Deanship of Graduate Studies
AL - Quds University

On Decision Fusion for Wireless Sensor Networks over Fading Channels

Bashar Mufid Husain

M.Sc. Thesis

Jerusalem - Palestine

1436 - 2015

On Decision Fusion for Wireless Sensor Networks over Fading Channels

Prepared By:

Bashar Mufid Husain

B.Sc.:Electronics Engineering, Al-Quds University, Palestine

A thesis submitted in partial fulfillment of the requirements for the master degree of Electronics and Computer Engineering/ Faculty of Engineering/ Graduate Studies

Supervisor: Dr. Ali Jamoos

Jerusalem - Palestine

1436 - 2015

Al-Quds University
Deanship of Graduate Studies
Master of Electronics and Computer Engineering

Thesis Approval

On Decision Fusion for Wireless Sensor Networks over Fading Channels

Prepared By: Bashar Mufid Husain
Registration No: 21120113

Supervisor: Dr. Ali Jamoos

Master thesis submitted and accepted. Date:——————
The names and signatures of the examining committee members are as follows:

1- Head of Committee	Dr. Ali Jamoos	Signature:————
2- Internal Examiner	Dr. Samer Bali	Signature:————
3- External Examiner	Dr. Murad Abusubaih	Signature:————

Jerusalem - Palestine

1436 - 2015

Dedication

To my mother, father, sisters, brothers,

friends and all of my family

Declaration

I certify that this thesis submitted for the degree of Master is the result of my own research, except where otherwise acknowledged, and that this thesis (or any part of the same) has not been submitted for higher degree to any other university or institution.

Signed:.......................

Bashar Mufid Husain

Date:.......................

Acknowledgements

First of all, I thank God for every thing.

I am very grateful to my supervisor Dr. Ali Jamoos. I feel it is a great fortune to be supervised by Dr. Ali. Dr. Ali is a knowledgeable scholar, deep thinker and hard worker. He has a keen insight into the research topics and gives very helpful instructions to me. Besides, his enthusiasm, responsibility and rigor make him a role model to my future career. I could not have obtained this degree in such an enjoyable way, nor would I have the same strong motivation and interest toward research, if not for Dr. Ali. In addition to academics, he gave me many personal helps when I was in need, which I am equally, or even more, thankful to him.

As always, I am thankful to my parents for supporting me to pursue my academic goal. Their encouragement and support through all these years meant more than what I can express in words.

Last but by no means least, I am thankful to all my teachers and friends. Their support is indispensable to my completing the master degree.

Abstract

Wireless sensor networks (WSNs) have become a rich research area over the last years. That is because of its high flexibility, robustness, mobility and cost effectiveness. WSNs have a wide application such as security, environment monitoring and battlefield surveillance. Many aspects in the design of WSN must be considered. One of these aspects is how to deal with the observed and collected data at the fusion center (FC) in order to obtain a global decision regarding the absence or the presence of a certain target or phenomena.

In this thesis, the problem of fusion of decisions transmitted over Rayleigh fading channels in wireless sensor networks (WSNs) is revisited. The likelihood ratio test (LRT) is considered as the optimal fusion rule when applied at the FC. However, applying the LRT at the FC requires both the channel state information (CSI) and the local sensors performance indices. Acquiring these information is considered as an overhead in an energy and bandwidth constrained systems such as WSNs.

To avoid these drawbacks, we propose a modification to the traditional three-layer system model of WSN where the LRT is applied as a local decision making method at the sensors level. Applying the LRT at the sensors level does not require the CSI or the local sensors performance indcies. It only requires the signal-to-noise ratio (SNR). Moreover, a new fusion rule based on selection combing (SC) is proposed. This fusion method has the lowest complexity when compared to other diversity combing based fusion rules such as the equal gain combiner (EGC) and the maximum ratio combiner (MRC).

Simulation results show that the performance of the proposed model where the LRT takes a place at the sensors level either the EGC, maximal radio combiner (MRC) or SC applied at the FC outperforms the traditional model that applies the same fusion rules at the FC. In addition, applying the EGC at the FC for the proposed WSN system model provides comparable performance to the traditional model that applies the LRT at the FC. Moreover, the performance of SC based fusion rule is investigated. Further, Simulation results show that the SC has lowest performance when compared to the other fusion rules, but on the other hand, it has the lowest implementation complexity among the other fusion rules such as EGC,

LRT , MRC , and Chair-Varshney.

Keywords: Wireless Sensor Networks (WSNs), Decisions fusion, fading channels, likelihood ratio test (LRT), EGC, MRC, SC.

List of Figures

1.1 WSN structures 3

1.2 Serial topology for WSN 4

1.3 Tree topology for WSN 5

2.1 Traditional three-layer WSN system model [28] 10

2.2 Conditional probabilities of false alarm and detection 12

2.3 ROC curves for fusion rules presented in [28] in addition to SC , average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$. 16

2.4 Performance comparison among the fusion rules as a function of average channel SNR, system level probability of false alarm $P_{f_o} = 0.01$, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$. 18

2.5 Performance comparison among the fusion rules as a function of the total number of sensors in the network K, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$. 19

2.6 Performance comparison among the fusion rules whose performance indices are not identical, average channels SNR = 5 dB, system level probability of false alarm $P_{f_o} = 0.01$ and total number of sensors in the network $K = 8$. 20

3.1 Proposed three-layer WSN system model where the LRT is applied at the sensors level 23

3.2 The performance of the LRT applied at the sensors level, $P_f = 0.05$. . 26

4.1 ROC curves for different fusion rules applied at the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$. 30
4.2 ROC curves for the LRT fusion rule applied at both the traditional and the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$. 31
4.3 ROC curves for the LRT-CS fusion rule applied at both the traditional and the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$. 32
4.4 ROC curves for the Chair-Varshney fusion rule applied at both the traditional and the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$. 32
4.5 ROC curves for the MRC fusion rule applied at both the traditional and the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$. 33
4.6 ROC curves for the EGC fusion rule applied at both the traditional and the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$. 33
4.7 ROC curves for the SC fusion rule applied at both the traditional and the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$. 34
4.8 Probability of detection as a function of average channel SNR, $P_d = 0.5$, $P_f = 0.05$, system probability of false alarm $P_{f_o} = 0.01$ and total number of sensors k = 8. 35
4.9 Probability of detection as a function of total number of sensors K, $P_d = 0.5$, $P_f = 0.05$, system probability of false alarm $P_{f_o} = .01$ and the average channel SNR is 5 dB. 36
4.10 Probability of detection as a function of average channel SNR, sensors have different detection performance, total number of sensors K =8, and system probability of false alarm $P_{f_o} = 0.01$. 37

4.11 Probability of detection as a function of the mean value of the average channel SNR, $P_d = 0.5$, $P_f = 0.05$, system probability of false alarm $P_{f_o} = 0.01$ and total number of sensors k = 8. 39

Acronyms and Abbreviations

WSN	Wireless Sensor Network
LRT	Likelihood Ratio Test
LRT-CS	Likelihood Ratio Test-Channel Statistics
EGC	Equal Gain Combiner
MRC	Maximum Ratio Combiner
SC	Selection Combiner
ROC	Receiver Operating Characteristics Curve
SNR	Signal to Noise Ratio
AWGN	Additive White Gaussian Noise
FC	Fusion Center
CSI	Channel State Information
MIMO	Multiple Input Multiple Output

Contents

Dedication iv

Declaration v

Acknowledgments vi

Abstract vii

List of Figures ix

Acronyms and Abbreviations xii

Table of Contents xiii

1 Introduction 1

1.1 Overview of Wireless Sensor Networks 2

1.2 Literature Review 5

1.3 Thesis Contributions and Organization 7

2 Traditional Three-Layer WSN System Model 9

2.1 Traditional Three-Layer WSN System Model 10

2.1.1 Layer 1: Sensors 11

2.1.2 Layer 2: Fading and Noisy Channels 12

2.1.3 Layer 3: Fusion Center: 13

2.2 State of the Art Fusion Rules 13

3 Proposed Three-Layer WSN System Model **21**
3.1 Motivation 22
3.2 LRT Based Decisions 22

4 Simulation Results **28**
4.1 Performance Comparison Among Different Fusion Rules Applied at the Proposed WSN Model 29
4.2 Performance Comparison Between the Proposed and the Traditional WSN Model 30
4.3 The Effect of the Channel SNR Between the Sensors and the FC . . . 34
4.4 The Effect of the Total Number of Sensors K 35
4.5 Sensors With Non-Identical Indices 37
4.6 Sensors With Non-Identical Channels to the FC 38

5 Conclusions and Future Work **40**
5.1 Conclusions 41
5.2 Future Work 42

Notations **43**

Bibliography **44**

Abstract in Arabic **48**

Chapter 1

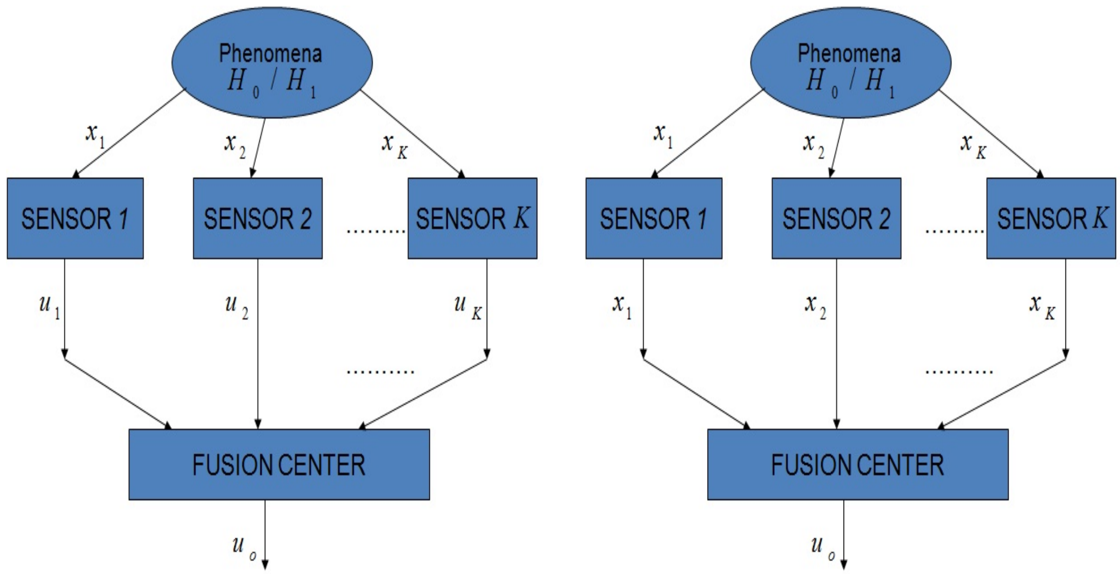
Introduction

1.1 Overview of Wireless Sensor Networks

Pervasive sensing technology has the potential to enhance information gathering and processing in diverse applications. A typical wireless sensor network (WSN) employs multiple sensors, each equipped with devices capable of sensing, processing, and communication. The advantages of WSN include flexibility in deployment and scalability, low cost and fast initial set-up [1, 2]. Recent advances in micro-sensors have enabled WSN to a wide range of applications, such as battlefield surveillance, environmental monitoring, and health care applications [3–8].

Each sensor node in the network has the capability to observe a certain target and to send data or decisions through a parallel access channel to the fusion center (FC), which makes a global decision about the absence or the presence of the observed target. Significant challenges exist and need to be addressed in order for the envisaged application to become a reality. For instance, the individual sensors are incredibly resource constrained. They have limited storage capacity, and communication bandwidth. In addition, in many WSN applications, sensors operate on irreplaceable power supply, making it necessary to conserve power for prolonged lifetime. From energy consumption perspective, transmitting or receiving one kilobyte of information is equivalent to computing 3 million of instructions [34], so it is recommended to make a computation in the sensor level instead of transmitting whenever it is possible.

The structure of any WSN could be either decentralized or centralized as shown in Figure 1.1a and Figure 1.1b [9]. In the decentralized scheme, each sensor receives a noisy measurements and makes a decision regarding a certain phenomena and sends its decision to the FC where the global decision about the phenomena is taken. In the centralized scheme, the sensors receive a noisy measurements and transmit their raw information to the FC to make a global decision. In this scheme, there are no decisions regarding the phenomena obtained by the sensors and the sensors just re-transmit the received measurement to the FC. While the centralized scheme performs better than the decentralized scheme, the power consumption and the channel bandwidth requirements for the centralized scheme is much more than that for the decentralized scheme because each sensor transmits a raw data to the FC, so the decentralized scheme is of particular interest [9].



(a) Decentralized (b) Centralized

Figure 1.1: WSN structures

There are three main topologies for WSN, parallel, serial and tree [10]. Figure 1.1 shows the parallel topology for WSN which is the most common topology considered in literature [9]. In this topology, each sensor, k, receives an observation donated by x_k regarding a certain phenomena. All sensors make their local decisions regarding the phenomena and transmit their decisions, u_k, to the FC. The global decision, u_o, in the case of parallel topology is made based on the local decisions for all sensors and not on their individual received observations.

The serial topology is shown in Figure 1.2. Considering K sensors in the network, only the first sensor makes the decision based on its own observation, while the other $K-1$ sensors make their decisions based on their own received observations and the received decisions from the previous sensors. The global decision in serial topology based WSN is generated at the Kth sensor in the network.

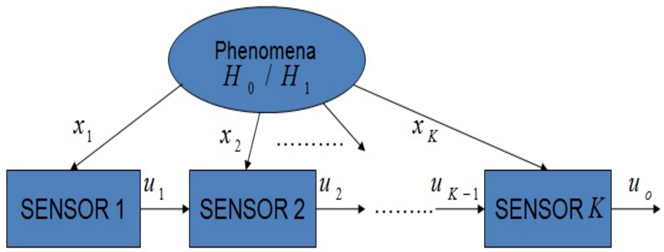


Figure 1.2: Serial topology for WSN

The tree topology for WSN is shown in Figure 1.3. Considering K sensors in the network, the network is divided into levels up to $\frac{K}{2}$ levels. In Level 1, $\frac{K}{2}$ sensors receive their own observations and transmit their decisions to the next sensor in Level 2. The remaining $\frac{K}{2}$ sensors in the network receive their own observations regarding the phenomena and also receive the decisions from two sensors in the higher level. Decision fusion is applied and the sensors transmit their decisions and observations to the sensor in the next level. The final decision takes place at the $\frac{K}{2}th$ level.

