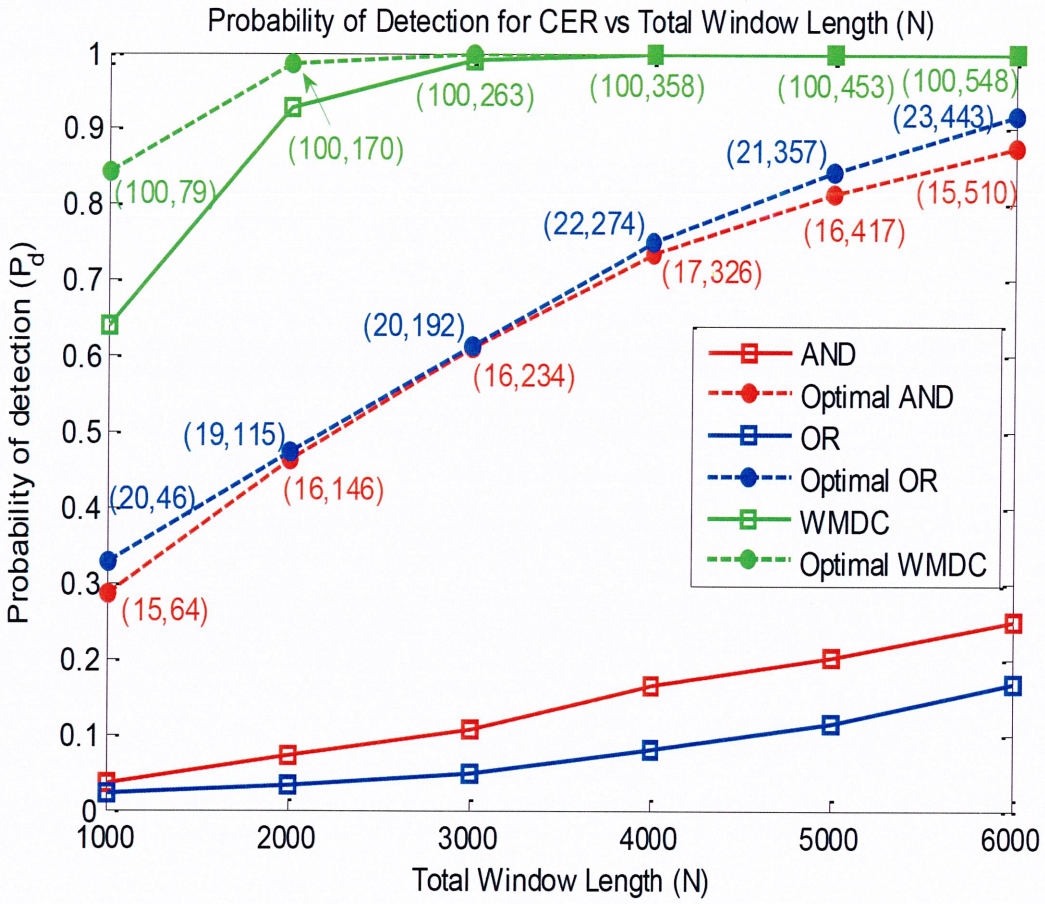


Fig. 4.14 P_d vs N, M=100, η=0.9, SNR at FC=-13 dB

Fig. 4.15 is showing the test of the WCER network under the same initial conditions at different received SNR levels at FC which considered to be located 120 km away from the PU source at the center of the SU network distributed in a 900 km² square. Optimized WCER is outperforming optimized hard fusion CER under same conditions in all tested cases. In high SNR environments, WCER without optimization is outperforming hard fusion CER schemes and the optimization of the sensing window will be less significant since the individual sensing results will improve significantly. In low SNR environments, optimized CER-AND and CER-OR can outperform the full window WCER.

