ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

PREDICTIVE AND ADAPTIVE CHANNEL ESTIMATION MODELS FOR COOPERATIVE WIRELESS COMMUNICATIONS

Ph.D. THESIS

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

İŞBİRLİKLİ KABLOSUZ HABERLEŞME İÇİN ÖNGÖRÜSEL VE ADAPTİF KANAL KESTİRİM MODELLERİ

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Omar Gatera, a Ph.D student of İTU Graduate School of Science Engineering and Technology, student ID 504112309 successfully defended the thesis entitled ‘‘PREDICTIVE AND ADAPTIVE CHANNEL ESTIMATION MODELS FOR COOPERATIVE WIRELESS COMMUNICATIONS’’, which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signature below.

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To my spouse and children,

FOREWORD

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Istanbul, March, 2017. Omar GATERA.

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ABBREVIATIONS

1G	:	First generation
2G	:	Second generation
3G	:	Third generation
3GPP	:	Third Generation Partnership Project
4G	:	Fourth generation
5G	:	Fifth generation
AF	:	Amplify and Forward
AWGN	:	Additive White Gaussian Noise
BER	:	Bit Error Rate
BEP	:	Bit Error Probability
BLM	:	Bayesian Linear Model
BS	:	Base station
CDF	:	Cummulative Distribution Function
CRLB	:	Cramer Rao Lower Bound
CSI	:	Channel State Information
CSIR	:	Channel State Information at the Receiver
DaF	:	Demodulate and Forward
DF	:	Decode and Forward
DOF	:	Degree of Freedom
DSSS	:	Direct Sequence Spread Spectrum
EGC	:	Equal Gain Combining
EM	:	Expectation Maximization
FDMA	:	Frequency Division Multiple Access
GLRT	:	Generalized Likelihood Ratio Test
IID	:	Independent and Identically Distributed
IP	:	Internet Protocol
ISI	:	Intersymbol Interference
KF	:	Kalman Filter
LANs	:	Local Area Networks
LMMSE	:	Linear Minimum Mean Square Estimation
LMS	:	Least Mean Square
LRT	:	Likelihood Ratio Test
LTE	:	Long Term Evolution
LS	:	Least Squares
LOS	:	Line of Sight
MAP	:	Maximum A Posteriori
MCP	:	Multicell Processing
MGF	:	Moment Generating Function
MIMO	:	Multiple Input Multiple Output
MLE	:	Maximum Likelihood Estimation
MMSE	:	Minimum Mean Square Error
M-PSK	:	Mary-Phase Shift Keying
MRC	:	Maximum Ratio Combining
MS	:	Mobile Station
MSE	:	Mean Square Error

NLOS	:	Non-Line of Sight
OFDM	:	Orthogonal Frequency Division Multiplexing
PDF	:	Probability Density Function
PER	:	Packet Error Rate
PIC	:	Parallel Interference Cancellation
QPSK	:	Quadrature Phase Shift Keying
QoS	:	Quality of Service
RS	:	Relay Station
ROC	:	Receiver Operating Characteristic
RLS	:	Recursive Least Squares
SAGE	:	Space Alternating Generalized Expectation Maximization
SC	:	Selection Combining
SDA	:	Steepest Descent Algorithm
SEP	:	Symbol Error Probability
SLC	:	Square Law Selection
SLS	:	Square Law Combining
SNR	:	Signal to Noise Ratio
SSC	:	Switch and Stay Combining
TDMA	:	Time Division Multiple Access
WLANs	:	Wireless Local Area Networks
WiMAX	:	Worldwide Interoperability for Microwave Access
ZF	:	Zero Forcing
ZMCSCG	:	Zero Mean Circular Symmetric Complex Gaussian

SYMBOLS

S	:	Source station
R	:	Relay Station
D	:	Destination station
$\boldsymbol{H}$	:	Channel matrix
T	:	Test statistic
H_0	:	Hypothesis for the absence of the signal
H_1	:	Hypothesis for the presence of the signal
u, s	:	Transmitted signal components
y, r	:	Received signal components
w	:	Noise
$h_{sd}, h_{si}, h_{id}, f_{si}, g_{id}$	:	Channel components
n	:	Cascading order
N	:	Number of symbols
k	:	Time
T_s	:	Symbol period
υ	:	Speed
a_{ij}, ρ	:	Temporal correlation coefficients
f_D	:	Doppler frequency
f_c	:	Carrier frequency
W	:	Tap weight
d	:	Desired signal
e	:	Error signal
μ	:	Gradient step size
λ	:	Threshold
γ	:	Instantaneous SNR
$\overline{\gamma}$	:	Average SNR
P_s	:	Source power
P_i	:	Relay power
E_s	:	Source energy
E_i	:	Relay energy
G_i	:	Amplification gain
N_0	:	Noise power
$\sigma^2, \sigma_s^2, \sigma_i^2, \sigma_M^2$	:	Signal variance
$\varepsilon_{sd}, \varepsilon_{si}, \varepsilon_{id}$	:	Varying components
$\delta_{sd}^2, \delta_{si}^2, \delta_{id}^2$	:	Variances of the varying components
$\mathrm{sgn}(.)$	:	Sign function
$\Re(.)$	:	Real function
$J_0(.)$	:	Zero order Bessel function
$tr[.]$	:	Trace operator
$\Gamma(.)$	:	Gamma function