Of central interest in this thesis is making use of signal processing algorithms for a WSN engaged in a detection task. As with any detection problem, including classical distributed detection theory, decision making is confronted with the uncertainty in the state of the phenomenon. This uncertainty may be due to observation noise and propagation distortion from the target of interest to the sensors. In WSN, one is also confronted with another level of uncertainty due to the unreliable transmission medium between the sensors and the FC.

The major theme of this thesis is the investigation of signal processing algorithms that could be applied in the case where the sensors receive a noisy measurements and transmit there decisions to the FC through wireless channels that undergo noise and fading.

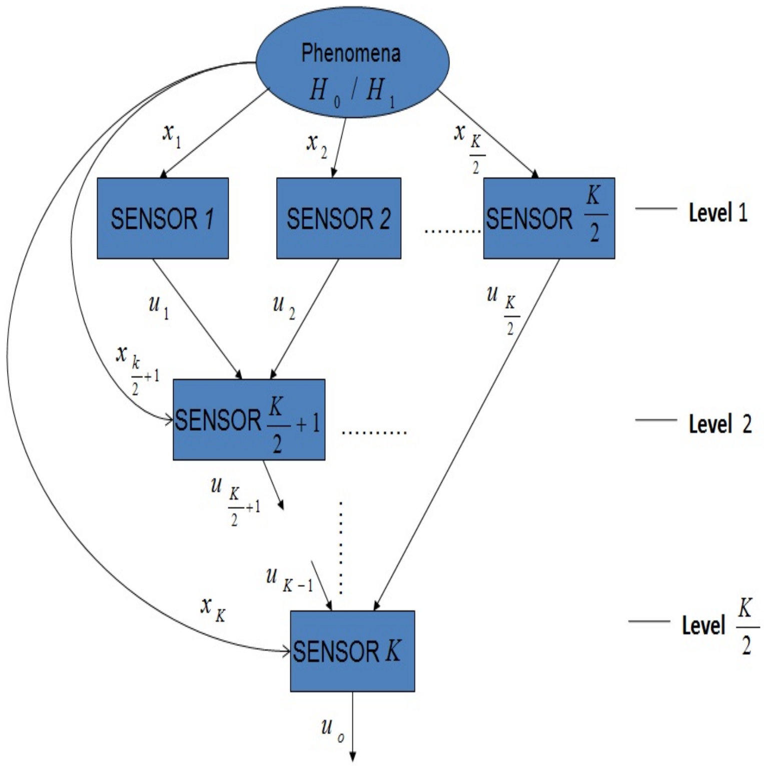


Figure 1.3: Tree topology for WSN

1.2 Literature Review

The problem of distributed detection has been studied extensively in the past decades. In [11], distributed detection algorithm proposed in the case of two sensors. A thorough and relatively recent survey on distributed detection can be found in [12] and [13].

For the classical parallel decentralized detection problem involving K peripheral sensors and FC, there are two signal processing problems that are of particular interest. The first is the fusion rule design that combines received information from peripheral sensors for final decision making. The second is the decision rule design at local sensors.

Decisions fusion represents a formal framework that deals with a data collected from different resources to obtain a greater quality of global decision about a certain phenomena [14]. Decisions fusion with uncertainty has been investigated and a Bayesian sampling approach has been proposed to address this issue [15].

Fusion of decisions under communication constraints has been investigated by various authors earlier. In [16] and [17], optimum fusion rule has been obtained under the conditional independence assumption. Fusion of decisions which are correlated to each other has been studied in [18]. Distributed detection in a constrained system has been also considered in [19–22]. Decisions fusion in WSN operated in MIMO channel has been investigated in [23]. A universal detector for the binary decisions made by sensor nodes has been constructed in [24]. Optimal local sensor detection does not necessarily yield a global optimal detection and compromises should be made with each other as well as the fusion rule at the FC.

Channel-aware distributed detection has been proposed in [25–27] which integrates the wireless channel conditions in algorithm design. Fading channels receive more attention in recent research reports [28]. A majority logic fusion rule which integrates the fading channels between the sensors and the FC has been proposed in [29]. Fusion of decisions transmitted over Rician fading channels has been investigated in [30,31]. Most designs typically assume that the channel state information (CSI) is known at the FC. In [28], a new fusion rule which requires only the channel statistics instead of the instantaneous CSI has been developed. This is more practical since the exact knowledge of CSI may be costly to acquire. On the other hand, this fusion rule requires the local sensors performance indices, so in the case of fast fading channels, the sensors performance indices need to be synchronously updated for different channel states. This adds considerable overhead which may not be affordable in resource constrained systems.

In [28], five different fusion rules have been investigated. These fusion rules are the likelihood ratio test (LRT), equal gain combiner (EGC), maximum ratio combiner (MRC), Chair-Varshney and the likelihood ratio test based on channel statistics (LRT-CS). It is shown in [28] that the LRT fusion rule is the optimum fusion rule. That is because the LRT assumes complete knowledge about the CSI and the local sensors performance indices at the FC. Acquiring CSI at the FC is mainly done through channel estimation process and also the performance indices must be transmitted by each sensor to the FC. That's, applying LRT at the FC is too costly since WSNs are known to be a constrained system in term of communication bandwidth and energy consumption. On the other hand, the EGC is the simplest fusion rules since it does not require any knowledge about the channel or the local sensors performance indices.

In this thesis, we consider the distributed detection problem in a resource constrained WSN. The model with a parallel fusion structure by incorporating the fading communication links will be specified in detail in the next chapter. We focus on the design of WSN from a signal processing perspective. The proposed approach will help fully utilize available resources and exploit the full potential of WSN.

Our goal is to incorporate the communication aspects into the data processing stage; specifically, we will make use of signal processing algorithms, both at the FC and local sensors, that can intelligently cope with channel fades in the decision making stage. To motivate this, we note that in the context of wireless communications, diversity techniques are a powerful way to combat channel fading. For example, multiple channels can be utilized to transmit the same information to combat time selective fading. One of the major contributions of this work is to recognize and exploit the diversity that is already built into WSN in the form of multiple sensors.

1.3 Thesis Contributions and Organization

In this thesis, we consider the traditional parallel decentralized WSN system model that incorporates fading channels and make the following contributions ([32] and [33]) :

1. Propose a modification to the traditional three-layer WSN system model where the LRT is applied at the sensors level as a local decision making method for each sensor.

2. Apply a diversity combining technique, mainly the selection combiner (SC), to the traditional three-layer WSN system model at the FC as a decisions fusion method.

The following chapters will discuss the above contributions in detail. Chapter 2 presents the traditional three-layer WSN system model and the state of the art decisions fusion rules. This chapter will describe the traditional system model where the sensors receive a noisy measurements and transmit their hard decisions through channels which undergo additive white Gaussian noise (AWGN) and Rayleigh fading and a coherent transmission is assumed. The fusion rules presented in [28] will be also described briefly in this chapter. Moreover, we propose to make use of the SC as a decisions fusion method in the traditional system model where the sensors transmit their hard decisions without making any kind of signal processing at the sensors level.

In chapter 3, we mainly present the proposed WSN system model. The LRT fusion rule is assumed to be the optimal fusion rule [28] and applying this fusion rule at the FC requires both the CSI and the local sensors performance indices. Acquiring these information is considered as an overhead. In this chapter, we propose a modification to the traditional three-layer WSN model where the LRT is applied at the sensors level. Applying the LRT at the sensors level requires only the channel signal to noise ration (SNR).

In chapter 4, a comparative simulation study is carried out between the proposed model and the traditional model. The performance of the SC is also examined in this chapter and compared to other fusion rules such as EGC, MRC, LRT, LRT-CS and Chair-Varshney. Discussion of obtained simulation results is presented in this chapter.

Conclusions and recommendations for future work are drawn in chapter 5.

Chapter 2

Traditional Three-Layer WSN System Model

In this chapter, we describe the traditional three-layer WSN system model that incorporates fading and noisy channels between the sensors and the FC. The system model is divided into three layers and each layer is illustrated in details in the next sections. Moreover, we present the state of the art decision fusion rules which have been described and derived in [28] and we propose a new fusion rule which is based on SC.

2.1 Traditional Three-Layer WSN System Model

The traditional three-layer system model describing WSN in the presence of fading and noisy channels is illustrated in Figure 2.1. This system model is considered as extension to the parallel decentralized fusion model shown in Figure 1.1a by incorporating the fading channel layer. There are two hypotheses under test,

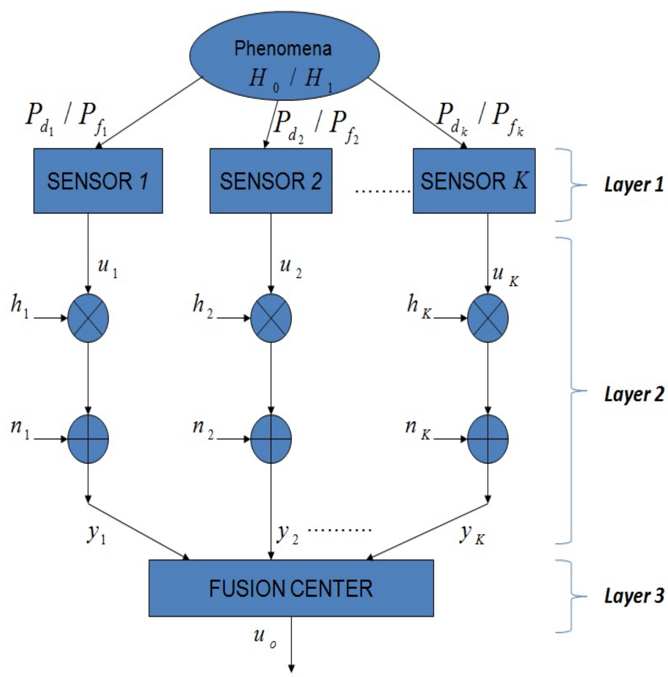


Figure 2.1: Traditional three-layer WSN system model [28]

H_1 (target present), and H_0 (target absent). Each sensor receives noisy measurements and processes these measurements in order to make decision regarding the hypothesis under test. Then, each sensor transmits the obtained binary decision to the FC through parallel access channels which undergo AWGN and Rayleigh fading.

In the conventional parallel fusion paradigm, the fading and noisy channel layer is not considered thereby the information sent from individual sensors is assumed to be perfectly recovered at the FC. For WSNs with limited resources, the effect due to channel fading and noise renders the information received at the FC not completely reliable. Corruption on the received local decisions will lead to performance loss if they are not properly considered. The model described in Figure 2.1 is specified in detail below.

2.1.1 Layer 1: Sensors

In this layer, all the local sensors receive noisy measurements regarding a specific hypothesis. In this work, we assume that the observations are independent of each other. After receiving its observation, x_k, each sensor, k, makes a hard (binary) decision: $u_k = 1$ is sent if H_1 is decided, and $u_k = -1$ is sent otherwise, where $k = 1, \ldots, K$ and K is the total number of sensors in the network. The hard binary decision is made by each sensor according to the following equation:

$$u_k = \left\{ \begin{array}{ll} 1 & : x_k > 0 \\ -1 & : x_k < 0 \end{array} \right\} \tag{2.1}$$

In addition, we assume that each sensor makes a binary decision based on its own observation. The detection performance of each local sensor node can be characterized by its corresponding probability of false alarm and detection, denoted by P_{d_k} and P_{f_k}, respectively, for the kth sensor:

$$\begin{aligned} P_{d_k} &= P(u_k = 1|H_1) \\ P_{f_k} &= P(u_k = 1|H_0) \end{aligned} \tag{2.2}$$

In general, these pairs (P_{d_k}, P_{f_k}) may not be identical and they are functions of SNRs as well as the detection threshold at each sensor. Figure 2.2 describes these two probabilities.

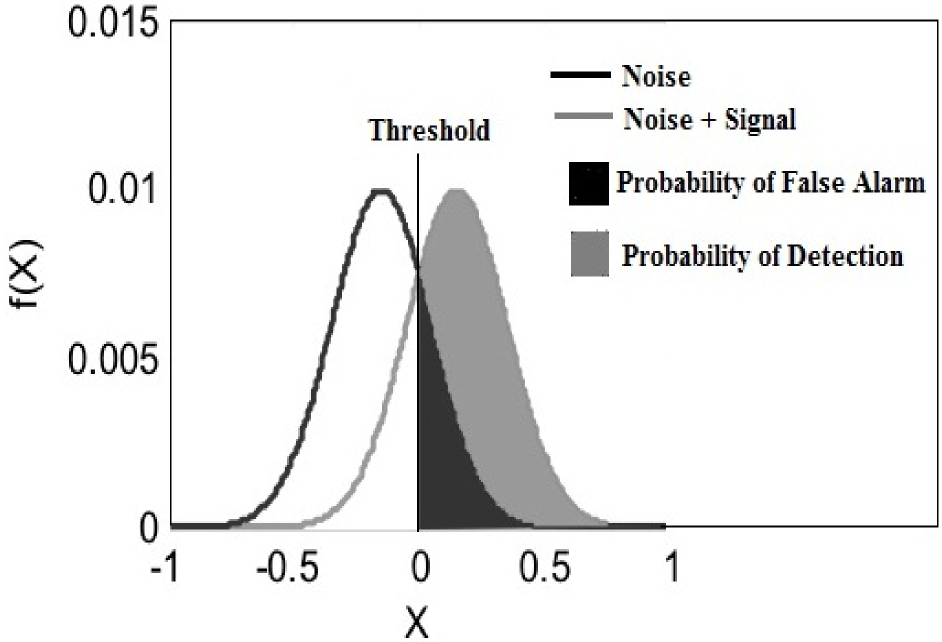


Figure 2.2: Conditional probabilities of false alarm and detection

2.1.2 Layer 2: Fading and Noisy Channels

Decisions at local sensors, denoted by u_k for $k = 1, \ldots, K$ are transmitted over parallel channels that are assumed to undergo independent fading. Since most of WSNs operate at short range and low bit rate due to power and energy limitations, the fading channels are assumed to be flat. We further assume phase coherent reception, thus the effect of a fading channel is further simplified as a real scalar multiplication given that the transmitted signal is assumed to be binary. The statistics of the real scalar, denoted by h_k, is determined by the fading type. For example, for homogeneous scattering background, Rayleigh distribution best describes the envelope of a fading signal. In the development of fusion rules, the gain of the fading channel is considered as a (possibly unknown) constant during the transmission of a single local decision. We assume that the channel noise is AWGN and uncorrelated from channel to channel. To summarize, each local decision u_k is transmitted through a fading channel and the output of the channel (or input to the FC) for the kth sensor is

$$y_k = h_k u_k + n_k \tag{2.3}$$

where h_k is the fading channel gain and n_k is a zero-mean Gaussian random variable with variance σ^2.