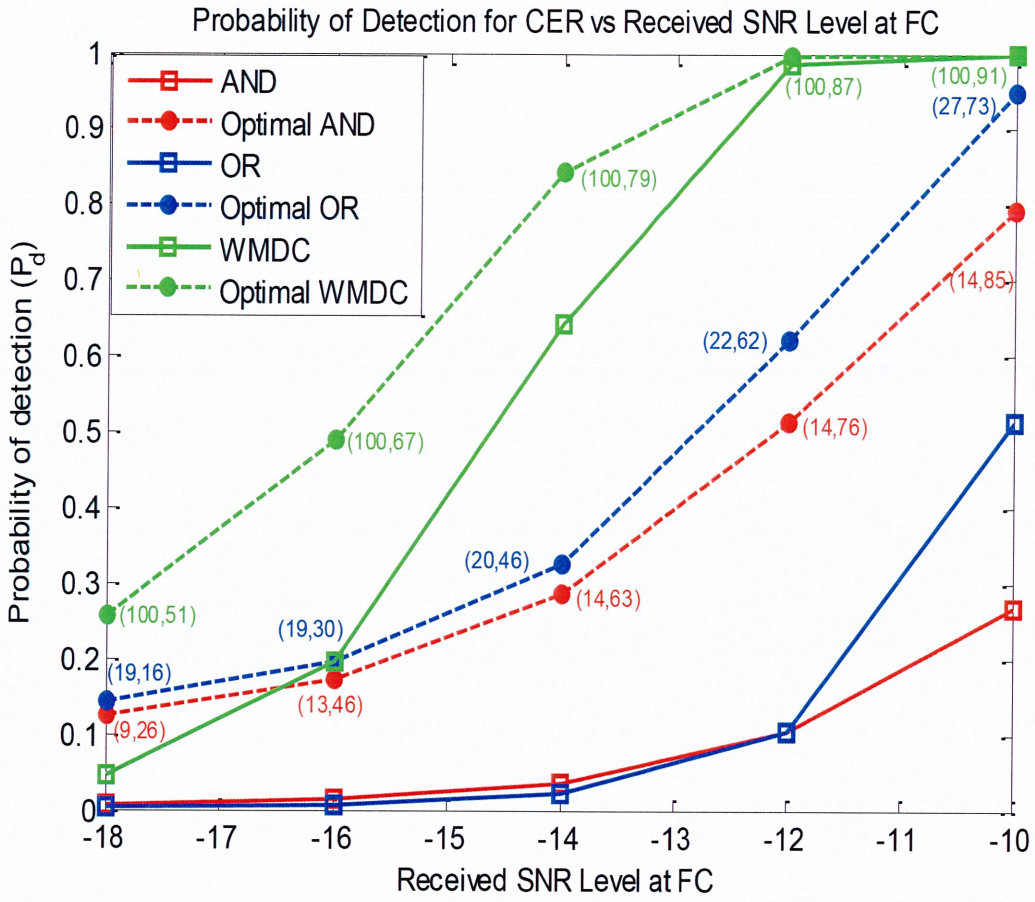


Fig. 4.15 P_d vs. Received SNR Level at FC, M=100, N=1000, η=0.9

4.5 Conclusion

In this chapter, the spectral efficiency of the weighted soft decision scheme using the optimization of the MDC to optimize weights was studied. The results was affected by the same parameters affecting hard fusion networks. Maximum performance was achieved by cooperating all SUs at full window length while maximum efficiency was achieved by cooperating the total number of users at an optimal window length less than the total window length.

Then, A modified soft decision weighted scheme is applied to improve the performance of the CER method. It was proved that WCER using weights optimized by the optimization of MDC can perform better than hard decision CER schemes. The maximum performance of the WCER can be achieved using a window length (n_{opt}) less than the allowable window length (N_{det}). Unlike CER-AND and CER-OR hard fusion schemes which have an optimal number of users (k_{opt}), the WCER should cooperate all SUs of network to reach maximum (P_d) for the network unless some SUs are receiving extremely low SNR levels.

Improving individual sensing results by increasing (N_{det}) can be done by increasing the total window length (N) or decreasing the targeted efficiency rate (η) will improve the network performance and will decrease the performance gap between the WCER and the optimized WCER.

It was also found that optimizing WCER sensing window length is more significant in low SNR environments. At high SNR environments, WCER without sensing window optimization can also outperform optimized CER-AND and CER-OR.

Chapter 5

Conclusion and Future Work

5.1. Conclusions

5.2. Future Work

Chapter 5

Conclusion and Future Work

This thesis introduced CER as a novel method of spectrum sensing targeting a constant network efficiency rate. In this chapter, section 5.1 is summarizing conclusions of the numerical results and analysis done and section 5.2 is showing some possible future work.

5.1 Conclusions

The main target of this thesis was to introduce a constant spectral efficiency/throughput cooperative spectrum sensing method. After a short introduction about cognitive radio technology. A survey about spectrum sensing was done in chapter 2, discussing some widely used detectors with a focus on energy detector which was used in this thesis. A brief view about cooperative spectrum sensing in section 2.3 stated that cooperative sensing could be classified into centralized, distributed, and relay-assisted schemes. It was also stated that cooperation can be done in a parallel or game theoretical models using a hard, soft or a quantized soft fusion model. In the same section, User selection types and some reporting channels were discussed.

Moving further to section 2.4 where the spectral efficiency of spectrum sensing was discussed. Individual spectral efficiency showed that its directly related to the SNR value of the received PU signal, the sensing window length as well as the targeted probability of detection.

The section was finalized with showing that spectral efficiency and the achieved throughput are directly related by the sampling time.

In chapter 3, the spectral efficiency in SU networks using hard combining fusion rules was studied showing that the spectral efficiency and network performance are related to the fusion rule, network size, number of cooperated users, window length, SNR values of received PU signals, and targeted probability of detection. It was proved that to achieve the maximum spectral efficiency, an optimal number of users should cooperate using an optimal sensing window. It was also proved that an optimal number of users should cooperate using the full window length to achieve the maximum performance.