$\Gamma(.,.)$	:	Incomplete Gamma function
$Q_c(.,.)$	:	Generalized Marcum Q-function
χ_c^2	:	Chi-squared random variables
c	:	Bandwidth product
$E[.]$	:	Expectation operator
ϕ	:	Characteristic function
P_d	:	Probability of detection
P_{fa}	:	Probability of false alarm
P_m	:	Probability of miss detection
P_e	:	Probability of error
$\overline{P}_e$	:	Average probability of error
P_{out}	:	Outage probability
C	:	Capacity
C_u, C_s	:	Covariance of the signal
$P(.), f_Y(y)$	:	Probability density function
$F_Y(y)$	:	Cummulative distribution function
G	:	Kalman gain
$\boldsymbol{R}$	:	Correlation matrix
$\boldsymbol{P}$	:	Cross correlation matrix
$\boldsymbol{Q}$	:	Correlation matrix of the measurement noise
M	:	Number of relays

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PREDICTIVE AND ADAPTIVE CHANNEL ESTIMATION MODELS FOR COOPERATIVE WIRELESS COMMUNICATIONS

SUMMARY

Multipath fading, path loss, shadowing and noise are the most commonly known channel impairments in wireless communication networks. Therefore, over the last decades, different methods and techniques have been investigated in order to improve the wireless channels and to recover the original transmitted signal at the receiver. Among them, multiple input multiple output (MIMO) systems have been proposed as an efficient technique that use multiple antennas at the transmitting and receiving stations to create diversity environment that can directly mitigate the effects of fading, increases the network's capacity and provides a more robust system.

Although, MIMO systems can provide significant diversity gain in wireless communication networks, the use of multiple antennas is not quite appropriate for wireless terminals due to the size of equipments, computational capacity and power consumption. Therefore, cooperative communications emerged as an alternative technique that can use single antenna at the transmitting and receiving stations. Cooperative communications use neighboring nodes to form virtual antenna array which provides space diversity gain equivalent to MIMO systems. Cooperative communications are cost effective, useful and the best technology of future generation wireless networks in terms of reducing the effect of multipath fading, extension of coverage, less infrastructure, low power consumption, and preserving the channel bandwidth.

Cooperative communication techniques have different schemes depending on the type of network. The cooperation can be achieved between users or mobile stations (MSs), base stations (BSs) or multicell processing (MCP) and between BSs and MSs through dedicated relay stations (RSs) or MSs adopted as RSs for other MSs. Cooperation with relay stations have highly been applied in literature due to their numerous advantages including extension of network coverage, reliable transmission, throughput enhancement, cost effective and easy implementation. Relaying cooperations use different protocols for signal processing and the most common protocols are amplify and forward (AF) and decode and forward (DF). AF is a simple cooperative signaling method that is used to amplify and to retransmit the noisy version of the original signal to the destination. Although noise is amplified, the destination receives independent faded versions of the signal that can help to make best decisions on the data detection. AF has gained too much attention in research and has been very useful in understanding the concept of cooperative communications. DF scheme is considered as digital repeater which decodes and re-encodes the received signals prior to retransmission. Although, it can provide higher performance with respect to noise, however, end to end delay constraints and feasibility have been a question in real world applications.

In this thesis, cooperative communication network with multiple relays is considered in order to handle the problem of channel impairments and to improve the signal

quality received in wireless networks. Furthermore, due to the nature of wireless communication networks, the receiver is always challenged by unknown channel state information (CSI) and unknown transmitted signal. Therefore, signal processing methods and techniques are indispensable at the receiver in order to estimate the channel between the source and the destination, and to recover efficiently the original transmitted signal.

In this way, Bayesian linear model (BLM) detector and least mean square (LMS) algorithm are proposed for their unique advantages of being efficient and appropriate for multipath wireless networks. BLM detector is based on computing the test statistic and comparing it with the predetermined threshold in order to decide on the presence or absence of the signal of interest. The presence of the signal is decided when the test statistic is greater than the threshold. The main advantages of the BLM detector is its linear computation, low implementation complexity and it is appropriate for multipath channel models. The LMS algorithm is a linear adaptive filter that is usually used to iteratively estimate the unknown parameters in dynamic or non dynamic environment. The LMS algorithm has attracted too much attention among adaptive filters due to its low computation complexity, feasibility and best performance results.