2.1.3 Layer 3: Fusion Center:

The FC is the most important part in WSN system which makes a global decision u_o regarding a certain phenomena based on the received y_k data for all k. This is done by making use of a certain fusion rule applied at the FC. According to the used fusion rule at the FC, some other parameters may be required in order to make the global decision such as the CSI and the local sensors performance indices. The following equation describes the function of the FC after forming a certain statistic Λ:

$$u_o = \left\{ \begin{array}{ll} 1 & : \Lambda > T \\ -1 & : \Lambda < T \end{array} \right\} \tag{2.4}$$

where T is the decision threshold at the FC.

2.2 State of the Art Fusion Rules

To facilitate our comparisons later, here we give a brief review of the fusion rules developed in [26] and [28].

1) The Optimal LRT: By assuming instantaneous channel state knowledge regarding the fading channel and the local sensor performance indices, i.e., the P_{d_k} and P_{f_k} values, the optimal LRT-based fusion rule has been derived in [26], with the fusion statistic Λ given by

$$\begin{aligned} \Lambda(\mathbf{y}) &= \log\left[\frac{f(\mathbf{y}|H_1)}{f(\mathbf{y}|H_0)}\right] \\ &= \sum_{k=1}^{K} \log\left[\frac{P_{d_k} e^{-\frac{(y_k-h_k)^2}{2\sigma^2}} + (1-P_{d_k})e^{-\frac{(y_k+h_k)^2}{2\sigma^2}}}{P_{f_k} e^{-\frac{(y_k-h_k)^2}{2\sigma^2}} + (1-P_{f_k})e^{-\frac{(y_k+h_k)^2}{2\sigma^2}}}\right] \end{aligned} \tag{2.5}$$

where σ^2 is the variance of AWGN for all channels. The LR value is then compared with a threshold at the FC to make a final decision. While the form of the LRT based fusion statistic is straightforward to implement, it does need both the local sensor performance indices and complete channel knowledge.

2) Chair-Varshney Fusion Rule: In [28], the following statistic, termed as the Chair-Varshney fusion statistic has been shown to be a high-SNR approximation to Λ.

$$\Lambda_1 = \sum_{sign(y_k)=1} \log \frac{P_{d_k}}{P_{f_k}} + \sum_{sign(y_k)=-1} \log \frac{1-P_{d_k}}{1-P_{f_k}} \tag{2.6}$$

Λ_1 does not require any knowledge regarding the channel gain but does require P_{d_k} and P_{f_k} for all k. This approach, however, suffers significant performance loss at low channel SNR.

*3) MRC Fusion Rule:*It has been shown in [28] that for small values of channel SNR, Λ in (2.5) reduces to

$$\hat{\Lambda}_2 = \sum_{k=1}^{K} (P_{d_k} - P_{f_k}) h_k y_k \tag{2.7}$$

Further, if the local sensors are identical, i.e., $P_{d_k} = P_d$ and $P_{f_k} = P_f$ for all k's, then Λ further reduces to a form analogous to a MRC statistic

$$\Lambda_2 = \frac{1}{K} \sum_{k=1}^{K} h_k y_k \tag{2.8}$$

Λ_2 in (2.7) does not require the knowledge of P_d and P_f provide $P_d - P_f > 0$. Knowledge of the channel gain is, however, required.

*4) EGC Fusion Rule:*Motivated by the fact that resembles a MRC statistic for diversity combining, a third alternative in the form of an EGC has been proposed in [28], which requires minimum amount of information:

$$\Lambda_3 = \frac{1}{K}\sum_{k=1}^{K} y_k \tag{2.9}$$

interestingly enough, this simple alternative fusion rule outperforms both MRC and Chair-Varshney fusion rules for a wide range of SNR in terms of its detection performance [28].

5) LRT-CS Fusion Rule: A new fusion rule based on the optimal LRT has been proposed in [28]. This fusion rule requires the knowledge about the wireless channel statistical characteristics instead of the instantaneous CSI. This fusion rule is given by

$$\Lambda_4 = \sum_{k=1}^{K} \log\left\{\frac{1+[P_{d_k} - Q(ay_k)]\sqrt{2\pi}ay_k e^{\frac{(ay_k)^2}{2}}}{1+[P_{f_k} - Q(ay_k)]\sqrt{2\pi}ay_k e^{\frac{(ay_k)^2}{2}}}\right\} \tag{2.10}$$

where $a = 1/(\sigma\sqrt{1+2\sigma^2})$ and $Q(\cdot)$ is the complementary distribution function of the standard Gaussian.

The above fusion rule outperforms both the EGC and ChairVarshney fusion rules and has better performance than the MRC fusion rule for most practical SNR values (except for very low SNR values) [28].

6) SC Fusion Rule: Diversity is already built into a WSN in the form of multiple sensors. EGC and MRC diversity combining techniques proposed in [28] as a fusion rules at the FC. Applying the MRC requires the CSI and thus it is has the highest implementation complexity compared to the EGC. We propose to make use of the SC as fusion rule at the FC in the traditional WSN system model. The SC has a lower implementation complexity compared to the MRC and the EGC and it is based on selecting the branch which has the highest instantaneous channel SNR. Equation (2.11) describes the proposed SC based fusion rule.

$$\Lambda(\mathbf{y}) = max\left\{|y_1|\ldots|y_K|\right\} \tag{2.11}$$

A performance comparison among the above fusion rules in term of receiver operating characteristics curves (ROC) is shown in Figure 2.3. These curves obtained by MATLAB simulation. In this simulation, first, a noisy data is generated for both phenomena (H_0 and H_1) then each sensor make its decision based on the sign of the received measurement according to equation (2.1). The obtained decisions are then transmitted to the FC by each sensor and it is assumed that the channel between each sensor and the FC undergoes independent Rayleigh fading and AWGN and the average channel SNR is 5 dB. The local sensors performance indices values, i.e., the P_{d_k} and P_{d_k} are 0.5 and .05 respectively. The global decisions are obtained by the FC according to equation (2.4). Through this simulation, we make use of a range of threshold (i.e. -30:30) in order to get a wide range of P_d and P_f.

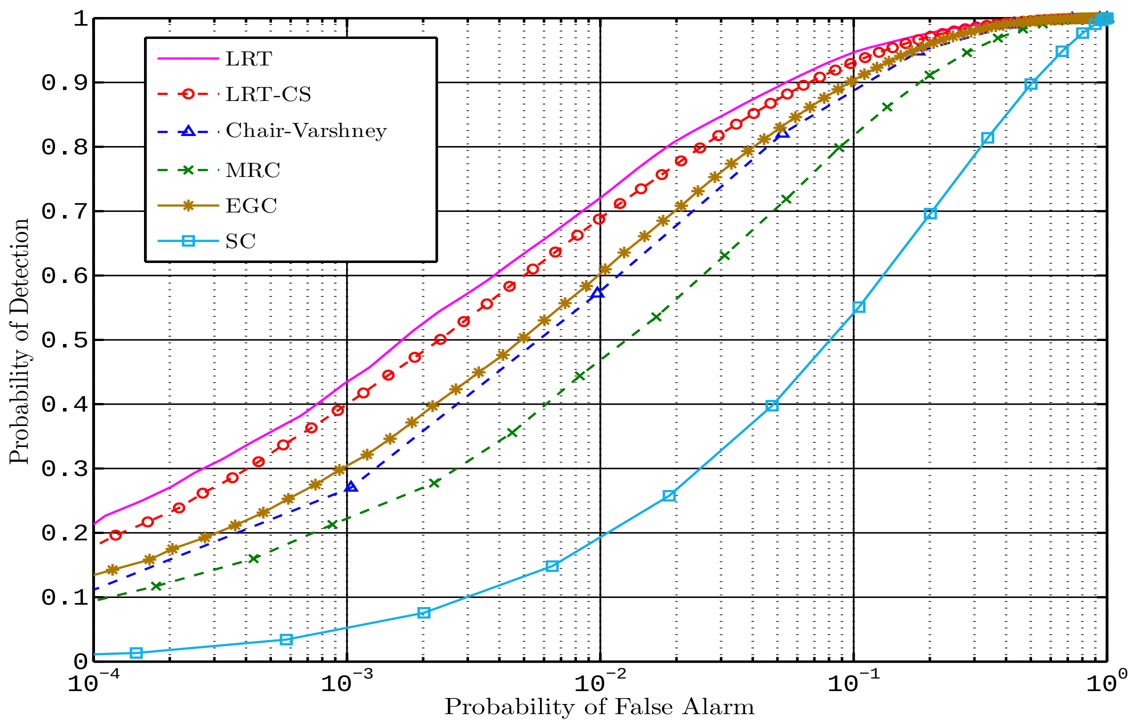


Figure 2.3: ROC curves for fusion rules presented in [28] in addition to SC , average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$.

It can be shown from Figure 2.3 that the performance of the LRT fusion rule is the best among the other fusion rules and that is because the LRT fusion rule assumes a complete knowledge about the CSI and the local sensors performance indices (P_{d_k} and P_{d_k}). Figure 2.3 shows that the EGC outperforms the MRC, while this result is not reasonable in the context of diversity combining, the inputs to the fading channels between the sensors and the FC are not identical, unlike diversity where all the inputs to the channels are identical and the same signal received from different antennas and thats describes the performance degradation of the MRC when compared to the EGC in this scenario. One more reason for this degradation of the MRC performance is because of the difference between the channels characteristics between the phenomena under interest and the sensors which are assumed to undergo AWGN only and those between the sensors and the FC which are assumed to undergo AWGN and Rayleigh fading. The SC fusion rule has the lowest performance compared to other fusion rules applied at the FC in the traditional WSN system model. However, SC fusion rule has the lowest implementation complexity among the other fusion rules where applying the SC does not involve any kind of mathematical operation such as summation and multiplication and it does not require any knowledge regarding the CSI.

Another performance comparison between the fusion rules presented in [28] and the proposed SC fusion rule in term of detection probability as a function of the average channels SNR is shown in Figure 2.4. The local sensors performance indices are identical and the channels between the local sensors and the FC are also identical for all sensors.

It can be noticed that the MRC fusion rule has a performance similar to that of LRT fusion rule in the case of low channels SNR and this result has been approved in [28] where it is proved that the performance of the LRT approaches that of the MRC at low channel SNR. In addition, Figure 2.4 shows that the EGC fusion rule outperforms both the MRC and the Chair-Varshney fusion rules for wide ranges of average channels SNR. Moreover, the EGC fusion rule has a performance similar to that of LRT-CS fusion rule in the case of low channels SNR. The EGC fusion rule provides the most robust detection performance among other fusion rules such as MRC and Chair-Varshney while requiring minimum amount of information. Figure 2.4 shows that for high channels SNR, the Chair-Varshney fusion rule has a performance similar to the of LRT and LRT-CS, so it is assumed as a high channel SNR approximation to LRT.

The Chair-Varshney fusion rule assumes that the local sensors performance indices, i.e., the P_{d_k} and P_{d_k} are totally known at the FC. Moreover, Figure 2.4 shows that the performance of the SC fusion is the lowest among all fusion rules.

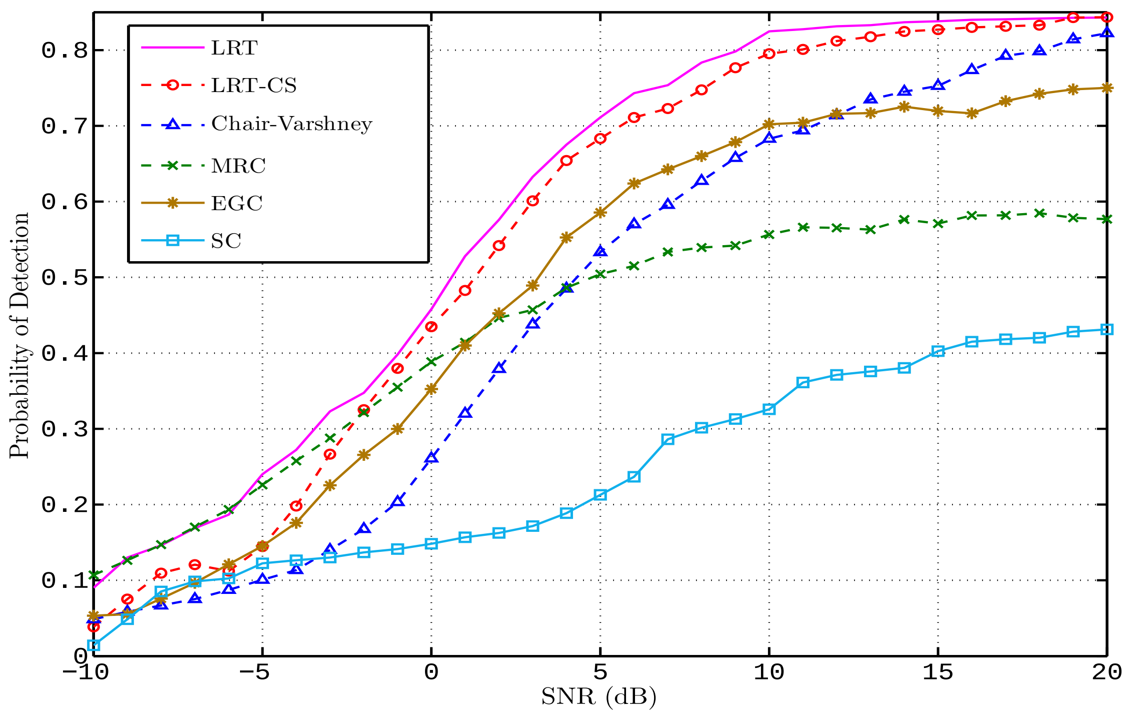


Figure 2.4: Performance comparison among the fusion rules as a function of average channel SNR, system level probability of false alarm $P_{f_o} = 0.01$, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$.