Changing the target of the cooperation from the achievement of a targeted probability of detection to the achievement of a targeted constant efficiency rate was the scope of work in section 3.3. Closed forms for probability of detection in SU networks combined by hard fusion rules AND & OR were obtained and simulated to achieve the maximum performance of the SU network under the new constrains. The maximum performances were achieved using an optimal number of cooperated users less that the network size at an optimal window length less than the total allowable sensing window length. At their optimal values, OR networks performs better than the AND networks in terms of performance. OR networks can be considered faster since it need a shorter window length to reach its maximum performance compared to AND networks. from the view of number of cooperated users, AND networks need a less number of users to cooperate to reach its maximum performance.

Also in chapter 3, the study of the changing of different simulation parameters on hard fusion CER networks was done. Firstly, increasing

the allowable detection window which can be controlled be changing the total window length or changing the targeted efficiency rate showed that the performance will increase when a longer detection window is used. Secondly, the change of the received SNR levels in the network showed that the performance will increase as the received SNR levels are getting higher.

Starting with the study of spectral efficiency on SU networks using weighted soft combining where weights were optimized by the optimization of the minimum deflection coefficient (MDC) in chapter 4. It was proved that the whole SU network should cooperate at an optimal window length to achieve maximum efficiency rate and the whole SU network should cooperate using full window length to achieve the network maximum performance.

In section 4.3, an improvement to the CER method was done using an optimized weighted soft decision scheme where the weights were optimized using the optimization of MDC. The WCER outperforms hard decision CER schemes in terms of maximum performance even though it needs the total number of users cooperating at a longer window length compared to hard decision CER schemes at a similar scenario.

Testing the effects of changing the allowable widow length by changing the total window length or the targeted efficiency rate showed that WCER can outperform optimized hard fusion CER as the detection window increases. Optimizing the sensing window length for WCER will also add some improvement to the network performance. However, this improvement will be less significant as the detection window become longer.

Optimizing the detection window length of WCER is also improving the performance of the network significantly in low SNR

environments. When the SNR values increases, the performance gap between optimized and non optimized WCER is becoming smaller since the individual sensing results is improving significantly.

5.2 Future Work

This Thesis has some possible future work including:

- Applying other hard combining fusion rules to CER as well as quantized soft decision fusion rules.
- Applying CER to different detectors discussed in section 2.2.
- Studying the effect of sensing and reporting channel noise variances on WCER.
- Testing CER performance over different fading channels (Rayleigh, Ricean, Nakagami, correlated log-normal, etc)
- Applying different optimization methods to CER.
- Targeting both detection and efficiency rates for WCER to find the optimal solution in terms of number of cooperative users, window length and applied weights.
- Targeting minimum error probability rate under constant efficiency constrains and find the optimal conditions in terms of number of users and sensing window length.
- Localization of primary user signal source under constant efficiency constrains.

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الملخص

تستخدم الاتصالات اللاسلكية الإدراكية مؤخرا لزيادة فاعلية الطيف الترددي و تستهدف هذه الأطروحة موضوعاً مهماً في مجال الاتصالات اللاسلكية الإدراكية و هو استخدام التعاون بين المستخدمين في شبكة إدراكية واحدة لتحسين استشعار الطيف الترددي للشبكة.

تقدم هذه الأطروحة معدل الكفاءة الطيفية للشبكة كهدف جديد لاستشعار الطيف الترددي التعاوني بدلا من معدل الاستشعار أو معدل خطأ الاستشعار حيث أن معدل الكفاءة الطيفية الثابت ينتج معدلا ثابتا لخرج الشبكة.

و يتم في هذه الأطروحة استهداف معدلات متعددة للكفاءة الطيفية باستخدام شبكات استشعار تعاونية ذات أحجام متعددة و ذات قواعد اندماج مختلفة حيث تم الحصول على أعلى معدل ممكن للاستشعار من خلال تعاون العدد الأمثل من المستخدمين الذين يستقبلون أعلى معدلات الإشارة إلى الضوضاء و يكون هذا العدد أقل من إجمالي عدد المستخدمين في الشبكة خلال وقت الاستقبال الأمثل الذي يكون أقل من وقت الاستقبال المتاح للكفاءة الطيفية المستهدفة من خلال استشعار الطيف الترددي التعاوني.

كما تم تعديل قواعد الاندماج إلى قاعدة اندماج وزنية للحصول لتطوير معدل الاستشعار الأقصى للشبكة حيث تم الحصول على الإضافات الوزنية المثلى باستخدام الحل الأمثل لمعامل الانعكاس المعدل. و تم الحصول على الأداء الأقصى للشبكة عن طريق تعاون جميع المستخدمين في الشبكة الإدراكية خلال وقت الاستقبال الأمثل الذي يعتبر أقل من وقت الاستقبال المتاح للكفاءة الطيفية المستهدفة باستشعار الطيف الترددي التعاوني.

جـــامعة البحـــرين

كليـــة الهندســـة



قسم الهندسة الكهربائية
و الإلكترونية

نظم الاتصالات اللاسلكية الإدراكية التعاونية

أطروحة مقدمة كجزء من متطلبات الحصول على درجة الماجستير
في الهندسة الكهربائية و الإلكترونية

إعـــداد

حمد فاضل الدوسري

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مملكـــة البحـــرين

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