In this thesis, the original contributions are divided in two chapters (i.e., Chapter 2 and Chapter 3). In chapter 2, a cooperative wireless network with multiple relays operating in stationary environment is considered and two main assumptions are put forth; the first assumption states that the channel state information (CSI) is available at the destination and the original transmitted signal is corrupted by noise and other unwanted signals. Therefore, the BLM detector is proposed, derived and implemented in multiple relays network for the purpose of recovering efficiently the transmitted signal. Hence, presenting a wireless network structure that can resist against wireless channel impairments. In this part; single source, multiple AF relays, and single destination are considered. The effects of relays positions from the source and destination are evaluated. Different performance metrics are assessed such as the receiver operating characteristics (ROCs), bit error probability and minimum mean square error (MSE). Extensive numerical results show that the detection performance of the BLM detector is superior compared to existing energy detection methods and is proportional with the number of relays in the network, and the relay positioned far from the source affects the system performance more than the relay located closer to the destination.

The second assumption states that the channel state information (CSI) is not available at the destination, and the transmitted signal is corrupted by noise and could not be known by the receiver. Therefore, a novel LMS-BLM algorithm is proposed, derived and implemented in cooperative wireless network for the purpose of channel estimation and signal recovery at the destination. The algorithm is functionning in such a way that the channel tap weights are only updated when the BLM detector decides the presence of the signal otherwise the CSI remains unchanged. The wireless network considered in this part is comprised of single source, multiple AF relays and single destination, and the mode of transmission is half duplex signal transmission. Different performance metrics are assessed such as receiver operating characteristics (ROCs), complementary ROCs, average probability of error and mean square error (MSE) learning curve. Mathematical and numerical analysis show that the proposed algorithm is effective in providing satisfied detection performance and low mean square error (MSE) at the receiver, and the receiver is highly controled by the gradient step size for the best convergence and stability of the algorithm. It is also observed that the position of the relays from the source should be reduced in order to improve the system performance.

In chapter 3, a cooperative wireless network with multiple relays operating in non stationary environment is considered. In this chapter, the main issue is multipath time varying channels. Time varying channels are severe and challenging in wireless networks which requires robust methods and techniques in order to ensure sustainable system performance. This chapter is also divided in two parts: The first part assumes that the channel state information (CSI) is available at the destination and the performance of the BLM detector in multiple relays with time varying channels is investigated. Different performance metrics are evaluated such as receiver operating characteristics (ROCs), minimum mean square error (MSE) and bit error probability (BEP) in various nodes speeds and different number of relays. The results show that the BLM detector is effective and its performance decreases at high speed of relays or destination which can be improved by increasing the number of relays in the network. The results also show that the system performance decreases when the cascading order increases.

In the second part of chapter 3, it is also considered that the CSI is not available at the destination and the evaluation of performance of the LMS-BLM receiver in multiple relays with time varying channels is carried out. During simulations, different performance metrics are evaluated such as the ROCs, MSE learning curve and bit error probability.The results show that the joint LMS-BLM receiver provides superior performance and this can be affected by the high speed of nodes and instability of the algorithm. Therefore, it is recommended to choose the appropriate step size value in order to control the convergence and stability of the receiver, and to ensure that the number of relays is sufficient so that the performance is sustainable. The findings also show that the high speed of relays affects the system performance more than the speed of the destination. Therefore, the speed of relays should be put into account when designing the wireless networks.

The findings of this reseach work have proven that the joint LMS-BLM receiver can provide higher detection performance and it is effective for signal recovery in wireless networks for both stationary and non stationary environments. Its performance can be particularly improved in networks with multiple relays. Numerical analysis also confirmed that the proposed algorithm can be applied in the current and future wireless networks with carrier frequencies in the range of 2GHZ and low symbol periods of signal transmissions.

İŞBİRLİKLİ KABLOSUZ HABERLEŞME İÇİN ÖNGÖRÜSEL VE ADAPTİF KANAL KESTİRİM MODELLERİ

ÖZET

Kablosuz haberleşme ağlarında çok yollu sönümleme, gölgeleme ve gürültü bilinen en yaygın kanaldan kaynaklı bozucu etkenlerdir. Bu yüzden son yıllarda birçok farklı yöntem ve teknikler, kablosuz kanalları iyileştirmek ve alıcıda iletilen işareti geri oluşturmak için araştırılmaktadır. Bunların arasında verici ve alıcı istasyonlarda çoklu anten kullanan ve etkin bir teknik olan çok giriş çok çıkışlı sistemler (MIMO), sönümleme etkisini doğrudan kaldıran, ağ kapasitesini arttıran ve daha güçlü bir sistem sağlayan çeşitleme ortamı yaratmak için önerilmiştir.

Kablosuz haberleşme ağlarında MIMO sistemler kaydadeğer çeşitleme kazancı sağlamalarına rağmen çok anten kullanımı; araç-gereç boyutu, hesaplama karmaşıklığı ve güç tüketimi nedenleriyle kablosuz terminaller için uygun değildir. Bu yüzden, işbirlikli haberleşme, alıcı ve verici istasyonlarda tek anten kullanan alternatif bir teknik olarak doğdu. İşbirlikli haberleşme, sanal anten dizisini şekillendirmek için MIMO sistemlerdekine denk olan uzay çeşitleme kazancı sağlayan komşu düğümleri kullanır. İşbirlikli haberleşme, maliyet verimli, kullanışlı ve çok yollu sönümleme etkisini azaltan, kapsama alanını artıran, daha az yer kaplayan, düşük güç tüketen ve kanal band genişliğini koruyan gelecek nesil kablosuz ağların en iyi teknolojisidir.