A comparison among the fusion rules presented in [28] and the proposed SC fusion rule in term of detection performance as a function of the total number of sensors in the network K is shown in Figure 2.5. While the LRT fusion rule provides the best performance among all the fusion rules even for small number of sensors, the EGC fusion rule provides also a robust performance in term of detection probability compared to MRC and Chair-Varshney fusion rules in the case of small number of sensors in the network.

It can be shown from Figure 2.5 that the fusion rules which require only the knowledge about the channel such as MRC or that require only the knowledge about the local sensors performance indices such as Chair-Varshney provide a lower performance in the case of small number of sensors in the network while the fusion rules which assume a knowledge about both the channel and the local sensors performance indices provide the best performance. However, the EGC requires a minimum amount of information and provides a better performance than MRC and Chair-Varshney fusion rules. Figure 2.5 shows that the SC has the lowest performance compared to other fusion rules.

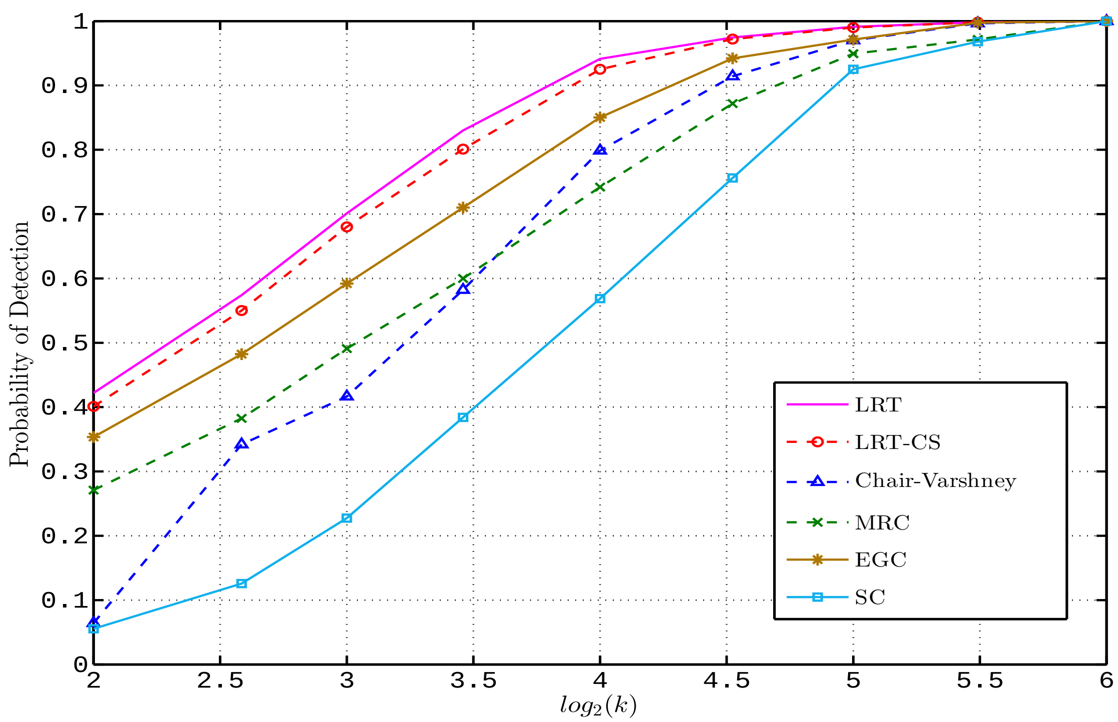


Figure 2.5: Performance comparison among the fusion rules as a function of the total number of sensors in the network K, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$.

Figure 2.6 shows a performance comparison among the fusion rules presented in [28] and the proposed SC fusion rule as a function of the average channel SNR.

In this particular case, the local sensors have a non identical performance indices, where $\vec{P}_{d_k} = [0.1, 0.2, 0.3, \ldots, 0.8]$ and $K = 8$. However, all sensors share the same P_f which is fixed at 0.05. All wireless channel between the local sensors and the FC have the same average SNR. From Figure 2.6 we can see that there is a performance degradation when comparing to Figure 2.4 specially for EGC, MRC, while LRT, LRT-CS and Chair-Varshney still have good performance and that is because the local sensors performance indices are being considered in LRT, LRT-CS and Chair-Varshney fusion rules.

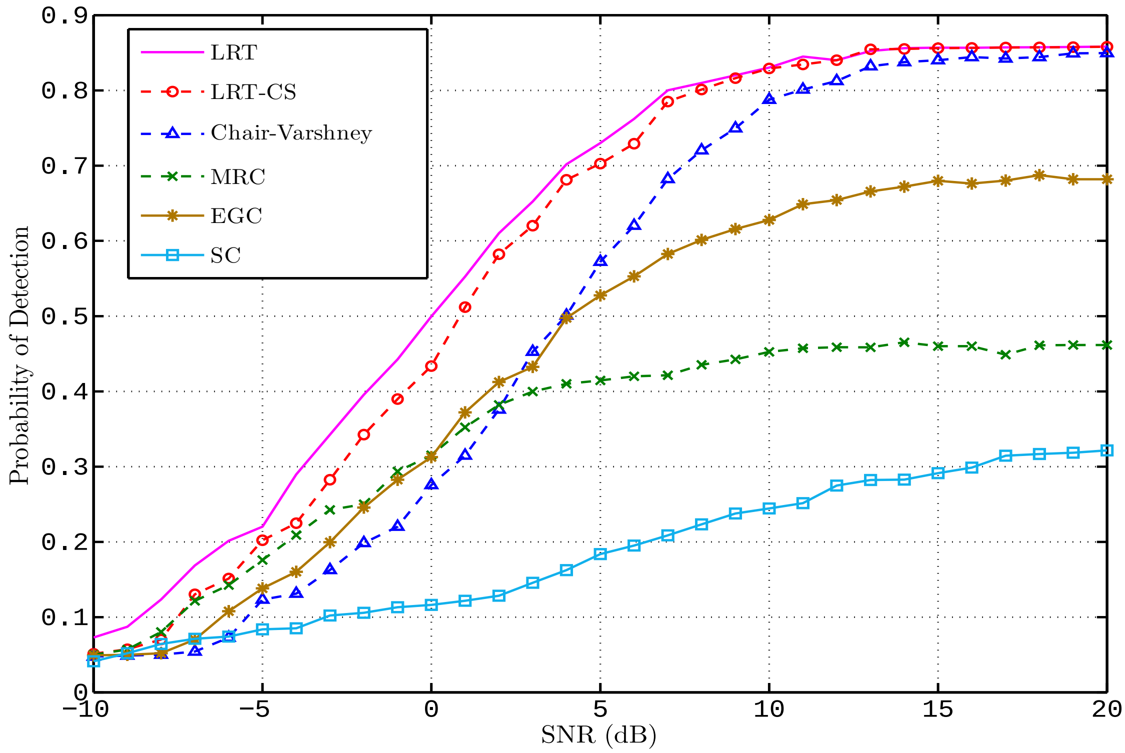


Figure 2.6: Performance comparison among the fusion rules whose performance indices are not identical, average channels SNR = 5 dB, system level probability of false alarm $P_{f_o} = 0.01$ and total number of sensors in the network $K = 8$.

Chapter 3

Proposed Three-Layer WSN System Model

3.1 Motivation

It was shown in the previous chapter that the LRT fusion rule is considered to be the best fusion rule [28] since it takes into account the complete knowledge of the instantaneous CSI and the local sensors performance indices values. However, for a WSN with very limited resources (energy and bandwidth), it is prohibitive to spend resources on estimating the channel every time a local sensor sends its decision to the FC and also acquiring the knowledge about the local sensors performance indices, i.e., P_{d_k} and P_{f_k}) values require the local sensors to transmit these values through the channel which is considered as an overhead. From energy consumption perspective, transmitting or receiving one kilobyte of information is equivalent to computing 3 million instructions [34], so it is recommended to make a computation in the sensor level instead of transmitting whenever it is possible.

3.2 LRT Based Decisions

Assuming that there are two hypothesis under test (H_0 and H_1), the received noisy signal at each sensor k can be described by the following equation:

$$x_k = \left\{ \begin{array}{ll} S + N_k & : H_1 \\ N_k & : H_0 \end{array} \right\} \tag{3.1}$$

where S represents the signal in the case of H_1 and N is AWGN with variance of σ_N^2. In this work, we assume that the absence or the presence of the signal under interest (S), i.e., H_1 or H_0 respectively, is described by either 1 or 0 as shown in equation (3.2).

$$S = \left\{ \begin{array}{ll} 1 & : H_1 \\ 0 & : H_0 \end{array} \right\} \tag{3.2}$$

The decision made by each sensor in the traditional WSN model is based on the following equation:

$$u_k = \left\{ \begin{array}{ll} 1 & : x_k > 0 \\ -1 & : x_k < 0 \end{array} \right\} \tag{3.3}$$

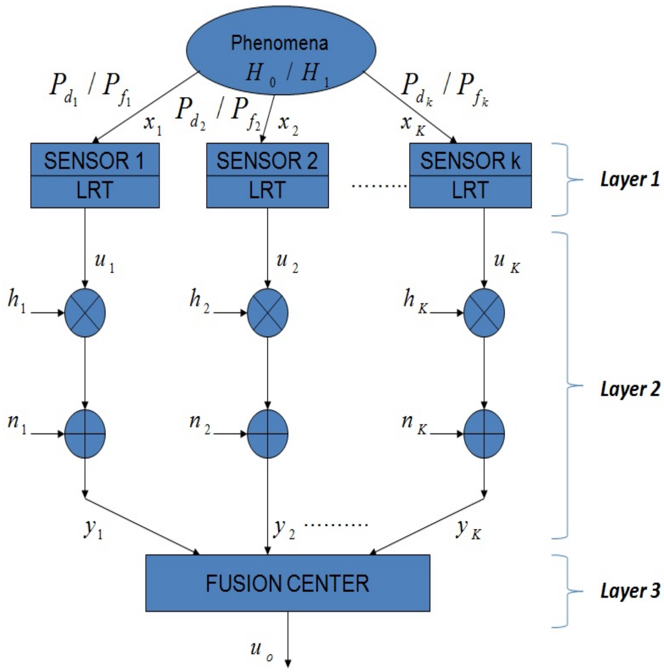


Figure 3.1: Proposed three-layer WSN system model where the LRT is applied at the sensors level

We propose to modify the traditional three-layer WSN system model shown in Figure 2.1 by applying the LRT at each sensor. The proposed three-layer WSN system model is shown in Figure 3.1.

The general form of the LRT based decision model is described by equation (3.4) , it is a measure of how much likely one of the phenomenas (H_1) presents than the other phenomena (H_0).

$$\Lambda(x) = \log \frac{p(x|H_1)}{p(x|H_0)} \underset{H_0}{\overset{H_1}{\lessgtr}} T \tag{3.4}$$

where T is the decision threshold. The received information (x_k) follows the normal distribution with mean of zero and variance of σ_N^2 in the case of H_0 and mean of one in the case H_1 as described in the following equation:

$$\begin{aligned} H_0 : \quad & x_k \sim N(0, \sigma_N^2) \\ H_1 : \quad & x_k \sim N(1, \sigma_N^2) \end{aligned} \tag{3.5}$$

The required PDFs are therefore [35]:

$$\begin{aligned} p(x_k|H_0) = \quad & \frac{1}{\sqrt{2\pi\sigma_N^2}} exp\left\{-\frac{1}{2}(\frac{x_k}{\sigma_n})^2\right\} \\ p(x_k|H_1) = \quad & \frac{1}{\sqrt{2\pi\sigma_N^2}} exp\left\{-\frac{1}{2}(\frac{x_k-1}{\sigma_n})^2\right\} \end{aligned} \tag{3.6}$$

assuming independent identically distributed (i.i.d) measurements among the sensors. Substituting equation (3.6) into (3.4) yields to the LRT statistics $\Lambda(x_k)$:

$$\Lambda(x_k) = \log \left\{ \frac{e^{-\frac{(x_k-1)^2}{2\sigma_N^2}}}{e^{-\frac{(x_k)^2}{2\sigma_N^2}}} \right\} \tag{3.7}$$

Assuming all sensors are receiving a noisy measurements with SNR corresponds to the sensors performance indices, i.e., P_{d_k} and P_{f_k}. It can be noticed from equation (3.7) that applying the LRT at the sensors level requires no prior information regarding the channel and it only requires the instantaneous channel SNR. Each sensor makes a local decision regarding the absence or the presence of a certain hypothesis, H_1 and H_0 respectively, according to the following equation:

$$u_k = \left\{ \begin{array}{ll} 1 & : \Lambda(x_k) > T \\ -1 & : \Lambda(x_k) < T \end{array} \right\} \tag{3.8}$$