İşbirlikli haberleşme teknikleri, ağ türüne bağlı olarak değişen farklı yapılara sahiptir. İşbirlikli çalışma, kullanıcılar veya gezgin istasyonlar (MS) arasında, baz istasyonları (BS) veya çok hücreli işlemede ve BS ile MS arasında aktarma istasyonları (RS) yoluyla veya diğer MS için RS olarak uyarlanmış MS yoluyla gerçekleştirilebilir. RS kullanan birlikte çalışma, ağ kapsama alanının genişletilmesi, güvenilir haberleşme, hacim arttırılması, maliyet verimliliği ve kolay uygulanabilirliği gibi özellikleri dahil eden sayısız üstünlüklerinden dolayı literatürde oldukça fazla kullanılmıştır. Aktarma işbirlikleri işaret işleme için farklı protokolleri kullanır ve bunlar arasında en yaygın kullanılanları kuvvetlendir ve aktar (AF) ile çöz ve aktar (DF) protokolleridir. AF, iletilen işaretin gürültülü halini kuvvetlendirerek yeniden hedefe gönderen basit bir işbirlikli işaretleşme yöntemidir. Gürültünün de kuvvetlenmesine rağmen hedef, iletilen işarertin bağımsız sönümlenmiş hallerini alır ve veri sezimi için en iyi karar vermeyi gerçekleştirmeyi sağlar. AF, araştırmalarda oldukça dikkat çekmiştir ve işbirlikli haberleşmenin anlaşılmasında çok kullanışlı olmuştur. DF ise çözüp tekrardan kodlayarak alınan işareti yeniden ileten sayısal bir tekrarlayıcı devresidir. Gürültüye karşı yüksek başarım sağlamasına rağmen, uçtan uca gecikme kısıtları ve uygulanabilirlik gerçek dünya uygulamalarında bir sorun olarak yer tutmaktadır.

Tezde çoklu aktarma birimleri ile oluşturulan işbirlikli haberleşme ağları, kanal bozuklukları problemini çözmek ve kablosuz ağlarda işaret kalitesini arttırmak için ele alınmıştır. Dahası, kablosuz haberleşme ağ yapısı sebebiyle alıcı her zaman, bilinmeyen iletilen işaret ve bilinmeyen kanal durum bilgisi (CSI) problemleriyle karşı karşıya kalır. Bu yüzden, işaret işleme yöntem ve teknikleri, alıcıda kaynak ile

hedef arasındaki kanal kestirimini gerçekleştirmek ve iletilen işareti etkin bir şekilde geri oluşturmak için gereklidir.

Bu bilgiler ışığında, Bayesian doğrusal model (BLM) sezicisi ve en küçük ortalama kareler (LMS) algoritması, çok yollu kablosuz ağlar için uygunluk ve verimlilik gibi üstün özellikleri sebebiyle önerilmiştir. BLM sezicisi, ilgilenilen işaretin varlığına veya yokluğuna karar verebilmek için test istatistiği hesaplayarak ve bunu önceden belirlenmiş eşik değeri ile kıyaslayarak çalışır. Test istatistiği seçilen eşik değerinden büyük olduğunda işaretin varlığına karar verilir. BLM sezicisinin temel üstünlüğü, çok yollu kanal modelleri için doğrusal hesaplama yapması ve düşük uygulama karmaşıklığına sahip olmasıdır. LMS algortiması dinamik veya dinamik olmayan çevrelerde genellikle bilinmeyen parametreleri yinelemeli olarak kestirmekte kullanılan doğrusal uyarlamalı bir süzgeçtir. LMS algoritması, düşük hesaplama karmaşıklığı, uygulanabilirliği ve yüksek başarımı sayesinde uyarlamalı süzgeçler arasında oldukça ilgi çekmiştir.

Bu tezde, özgün katkılar iki bölümde (Bölüm 2 ve Bölüm 3) yer almaktadır. Bölüm 2'de durağan çevrelerde çalışan çoklu aktarma birimlerini kullanan işbirlikli kablosuz ağlar ele alınmıştır ve iki ana varsayım yapılmıştır; ilkinde hedefte kanal durum bilgisinin olduğunu ve iletilen işaretin gürültü ile istenmeyen işaretlerle bozulduğunu varsaydık. Bu yüzden, iletilen işareti etkin şekilde geri oluşturabilmek ve kablosuz kanal bozucu etkenlerine direnen bir ağ yapısı sunmak amaçlarıyla çoklu aktarma içeren ağlarda alıcıda BLM sezicisini önerdik ve uyguladık. Bu bölümde; tek kaynak, çoklu AF aktarma birimleri ve tek hedef birimlerinin olduğu durum düşünülmüştür. Kaynak ve hedeften kaynaklanan aktarma biriminin konumunun etkisi değerlendirilmiştir. Alıcı çalışma karakteristikleri (ROC), bit hata olasılığı (BER) ve ortalama karesel hata (MSE) gibi farklı başarım ölçütleri ele alınmıştır. Sayısal sonuçlar, BLM sezicisinin sezim başarımının, mevcut enerji sezim yöntemlerinden daha iyi ve ağdaki aktarma birimi sayısıyla orantılı olduğunu ve kaynaktan uzakta konumlanan aktarma biriminin sistem başarımını hedefe yakın konumlandırılmış aktarma birimindeki duruma göre daha çok etkilendiğini göstermektedir.

İkinci olarak, kanal durum bilgisinin hedefte bilinmediğini ve iletilen işaretin gürültü ile bozulduğunu ve alıcı tarafından bilinmediğini varsaydık. Aynı zamanda tek kaynaklı, çoklu aktarmalı ve tek hedefli yarı yönlü işaret iletimini ele aldık. Bu doğrultuda, alıcıda kanal kestirimi ve işaret kazanımı için güçlü LMS-BLM algoritmasını önerdik ve uyguladık. Algoritma, BLM sezicisinin işaretin varlığına karar verdiği zaman kanal katsayı ağırlıklarının güncellendiği şekilde çalışmaktadır aksi durumda kanal durum bilgisi değişmeden kalacaktır. Alıcı çalışma karakteristikleri (ROC), bütünleyici ROC, ortalama hata olasılığı ve ortalama karesel hata (MSE) öğrenme eğrileri ve en uygun eşik değeri gibi farklı başarım ölçütleri ele alınmıştır. Matematiksel ve sayısal analizler, önerilen algoritmanın alıcıda düşük MSE ve memnun edici bir sezim performansı sağlaması dolayısıyla verimlidir ve alıcı, algoritmanın kararlılığı ve en iyi yakınsama için türev adım boyutu tarafından kontrol edilmektedir. Kaynağa göre aktarma birimlerinin mesafesinin sistem başarımını arttırmak için azaltılması gerektiği gözlenmiştir.

Bölüm 3'te durağan olmayan ortamlarda çalışan çoklu aktarma birimleri kullanan işbirlikli kablosuz ağları ele aldık. Bu bölümde ana konular, çok yollu zamanla değişen kanallardır. Zamanla değişen kanallar, kablosuz ağlarda sürdürülebilir sistem başarımının temin edilmesi için güçlü yöntem ve teknikler gerektirdiğinden oldukça zorlayıcıdır. Bu bölüm aynı zamanda iki bölüme ayrılmıştır. İlk bölümde, hedefte kanal durum bilgisinin olduğunu varsaydık ve BLM sezicisinin başarımını çoklu aktarma birimli zamanla değişen kanallarda araştırdık. Alıcı çalışma karakteristikleri (ROC), en küçük ortalama karesel hata (MSE) ve bit hata olasılığı (BER) gibi farklı başarım ölçütleri çeşitli düğüm hızları ve farklı aktarma birimi sayısına göre ele alınmıştır. Sonuçlar, BLM sezicisinin verimli ve onun başarımının hedef veya aktarıcının yüksek hızlarında kötüleştiğini göstermekte ve ağdaki aktarıcı sayısının arttırılmasıyla iyileştirilebileceğini göstermiştir. Ayrıca sistem başarımının, seri dizilimin artmasıyla düşeceği de gösterilmiştir.

Bölüm 3'ün ikinci bölümünde hedef birimde CSI'nın bilinmediğini varsaydık ve LMS-BLM alıcısının çoklu aktarıcılı zamanla değişen kanallarda başarımını değerlendirdik. Benzetimlerde, alıcı çalışma karakteristikleri (ROC), ortalama karesel hata (MSE) öğrenme eğrileri ve bit hata olasılığı gibi farklı başarım ölçütleri ele alınmıştır. Sonuçlar, birleşik LMS-BLM alıcısının algoritmanın kararsızlığı ve düğümlerin yüksek hızından etkilenebilmesine rağmen üstün başarım sağladığını göstermektedir. Bu yüzden, alıcının kararlılığını ve yakınsaklığını kontrol edebilmek ve sürdürülebilir başarımı sağlamak için adım boyu parametresinin uygun seçilmesi önerilmektedir. Bulgular, aktarıcının yüksek hızlarda olmasının hedefin hızından yüksek olduğunda sistem başarımının daha çok etkilendiğini göstermiştir. Bu yüzden, aktarıcı hızları kablosuz ağ tasarımları yapılırken göz önüne alınmalıdır.

Bu araştırmadan elde edilen bulgular, birleşik LMS-BLM alıcısının, hem durağan hem de durağan olmayan kablosuz ağlarda kanal kestirimi için yüksek sezim başarımı sağladığını ve etkin olduğunu kanıtlamıştır. Algoritmanın başarımı çoklu aktarıcı kullanan ağlarda özellikle iyileştirilebilir. Sayısal analizlerle gösterildiği gibi önerilen yöntem, 2GHz menzilinde taşıyıcı frekanslarıyla ve düşük simge periyotlarıyla işaret iletiminde şimdiki ve gelecek kablosuz ağlarda uygulanabilir.