We assume that the communication channels are parallel access channels that undergo noise and fading. The fading distribution is assumed to be Rayleigh with unit power (i.e.,$E[h_k^2] = 1$). The performance of the LRT is mainly characterized by the probability of correctly recognize the presence of the signal while it is actually present (probability of detection) and the probability of wrongly recognize signal as present while it is actually absent (probability of false alarm). The probability of false alarm is defined as follows [35]:

$$\begin{aligned} P_f &= \int_T^{+\infty} p_\Lambda(\Lambda|H_0)d\Lambda \\ &= \int_T^{+\infty} \frac{1}{\sqrt{2\pi\sigma_N^2}} e^{\frac{-\Lambda^2}{2\sigma_N^2}} d\Lambda \end{aligned} \tag{3.9}$$

Equation (3.9) is the integral of a Gaussian pdf, so it can be solved by the error function ($erf(x)$) [36], which is defined as:

$$erf(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt \tag{3.10}$$

changing the variables $t = \Lambda/\sqrt{2\sigma_N^2}$, equation (3.9) can be rewritten as:

$$\begin{aligned} P_f &= \frac{1}{\sqrt{\pi}} \int_{T/\sqrt{2\sigma_N^2}}^{+\infty} e^{-t^2} dt \\ &= \frac{1}{2} \left\{ 1 - erf\left(\frac{T}{\sqrt{2\sigma_N^2}} \right) \right\} \end{aligned} \tag{3.11}$$

Finally, equation (3.11) can be solved to obtain the threshold T in term of the inverse error function(erf^{-1}) [36] as follows:

$$T = \sqrt{2\sigma_N^2} erf^{-1}(1 - 2P_f) \tag{3.12}$$

The probability of detection for the LRT test is defined as follows [35]:

$$\begin{aligned} P_d &= \int_T^{+\infty} p_\Lambda(\Lambda|H_1)d\Lambda \\ &= \int_T^{+\infty} \frac{1}{\sqrt{2\pi\sigma_N^2}} e^{\frac{-(\Lambda-1)^2}{2\sigma_N^2}} d\Lambda \end{aligned} \tag{3.13}$$

Again, applying the definition of the error function in equation (3.10) leads to:

$$P_d = \frac{1}{2}\left\{1 - erf\left(\frac{T-1}{\sqrt{2\sigma_N^2}}\right)\right\} \tag{3.14}$$

Substituting (3.12) in (3.14) and make use of the complementary error function(erfc(x)=1-erf(x)) [36] in order to eliminate the Threshold T leads to:

$$P_d = \frac{1}{2} erfc\left\{erfc^{-1}(2P_f) - \sqrt{\frac{SNR_{db}}{2}}\right\} \tag{3.15}$$

Equation (3.15) describes the performance of the LRT in term of fixed channel SNR and fixed probability of false alarm.

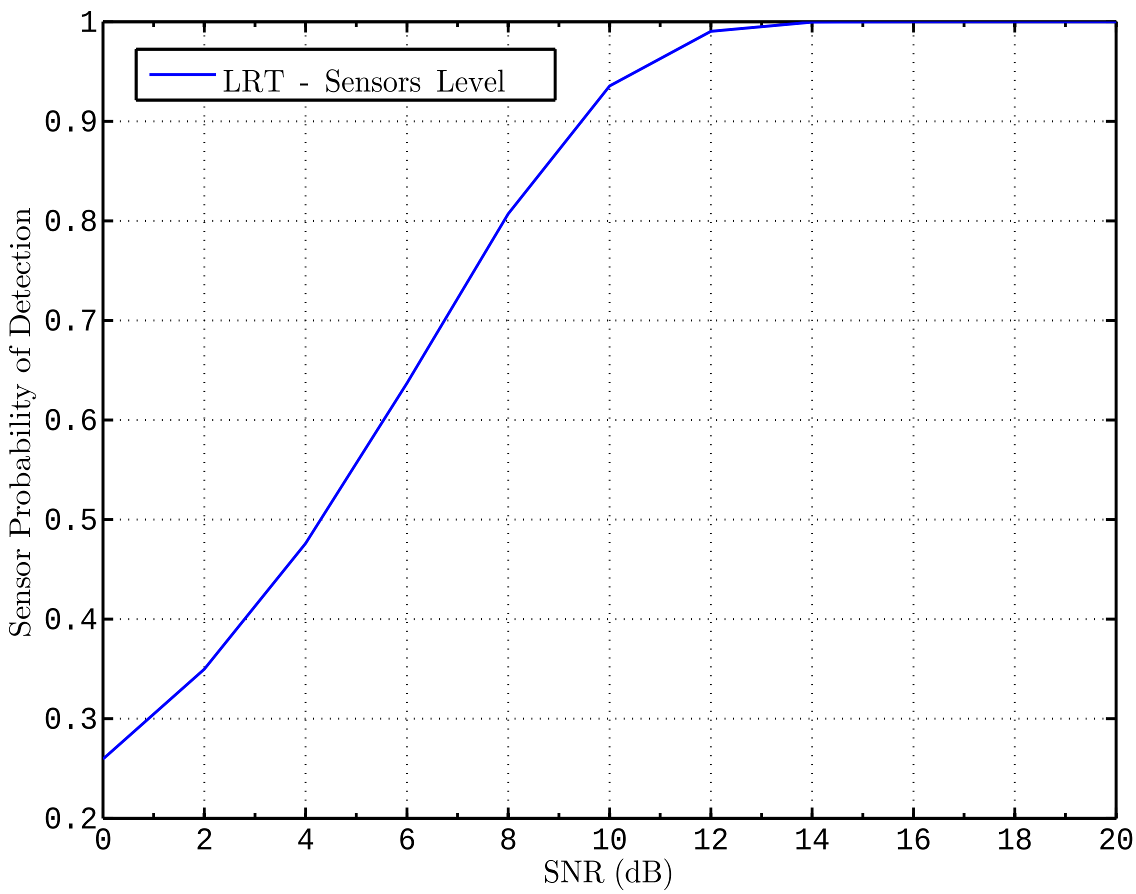


Figure 3.2: The performance of the LRT applied at the sensors level, $P_f = 0.05$.

The local sensors performance indices, i.e., P_{d_k} and P_{f_k}, are function of the threshold T and the channel SNR between the phenomena under interest and the local sensors. In this work we focus on the over all system performance at the FC. In order to facilitate our comparisons later between the proposed WSN system model and the traditional WSN model, we assume that the local sensors performance indices are same for both models and thus a certain channel SNR is chosen in each model in order to get the same performance indices for both models. Figure 3.2 shows the performance of the LRT decision making method at the local sensors layer. We assume a fixed P_{f_k} of 0.05.

It can be noticed from Figure 3.2 that a channel SNR of 4.3 dB will yield to a performance indices of $P_{d_k} = 0.5$ and $P_{f_k} = 0.05$. In addition, it can be shown from (3.12) that a threshold T=1 should be applied in order to get P_d=0.5 and P_f=0.05. Moreover, applying the traditional hard binary decision will yield to the same performance indices for channel SNR of 4.3 dB with a threshold of zero [26]. So we choose this channel SNR (i.e., 4.3 dB) in order to obtain the ROC curves and make a fair comparison later between the two models.

Chapter 4

Simulation Results

In this chapter, the relative performance of different fusion rules applied at the FC in the proposed WSN system model is examined. Moreover, a performance comparison between the traditional and the proposed WSN is carried out through simulation in order to obtain the ROC curves for different fusion rules and also to study the effect of various factors that may affect the performance of the FC such as the communication channel SNR, total number of sensors in the network (i.e., K) and the local sensors performance indices (i.e., P_{d_k} and P_{f_k}).

4.1 Performance Comparison Among Different Fusion Rules Applied at the Proposed WSN Model

In this scenario, we assume that all sensors receive noisy measurements and all have same channel SNR and thus having the same performance indices. Moreover, the channels between the sensors and the FC all have the same SNR. ROC curves for different fusion rules applied at the proposed WSN system model and channel SNR of 5 dB are plotted in Figure 4.1. The local sensors performance indices P_{d_k} and P_{f_k} are assumed to be .5 and .05 respectively. The total number of sensors in the network is fixed at eight.

Figure 4.1 shows that the LRT and the LRT-CS fusion rules have a performance similar to that when applied at the proposed WSN system model. It can be shown from Figure 4.1 that the performance of MRC applied at the proposed WSN system model is similar to that of Chair-Varshney fusion rule applied at the proposed model, however, the MRC fusion rule requires the knowledge of CSI.

In addition, Figure 4.1 shows that the EGC fusion rule applied at the proposed WSN system model shows a relatively better performance when compared to Chair-Varshney, MRC and SC fusion rules applied at the proposed model and provides a little performance degradation when compared to both LRT and LRT-CS.

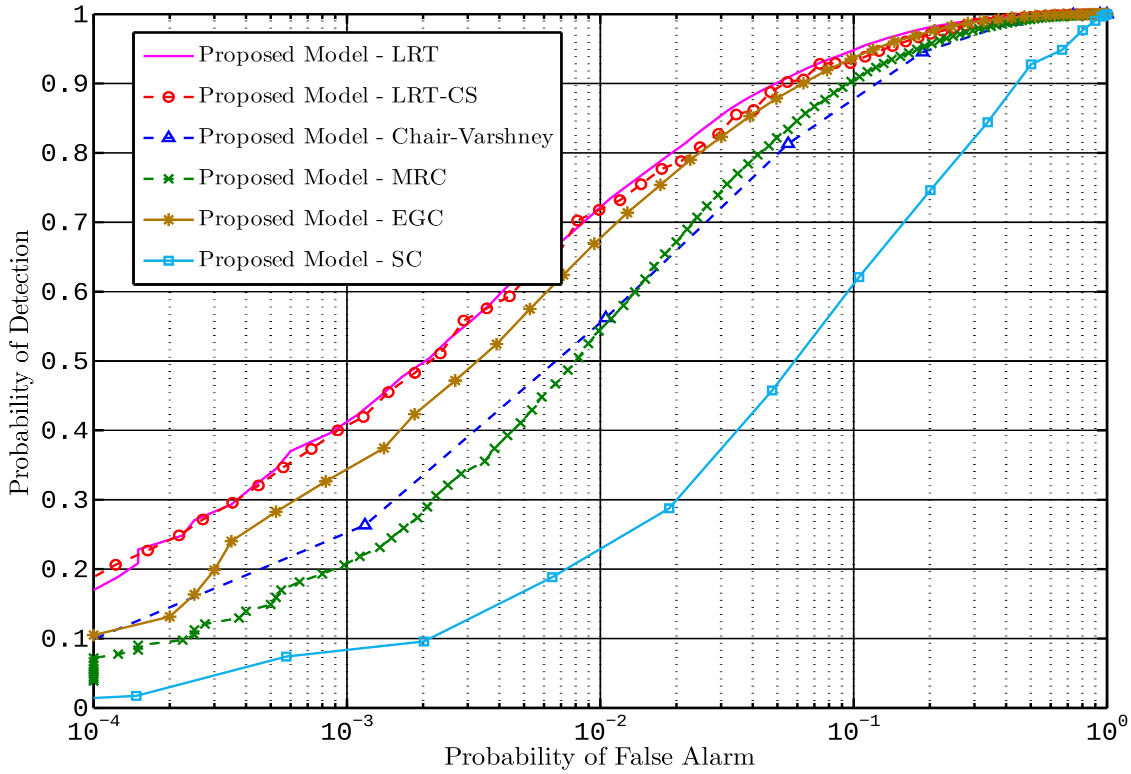


Figure 4.1: ROC curves for different fusion rules applied at the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$.

4.2 Performance Comparison Between the Proposed and the Traditional WSN Model

In this section, a comparison is made between the traditional and the proposed WSN model where a certian fusion rule is applied in both models. We assume that all sensors have the same channels SNR to the FC and also have same performance indices. The total number of sensors in the network, K, is fixed to eight.Figure 4.2, Figure 4.3 and Figure 4.4 show that the performance of the LRT, LRT-CS and Chair-Varshney fusion rules applied at the traditional WSN system model is nearly similar to the performance of these fusion rules applied at the proposed WSN system model and that is because LRT and LRT-CS fusion rules assume a complete knowledge regarding either the CSI or the channel statistics and the local sensors performance indices.

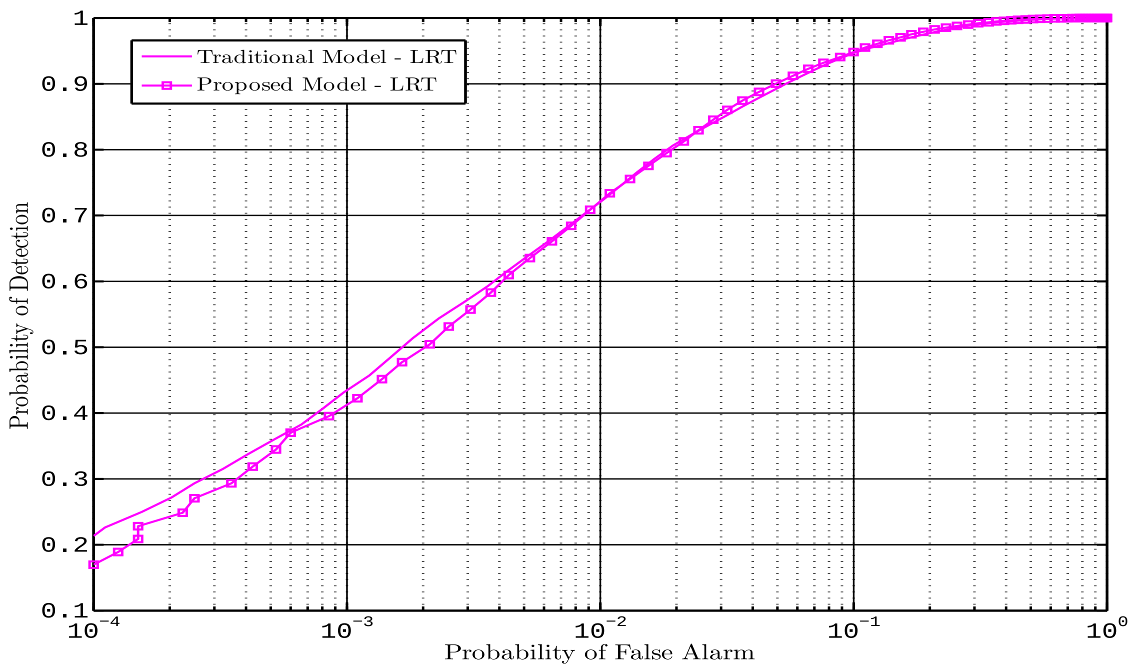


Figure 4.2: ROC curves for the LRT fusion rule applied at both the traditional and the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$.