1. GENERAL INTRODUCTION

1.1 Background and Motivation

During the last decades, the demand for wireless communication services has increased tremendously with high requirements of quality of services (QoS), high data rates, stable connectivity at any mobility conditions and high security services. Recent statistics have shown that the number of mobile subscribers has grobally increased massively during the year 2000 to 2010, the first bilion landmark passed in 2002 and the fifth billion in the middle of 2010. More than a million new subscribers per day have been added grobally during that period and 2020 forecasts show that worldwide mobile penetration should reach 119% of the population. Among mobile services, voice communication has been employed in a massive way and mobile terminals are the preferred method of voice communication whereby the mobile networks cover 90% of the world population [1]. This growth has been fueled by low cost mobile phones, competitions of communication service providers, the grobal economic changes and developments. Indeed, wireless communications have became an essential technology of choice in the current and future interaction between people and devices.

Due to the high demand of wireless communication services, wireless technologies have been the most active development and a rapidly growing field in communication industry. Mobile wireless technologies are divided into generations with the first generation (1G) being the analog mobile radio system, second generation (2G) being the first digital mobile system, the third generation (3G) being the digital mobile system handling broadband data and the Long-Term Evolution (LTE) which is also called the fourth generation (4G). The 4G service is set to offer a fast and secure IP network and roaming mobile broadband solution to devices. Now, the deployment of the fifth generation (5G) is another newest mobile wireless innovation that is expected to increase the capacity over wireless networks and to provide the speed three time faster than 4G [2, 3].

Wireless communications can be subdivided into different segments such as applications, systems or coverage regions. Some wireless applications are voice, internet access, web browsing, paging, short messaging, subscriber information services, file transfer, video teleconferencing, sensing, and distributed control. The evolution of wireless technologies has been accompanied by the evolution of mobile devices that can support new applications and services in order to meet the QoS required by users. The wireless systems including cellular telephone, wireless LANs, wide area wireless networks, data systems, satellite systems, and ad-hoc wireless networks, have been developed in order to meet the new technologies and customer requirements. Classification of wireless network by coverage regions include in building networks, campus, city, regional and global region networks [4].

Despite various advantages of wireless communication services, the performance gap between wireline and wireless networks appears to be growing due to the huge demand of wireless services and the nature of wireless communication channels. Generally, wireless communication systems have experienced many challenges that include signal distortion due to channel impairments such as shadowing, time varying multipath fading, cochannel and adjacent channel interference, noise and propagation loss. Thus, advanced signal processing algorithms and techniques have to be explored in order to improve the wireless channels, ensure sustainability, higher performance, and to meet the current and future wireless communications goals. In literature, scholars have investigated different techniques, most of them are diversity techniques and signal processing schemes (i.e., coding, modulation and detection) which have attracted too much attention with the need to recover efficiently the original transmitted signals at the receiver [5-8].

Motivated by the above background and associated challenges, this thesis has the aim of exploring the advantages of cooperative communications with a particular focus on relaying cooperation in providing diversity gain in wireless networks, and proposing methods and techniques based on adaptive channel estimation as well as data detection for the purpose of recovering the original transmitted signal at the receiver. The study in this thesis assumes two kinds of wireless network environments such as stationary and non stationary environments, discussing the knowledge of channel state information (CSI) at the receiver.

1.2 Cooperative Wireless Communications

In wireless communication networks, diversity techniques have been explored for their advantages to improve the wireless communication system. In this direction, multiple input multiple output (MIMO) systems have attracted too much attention in research as one of the techniques exploring the diversity gain. MIMO systems are considered as a key technique in modern wireless cellular networks that employ multiple antennas at both the transmitter and receiver stations. In MIMO systems, base stations (BSs) and mobile stations (MSs) are equipped with multiple antennas that make MIMO systems to be available at both the uplink and the downlink sides as represented in Figure 1.1. MIMO techniques can be employed in different ways such as transmit or receive diversity for enhancing the transmission reliability, spatial multiplexing for improving the system data rates and beamforming for increasing the network coverage [9-10].

Although using MIMO techniques can improve the wireless networks, in many ways the use of multiple antennas at the MSs is not quite appropriate due to the size of equipments, power consumption, signal processing and many other constraints. Thus, cooperative communications emerged as an alternative technology to reap the advantages of MIMO systems by employing single antenna at both the transmitter and receiver stations [9].