It can be shown from Figure 4.5, Figure 4.6 and Figure 4.7 that applying the diversity combining techniques such as MRC, EGC and SC at the proposed model can increase the performance when compared to the performance of diversity based fusion rules applied in the traditional WSN system model. Moreover, fusion rules based on diversity combining techniques such as the EGC and the SC require no information regarding the CSI or the local sensors performance indices and have a lower implementation complexity compared to LRT, LRT-CS, Chair-Varshney and MRC fusion rules.

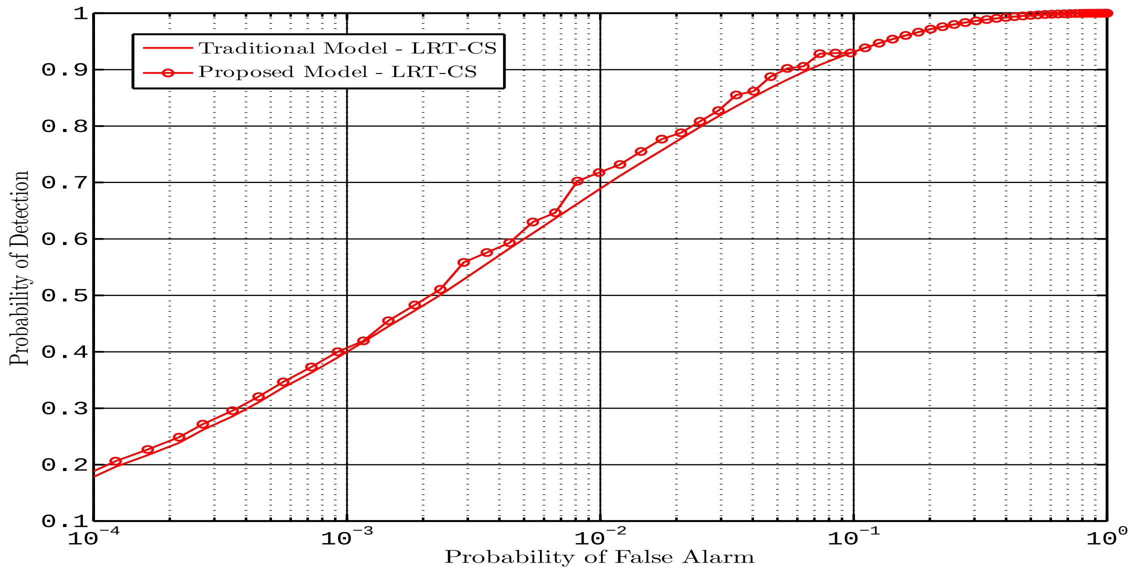


Figure 4.3: ROC curves for the LRT-CS fusion rule applied at both the traditional and the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$.

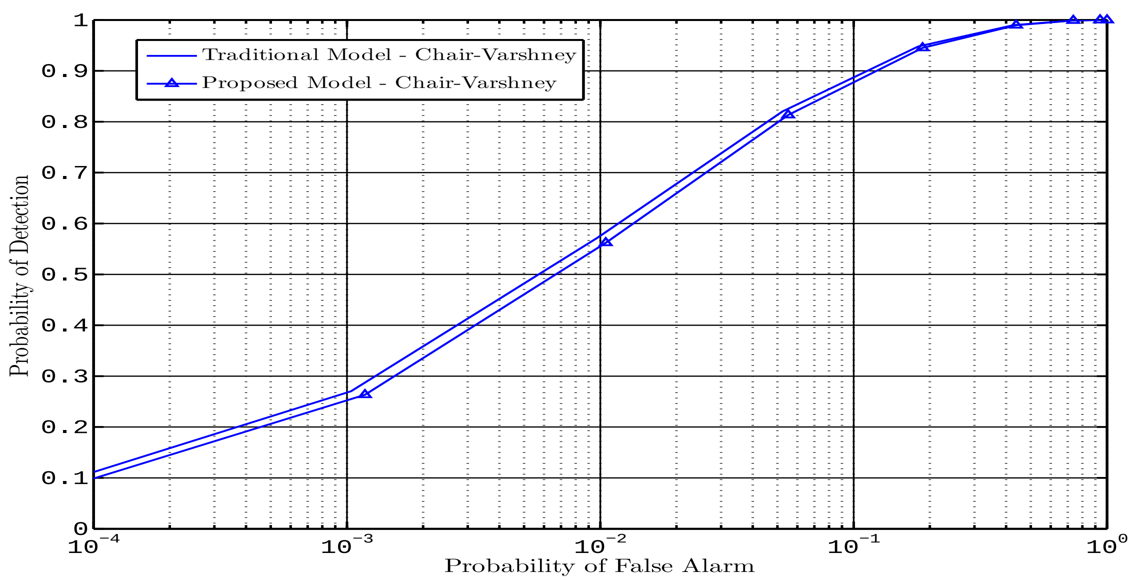


Figure 4.4: ROC curves for the Chair-Varshney fusion rule applied at both the traditional and the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$.

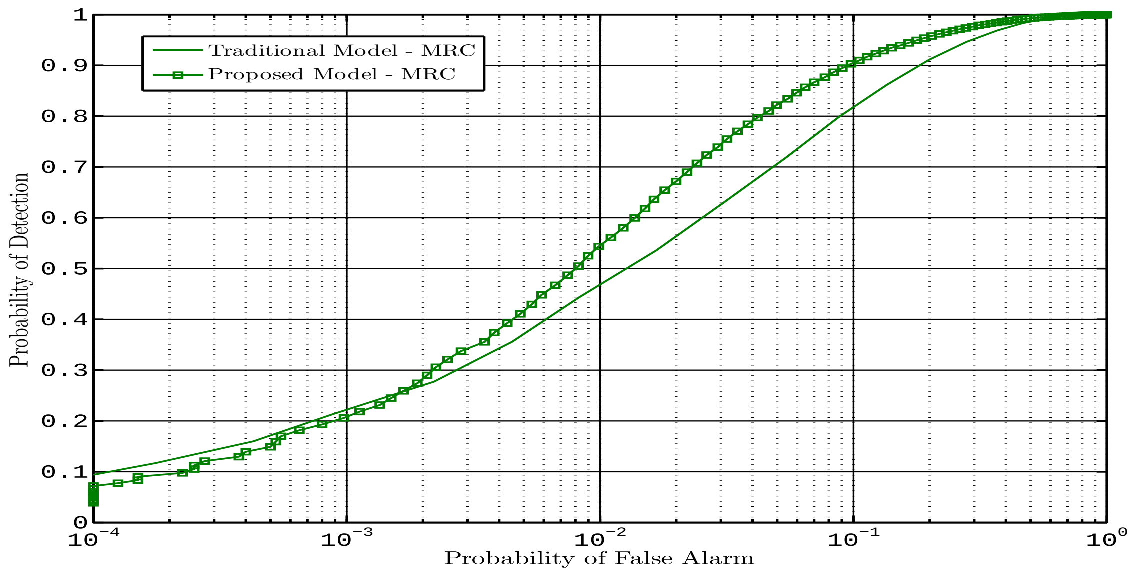


Figure 4.5: ROC curves for the MRC fusion rule applied at both the traditional and the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$.

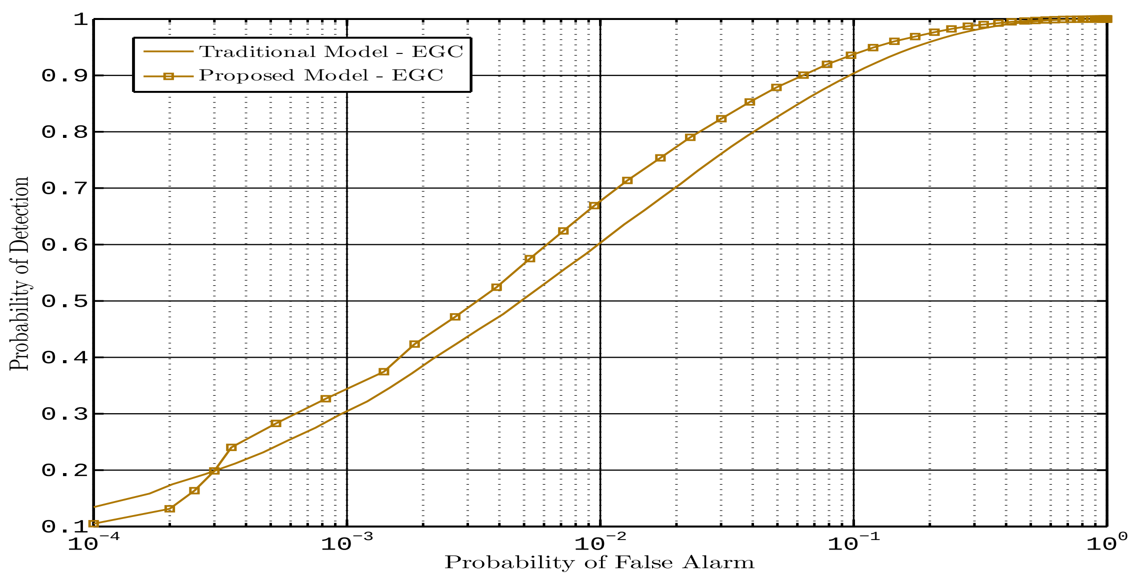


Figure 4.6: ROC curves for the EGC fusion rule applied at both the traditional and the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$.

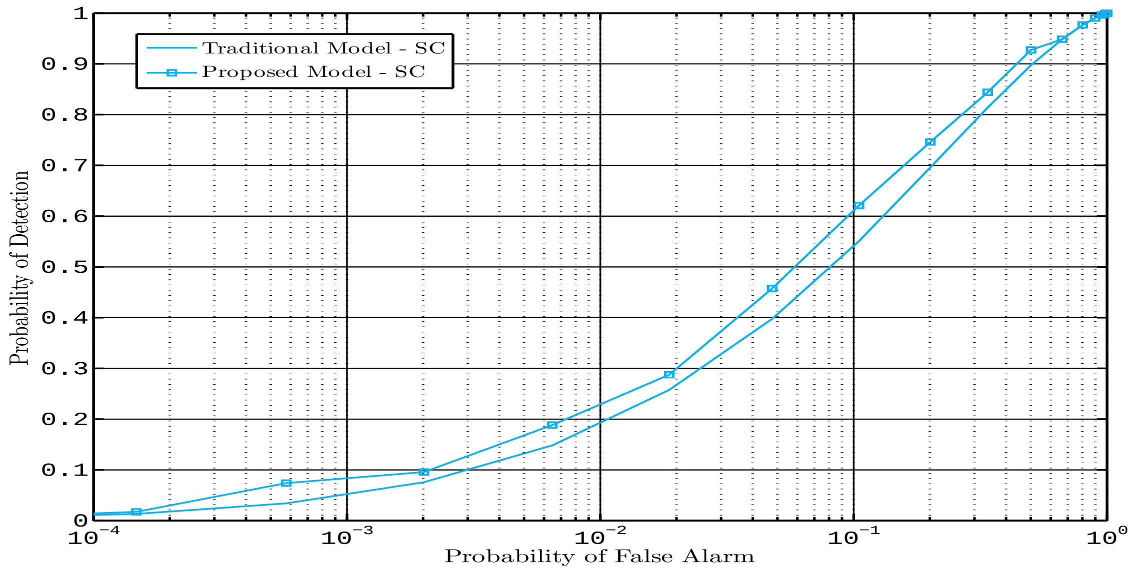


Figure 4.7: ROC curves for the SC fusion rule applied at both the traditional and the proposed WSN system model, average channel SNR = 5 dB, $P_d = 0.5$, $P_f = 0.05$ and total number of sensors $K = 8$.

4.3 The Effect of the Channel SNR Between the Sensors and the FC

In this scenario we assume that the local sensors performance indices are identical and also the channels SNR between the sensors and the FC are identical. However, the channels SNR to the FC in this scenario are not fixed and we study the effect of the channels quality for a wide rage of SNRs.

In Figure 4.8, a comparison in terms of the detection performance versus the average channel SNR between different fusion rules applied at both the traditional and the proposed WSN system models. The local sensors have identical performance indices. While the LRT shows the best performance among the other fusion rules in both WSN models, the EGC fusion rule applied at the proposed model provide a performance nearly similar to that of LRT-CS for a wide range of SNRs and better performance than other fusion rules such as MRC and ChairVarshney fusion rules.

Thus, applying the LRT at the sensors level and EGC at the FC which requires no information regarding the CSI and sensors performance indices can significantly raise the performance of the system when compared to EGC only applied to the FC.

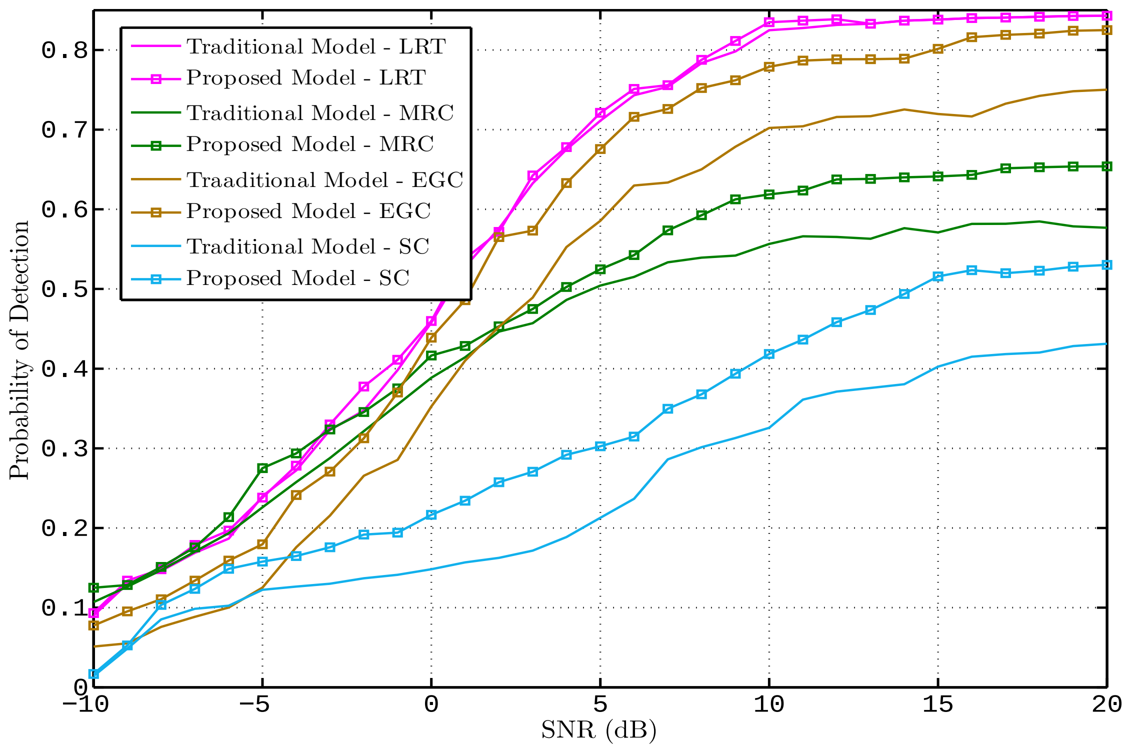


Figure 4.8: Probability of detection as a function of average channel SNR, $P_d = 0.5$, $P_f = 0.05$, system probability of false alarm $P_{f_o} = 0.01$ and total number of sensors k = 8.

Moreover, Figure 4.8 shows that the proposed WSN model could significantly increase the performance of MRC and SC fusion rules for high channels SNR.

4.4 The Effect of the Total Number of Sensors K

Performance comparison between different fusion rules as a function of total number of sensors K is shown in Figure 4.9. We assume that the average channel SNR is fixed to 5 dB, system probability of false alarm $P_{f_o} = .01$, the local sensors have a performance indices of $P_d = .5$, $P_f = .05$ and these indices are identical among all sensors.

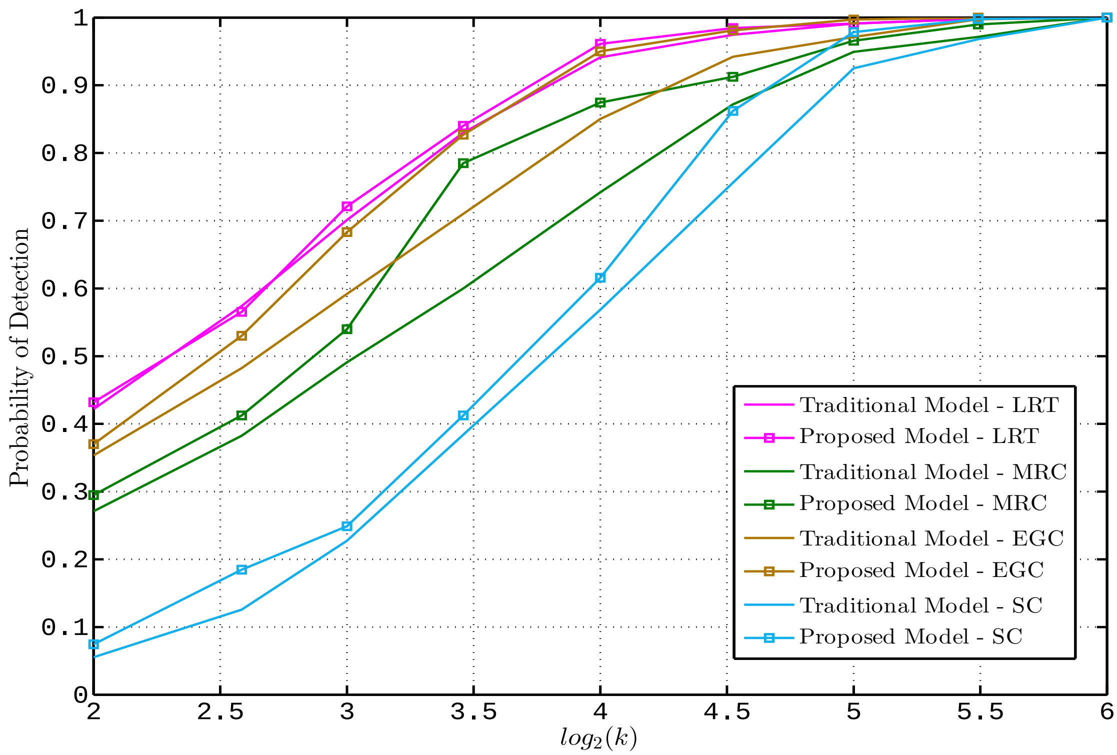


Figure 4.9: Probability of detection as a function of total number of sensors K, $P_d = 0.5$, $P_f = 0.05$, system probability of false alarm $P_{f_o} = .01$ and the average channel SNR is 5 dB.

It can be observed from Figure 4.9 that even for small number of sensors K, the performance of the EGC applied at the proposed model is nearly same to that of the optimum LRT and outperforms all other fusion rules and shows more robustness regarding the total number of sensors.

Figure 4.9 also shows that even for low channel SNR, the system probability of detection approaches 1 when K is very large. That is because the huge amount of decisions received by the FC from large number of sensors.

4.5 Sensors With Non-Identical Indices

A performance comparison as a function of average channel SNR in a special case where all the sensors have a non-identical performance indices is presented in Figure 4.10. All wireless channel between the local sensors and the FC have the same average SNR. In this special case, all sensors have the same probability of false alarm ($P_f = 0.05$) and a different probabilities of detection, where $\vec{P}_{d_k} = [0.1, 0.2, 0.3, \ldots, 0.8]$ and $K = 8$.

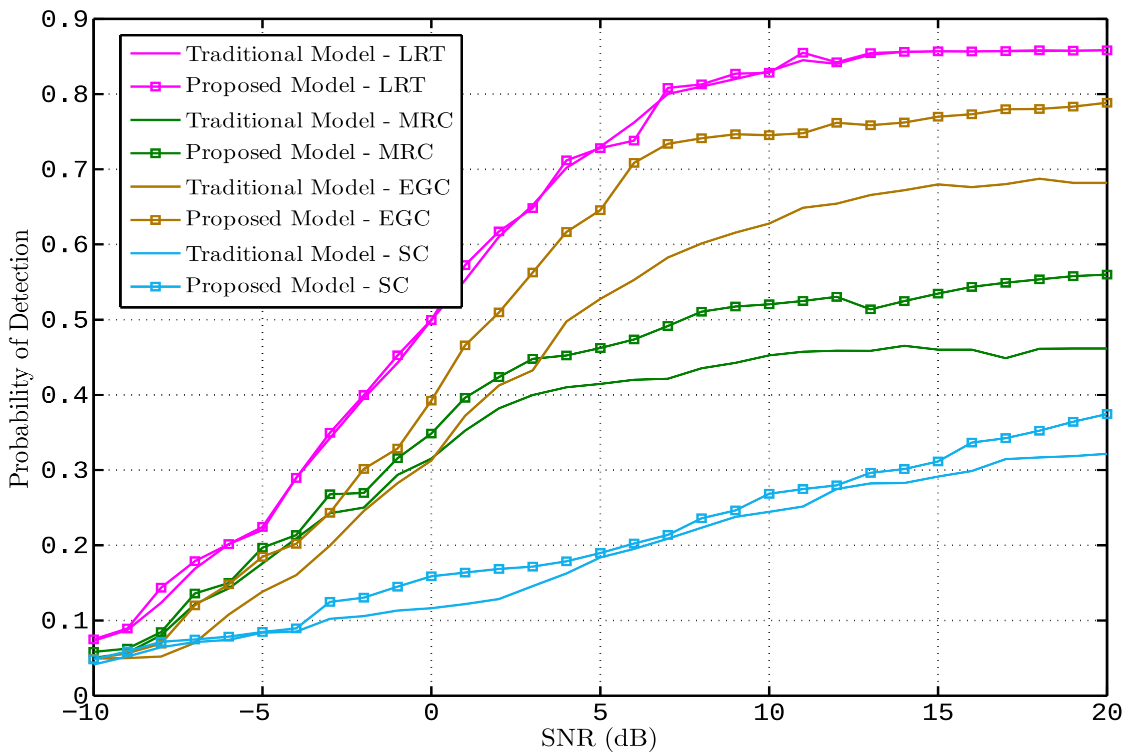


Figure 4.10: Probability of detection as a function of average channel SNR, sensors have different detection performance, total number of sensors K =8, and system probability of false alarm $P_{f_o} = 0.01$.

From Figure 4.10, it can be seen that the diversity based fusion rules has a lower performance compared to that of the LRT. In addition, the EGC fusion rule applied at the proposed model provides a relatively good performance when compared to SC and MRC and similar to that of the LRT. Thus, the EGC fusion rule applied at proposed WSN model could be a good alternative for the optimum LRT fusion rule.

4.6 Sensors With Non-Identical Channels to the FC

In this scenario, we investigate the performance of the different fusion rules for both the traditional and the proposed system models in the case where the sensors have identical performance indices ($P_d = .5$, $P_f = .05$) and non identical channels SNR to the FC.

A performance comparison among different fusion rules in terms of system probability of detection as a function of the arithmetic mean value of the average channels SNR is shown in Figure 4.11. We assume that $\overrightarrow{S} = [\overrightarrow{S} - 6, \overrightarrow{S} - 4, \overrightarrow{S} - 2, \overrightarrow{S}, \overrightarrow{S}, \overrightarrow{S} + 2, \overrightarrow{S} + 4, \overrightarrow{S} + 6]$ dB, where $\overrightarrow{S} = [SNR_1, SNR_2, \ldots, SNR_K]$ and $\overrightarrow{S}$ is the arithmetic mean of the average channels SNR.

It can be noticed from Figure 4.11 that the LRT fusion rule has a better performance in the case of small values of mean channels SNR, and that is because of the high SNRs components where it is assumed that there is 12-dB difference between the largest and the smallest average channel SNR. However, the other fusion rules still nearly have the same performance as shown in Figure 4.8. In addition, the proposed system model still have a robust performance in this scenario where the EGC is applied at the FC. Moreover, applying the SC and the MRC fusion rules at the proposed WSN system model can efficiently increase the performance when compared to these fusion rules applied at the traditional WSN system model.

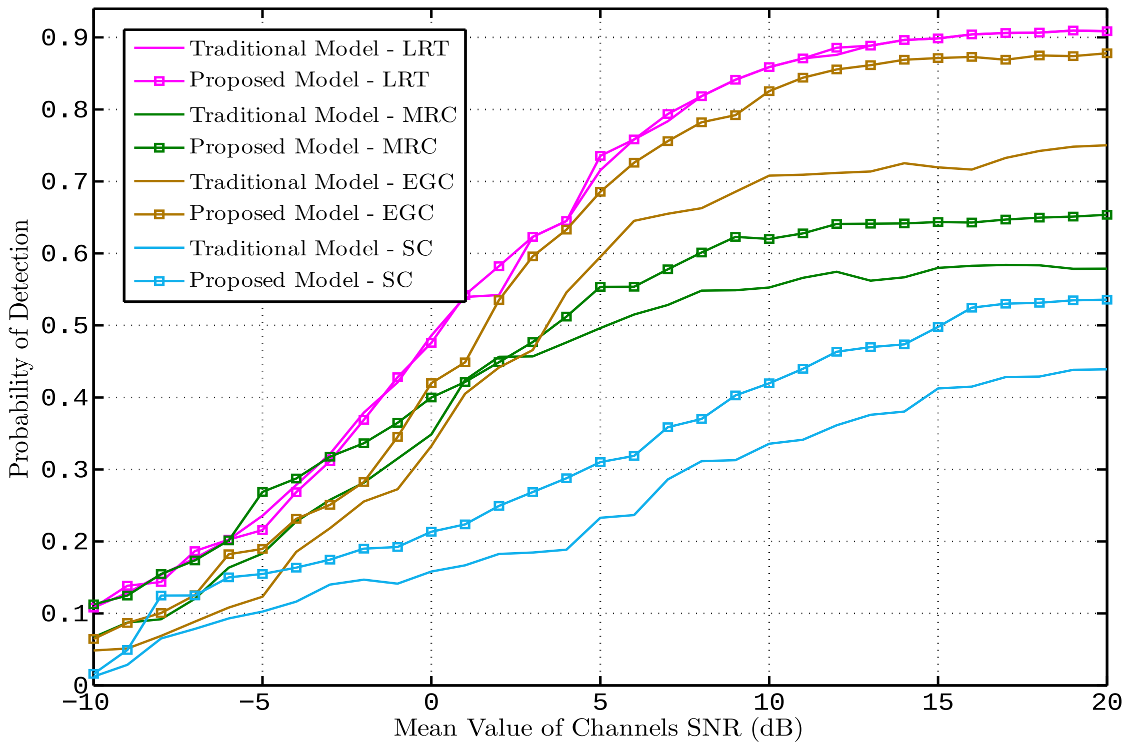


Figure 4.11: Probability of detection as a function of the mean value of the average channel SNR, $P_d = 0.5$, $P_f = 0.05$, system probability of false alarm $P_{f_o} = 0.01$ and total number of sensors k = 8.

Chapter 5

Conclusions and Future Work

5.1 Conclusions

In this thesis, the problem of fusion of decisions transmitted over Rayleigh fading channels in WSN is studied. Many decision fusion rules proposed in literature, these fusion rules are mainly applied at the FC and they have different performance and require a variety of information in order to obtain a global decision regarding a certain phenomena.