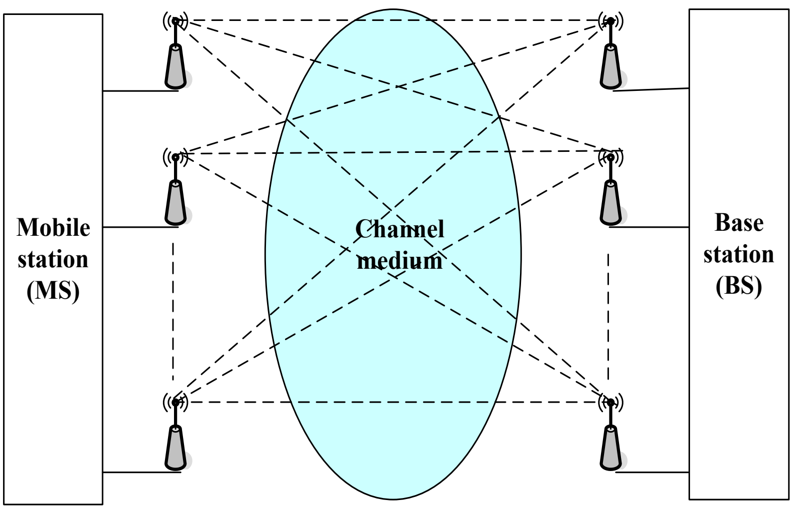

Figure 1.1 : MIMO Communications [9].

Cooperation can be done in various ways such as user or MSs cooperation, BSs cooperation which is also called multicell processing (MCP) and cooperation between BSs and MSs through dedicated relay stations (RSs) or MSs act as RSs as shown in Figure 1.2. In MCP, the cooperation is done at the BSs level where BSs cooperate among them in order to enhance the received signal at the destination. In MSs cooperation, neighboring MSs retransmit the same signal from the source, helping other MSs to get the quality signal. In relay cooperation, relay stations retransmit the signal from the source to the destination. In this scenario, MSs may act as relay stations in order to reduce additional equipments in the network [10-13].

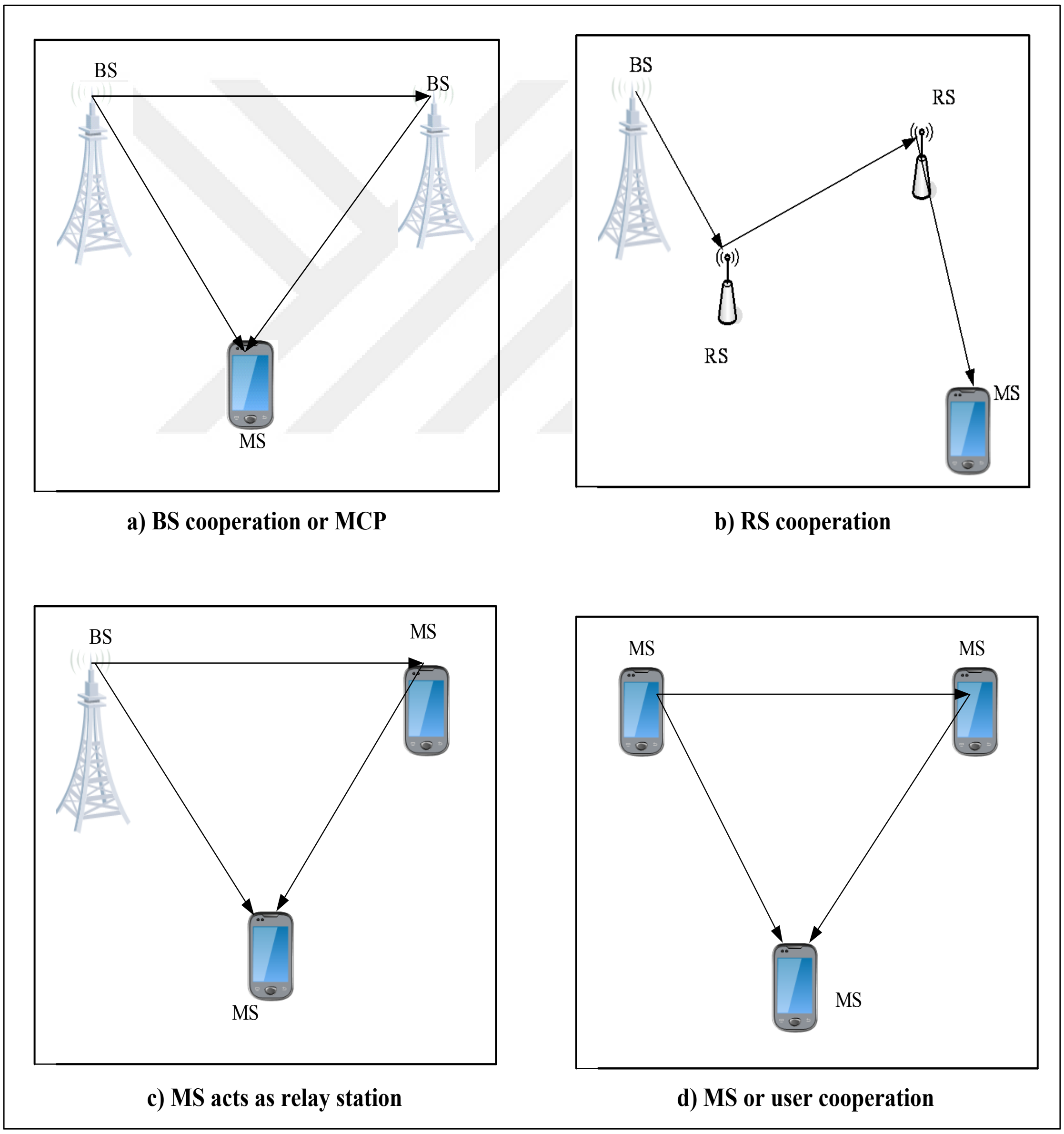

Figure 1.2 : Examples of various schemes for cooperative communications [13].