Considering an energy and bandwidth constrained system such as WSN, we propose a modification to the traditional three-layer system model of WSN where the LRT is applied locally to each sensor. Applying the LRT at the sensors level requires no prior information regarding the channel, it only requires the instantaneous channel SNR. This method aims to increase the performance of different fusion rules when applied to the FC by reducing the number of different decisions transmitted from the sensors to the FC. Moreover, we propose to make use of SC as decision fusion method applied at the FC. The SC has the lower implementation complexity compared to other diversity combining based fusion rules such as MRC and EGC where applying the SC does not involve any kind of mathematical operation such as summation and multiplications and it does not require any knowledge regarding the CSI.

A comparison has been performed through simulation among six different fusion rules, LRT, LRT-CS, CV, EGC, MRC, SC applied at both the traditional and the proposed WSN system models. The channels between the local sensors and the FC is assumed to undergo Rayleigh fading and AWGN. We investigate the effect of the system parameters on the overall system performance at the FC. We study the effect of the local sensors performance indices in the case in which all indiceis are identical and non-identical. We also investigate the effect of the total number of sensors in the network and the effect of the average channel SNR between the local sensors layer and the FC. Simulation results show that the proposed model provide a relatively good performance in terms of detection performance when compared to the traditional model specially for diversity based fusion rules such as EGC, MRC and SC. Moreover, applying the EGC fusion rule at the proposed WSN model could be considered as a good alternative for the optimum LRT fusion rule since the EGC applied at the proposed model provides a comparable performance to that of LRT and better performance than other fusion rules such as MRC and SC. In addition, the EGC fusion rule requires no information regarding the channel or the sensors performance indices. Simulation results show that the SC has the lowest performance among the other fusion rules.

5.2 Future Work

Several research problems exist and may extend the current work presented in this thesis and they are listed as below:

1. In this thesis, we consider the parallel decentralized fusion topology in WSN, however, we may consider extending the proposed model to other WSN topologies as shown in Section 1.1 in order to get a generalized solution for the problem of fusion of decisions in WSN.

2. We propose to make use of the SC as a fusion rule in the traditional WSN system model. There still exit other diversity combining techniques that may be used as a fusion rule because of their lower implementation complexity such as the square law and the switch and examine combining techniques.

3. In this work, we assume that the channel between the sensors layer and the FC is Rayleigh channel. However, in some scenarios there may exist a line of sight between the sensors and the FC, thus another fading distribution may be considered such as Rician fading distribution. We could investigate fusion of decisions that is transmitted over Rician fading channels and the ability to apply the proposed WSN model in the case of Rician and other fading channels.

Notations

u_o	global decision at the fusion center
u_k	local decision made by the sensor
x_k	noisy measurement received by sensor
n_k	additive white Gaussian noise
K	total number of sensors
H_0	target absent
H_1	target present
P_{d_k}	local sensor probability of detection
P_{f_k}	local sensor probability of false alarm
h_k	fading channel coefficient
Λ	fusion statisic
$E[h_k^2]$	fading channel coefficient power
σ^2	variance of white Gaussian noise
erf	Gaussian error function
T	decision threshold

Bibliography

[1] G. J. Pottie and W. J. Kaiser, "Wireless integrated network sensors," *Commun. ACM*, vol. 43, no. 5, pp. 51–58, May 2000.

[2] S. Kumar, F. Zhao, and D. Shepherd, "Collaborative signal and information processing in microsensor networks," *IEEE Signal Processing Magazine*, vol. 19, no. 2, pp. 13–14, Mar. 2002.

[3] D. Estrin, L. Girod, G. Pottie, and M. Srivastava, "Instrumenting the world with wireless sensor networks," in *Proc. 2001 IEEE International Conference on Acoustics, Speech, and Signal Processing*, Salt Lake City, UT, May 2001, pp. 2033–2036.

[4] S. Kumar and D. Shepherd, "Sensit: sensor information technology for the warfighter," in *Proc. 2001 International Conference on Information Fusion*, vol. 1, Montreal, Canada, Aug. 2001, pp. TuC1–TuC10.

[5] P. Bauer, M. Sichitiu, R. Istepanian, and K. Premaratne, "The mobile patient: wireless distributed sensor networks for patient monitoring and care," in *Proc. 2000 IEEE EMBS International Conference on Information Technology Applications to Biomedicine*, Arlington, VA, Nov 2000, pp. 17–21.

[6] A. Mainwaring, J. Polastre, R. Szewezyk, D. Culler, and J. Anderson, "Wirelesss sensor networks for habitat monitoring," in *Proc. 1st ACM Workshop on Wireless Sensor Networks and Applications*, Atlanta, GA, sep 2002, pp. 88–97.

[7] S. N. Simic and S. S. Sastry, "Distributed environmental monitoring using random sensor networks," in *Proc. Information Processing in Sensor Networks*, Palo Alto, CA, Apr. 2003, pp. 582–592.

[8] C. Lin, C. C. Federspiel, and D. M. Auslander, “Distributed environmental monitoring using random sensor networks,” in *Proc. International Conference on Enhanced Building Operations*, Richardson, TX, Oct. 2002.

[9] W. Dargie and C. Poellabauer, *Fundamentals of Wireless Sensor Networks: Theory and Practice*. England: Wiley, 2010.

[10] S. Khan, A.-S. K. Pathan, and N. A. Alrajeh, *Wireless Sensor Networks: Current Status and Future Trends*, 1st ed. Boca Raton, FL, USA: CRC Press, Inc., 2012.

[11] R. R. Tenney and N. R. Sandell, “Detection with distributed sensors,” *IEEE Trans. Aerospace Elec. Syst.*, vol. 17, no. 6, pp. 501–510, July 1981.

[12] R. Yiswanathan and P. K. Varshney, “Distributed detection with multiple sensors: Part i - fundamentals,” *Proceedings of the IEEE*, vol. 85, pp. 54–63, Jan. 1997.

[13] R. S. Blum, S. A. Kassam, and H. V. Poor, “Distributed detection with multiple sensors: Part ii - advanced topics,” *Proceedings of the IEEE*, vol. 85, pp. 64–79, Jan. 1997.

[14] W. Lucien, “Some terms of reference in data fusion,” *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 3, pp. 1190–1193, 1999.

[15] B. Chen and P. K. Varshney, “Bayesian sampling approach for decision fusion using hierarchical models,” *IEEE Trans. Signal Processing*, vol. 50, pp. 1809–1818, Aug. 2002.

[16] Z. Chair and P. K. Varshney, “Optimal data fusion in multiple sensor detection systems,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 22, pp. 98–101, Jan. 1986.

[17] P. K. Varshney, *Distributed Detection and Data Fusion*. New York: Springer, 1997.

[18] P. K. Willett, P. F. Swaszek, and R. S. Blum, “The good, bad, and ugly: distributed detection of a known signal in dependent gaussian noise,” *IEEE Trans. Signal Process.*, vol. 48, pp. 3266–3279, Dec. 2000.

[19] F. Gini, F. Lombardini, and L. Verrazzani, "Decentralized detection strategies under communication constraints," in *IEE Proc. Inst. Elct. Eng., Part F: Radar ,Sonar ,Navigation*, vol. 145, Aug 1998, pp. 199–208.

[20] C. T. Yu and P. K. Varshney, "Paradigm for distributed detection under communication constraints," *Opt. Eng*, vol. 37, no. 2, pp. 417–426, Feb. 1998.

[21] T. Kasetkasem and P. K. Varshney, "Communication structure planning for multisensor detection schemes," in *IEE Proc. Inst. Elct. Eng., Part F: Radar ,Sonar ,Navigation*, vol. 148, no. 2, Feb 2001, pp. 2–8.

[22] J. Chamberland and V. V. Veeravalli, "Decentralized detection in sensor networks," *IEEE Trans. Signal Process.*, vol. 51, no. 2, pp. 407–416, Feb. 2003.

[23] D. CIUONZO, G. ROMANO, and P. S. ROSSI, "Decision fusion in mimo wireless sensor networks with channel state information," in *Proc. IEEE Sensor Array and Multichannel Signal Processing Workshop (SAM'12)*, New Jersey, US, Jun. 2012, pp. 17–20.

[24] J. Xiao and Z. Luo, "Universal decentralized detection in a bandwidth-constrained sensor network," *IEEE Trans. Signal Process.*, vol. 53, no. 8, pp. 2617–2624, Aug. 2005.

[25] B. Chen, L. Tong, and P. K. Varshney, "Channel-aware distributed detection in wireless sensor networks," *IEEE Signal Process. Mag.*, vol. 23, no. 5, pp. 16–26, Jul. 2006.

[26] B. Chen, R. Jiang, T. Kasetkasem, and P. K. Varshney, "Channel aware decision fusion in wireless sensor networks," *IEEE Trans. Signal Process.*, vol. 52, no. 12, pp. 3454–3458, Dec. 2004.

[27] B. Liu and B. Chen, "Decentralized detection in wireless sensor networks with channel fading statistics," in *Proc. Int. Conf. on Signal Process.*, vol. 4, May 2006, pp. 857–860.

[28] R. Niu, B. Chen, and P. K. Varshney, "Fusion of decisions transmitted over rayleigh fading channels in wireless sensor networks," *IEEE Trans. Signal Process.*, vol. 54, no. 3, pp. 1018–1027, Mar. 2006.

[29] C. Kundu, S. Kundu, G. Ferrari, and R. Raheli, "Majority logic fusion of censored decisions in wireless sensor networks with rayleigh fading," in *Proc. 2012 National Conference on Communications (NCC)*, Feb 2012, pp. 1–5.

[30] Y. Wang, M. Xiong, D.-W. Yue, and R. He, "Decision fusion rules over rician fading channel for wireless sensor networks," in *Proc. 2009 5th International Conference on Wireless Communications, Networking and Mobile Computing (WiCom'09)*, Sept 2009, pp. 1–4.

[31] Y. X. guang, Y. W. hai, and S. Lin, "Decision fusion with censoring wireless sensors under rice fading channels," in *Proc 2009 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery (CyberC'09)*, Oct 2009, pp. 343–347.

[32] B. Husain and A. Jamoos, "Fusion of likelihood ratio test based decisions in wireless sensor networks," *Accepted to 2015 IEEE International Conference on Communications, Signal Processing and their Applications*, Dec. 2014.

[33] A. Jamoos and B. Husain, "Fusion of LRT-based decisions transmitted over fading channels in wireless sensor networks," *Submitted to the International Journal of Sensor Networks (IJSN)*, Sep. 2014.

[34] H. Karl and A. Willig, *Protocols and Architectures for Wireless Sensor Networks.* England: Wiley, 2005.

[35] Z. Yuan, H. Xue, Y. Cao, and X. Chang, "Exploiting optimal threshold for decision fusion in wireless sensor networks," *International Journal of Distributed Sensor Networks*, vol. 2014, Feb. 2014.

[36] F. W. J. Olver, D. W. Lozier, R. F. Boisvert, N. institute of standards, and technology (Etats-Unis)), *NIST handbook of mathematical functions.* Cambridge, New York: Cambridge University Press, 2010.

الموضوع: حول دمج القرارات عبر القنوات المضمحله في شبكات المجسات اللاسليكه

إعداد: بشار مفيد حسين

إشراف: د. علي جاموس

الملخص

يهدف هذا البحث الى دراسه مشكله دمج القرارات الناتجه من المجسات والمنقوله عبر القنوات المضمحله في مركز الدمج (Fusion Center). يعتبر اختبار النسب الاحتماليه (Likelihood Ratio Test) من الطرق القياسيه لدمج القرارت وايجاد قرار عام حول ظاهره معينه. استخدام هذه الطريقه في مركز الدمج يتطلب الحصول على المعلومات الخاصه بالقنوات المضمحله والمتمثله بمعاملات القناه بالاضافه الى مؤشرات الاداء الخاصه بالمجسات والحصول على هذه المعلومات يؤدي استهلاك المزيد من الطاقه بالاضافه الى استهلاك موارد القنوات حيث ان الحصول على مؤشرات الاداء يتم من خلال ارسال المجسات لمؤشراتها عبر القنوات. تم في هذه الدراسه اقتراح تعديل النموذج التقليدي لشبكات المجسات اللاسلكيه بحيث يتم تطبيق اختبار النسب الاحتماليه على المجسات بدلا من تطبيقه في مركز الدمج واستخدام الموحد ذي المعاملات المتساويه (Equal Gain Combiner) في مركز الدمج كطريقه لدمج القرارات الناتجه عن المجسات والمنقوله عبر القنوات المضمحله. استخدام اختبار النسب الاحتماليه في المجسات لا يتطلب الحصول على اي معلومات خاصه بالقناه وهو فقط يعتمد على النسبه اللحظيه للاشاره على التشويش (Signal to Noise Ratio). بالاضافه الى ذالك، استخدام الموحد ذي المعاملات المتساويه لا يحتاج الى اي معلومات حول القنوات او حول مؤشرات الاداء الخاصه بالمجسات. كما تم ايضاً اقتراح استخدام الموحد الذي يعتمد على اختيار الفرع ذي الطاقه الاعلى (Selection Combiner) كطريقه لدمج القرارات في النموذج التقليدي لشبكات المجسات اللاسلكيه. استخدام هذه الطريقه يهدف الى تقليل تعقيد بناء مركز الدمج.

تم محاكاه النظام بالكامل ومقارنه النموذج المقترح مع النموذج التقليدي، حيث تبين بأن اداء النموذج المقترح افضل من بعض الطرق الخاصه بدمج القرارات مثل الموحد ذي النسب العليا (Maximum Ration Combiner) وطريقه Chair-Varshney كما ان اداء النموذج المقترح اقل بقليل من اداء الطريقه القياسيه المستخدمه في دمج القرارات. كما تم ايضا دراسه تأثير بعض العوامل مثل عدد المجسات الكلي في الشبكه ،نسبه الاشاره على التشويش في القنوات المضمحله وتأثير مؤشرات الاداء الخاصه بالمجسات. يعتبر الموحد الذي يعتمد على اخيتار الفرع ذي الطاقه الاعلى الأقل اداءً مقارنه بجميع طرق دمج القرارات في مركز الدمج.