Cooperation schemes use protocols to process the signal from the source to the destination. Three kinds of protocols are described in relaying signal processing such as protocol I, protocol II and protocol III. All these protocols can transmit into phases which are phase I and phase II as represented in Table 1.1. In protocol I, the source transmits the message to the relay and the destination during relay-receive phase or phase I. During relay-transmit phase or phase II, the source is silent and relay forwards the processed message to the destination. In protocol II, the source only transmits the message to the relay during phase I. In phase II, the source and relay transmit simultaneousely the message to the destination. In protocol III, the source broadcasts the message to the relay and destination during phase I. In phase II, the source and the relay transmit the message to the destination [10-15].

Table 1.1 : Relaying protocols and transmission phases [12].

Phase	Protocol I	Protocol II	Protocol III
Phase I	S $\rightarrow$ R,D	S $\rightarrow$ R	S $\rightarrow$ R S $\rightarrow$ D
Phase II	R $\rightarrow$ D	R $\rightarrow$ D S $\rightarrow$ D	R $\rightarrow$ D S $\rightarrow$ D

For all protocols stated above, relaying schemes for signal processing are necessary in order to process the signal from the source. The most common relaying schemes are amplify & forward (AF) and decode & forward (DF) that can be subdivided in fixed or adaptive relaying schemes.

The AF which is also known as non generative relaying scheme, it simply scales the received signal and retransmits the amplified version to the destination. Its disadvantage is based on amplifying the signal together with the noise which requires the receiver to use a high quality noise filter in oder to detect the intended signal. The main advantages of this protocol are low implementation complexity and feasibility [10,14].

The DF which is known as regenerative relaying scheme refer to the relay that decodes the received signal in order to remove the noise and forwards a newly re-encoded signal to the destination. There are different types of DF relaying schemes: the basic DF, the selection DF, and the demodulate and forward (DaF) relaying scheme. In basic DF, the relay decodes the received signal, re-encodes it in phase I and forwards it to the destination in phase II. It means that the relay successfully decoded the received signal in phase I; otherwise it does not send or remains idle in phase II. In selection DF, if the relay failed to decode the received message from the source in phase I, the source is allowed to retransmit the message by itself in phase II. The diversity gain may be improved in selection DF mode if there is no condition that the relay should participate in cooperation. In many cases, the channel decoding or encoding is not possible due to the incapability of the transceiver, therefore, in this case the DaF can be used to demodulate the received signal on symbol by symbol at the relays and forward it to the destination [10-15].

1.3 Data Detection and Estimation Models

1.3.1 Data detection fundamentals

In practical situation for wireless communication systems, signals are more appropriately modeled as random processes. Depending on the nature of the signal to be transmitted such as speech, voice or video signals; it is unrealistic to assume that the signal is known by the receiver. Moreover, due to the transmission process, the received signal at the reveiver is corrupted by noise which makes it difficult for the receiver to differentiate the original signal from the noisy signal. Therefore, the receiver has to make decision according to the observation signal. Among various detection methods that exist in literature, the simple hypothesis testing problem is the simplest in which the probability density function (PDF) for each assumed hypothesis is completely known. In this problem, there are two hypotheses or binary hypothesis rules which refer to the absence of the signal or H_0 and the presence of the signal or H_1. Based on these hypothesis testing rules, four kinds of decisions cases can be available as follow [16]:

- Decide the presence of the signal (D_1) when H_1 is true
- Decide the absence of the signal (D_0) when H_0 is true
- Decide the presence of the signal (D_1) when H_0 is true
- Decide the absence of the signal (D_0) when H_1 is true

The first two cases are true decisions, whereas the last two cases are error decisions that correspond to type I error or false alarm and type II error or miss detection respectively.

In the theory of signal detection, some criteria are used for receiver decision. The primary approaches to simple hypothesis testing are the Bayesian approach based on minimizing of the Bayes risk and classical approach based on the Neyman Pearson theorem.

- Bayes test:

In this approach, the source outputs are governed by priori probabilities (P_1 and P_2 for one dimensional space and $P_1, P_2, ..., P_N$ for N dimensional space). These probabilities represent the observer's information (observation, S) about the source before the experiment is conducted. Secondly, each experiment is assigned a cost so that the decision rule will minimise the average cost or risk as low as possible. According to the binary hypothesis, the decision rule must be H_0 or H_1 which indicates that the rule divides the total observation space Z into two zones such as Z_0 and Z_1 as shown in Figure 1.3. Then, whenever, the observation falls in Z_0, it belongs to hypothesis H_0 and when it falls in Z_1, it belongs to hypothesis H_1 [17, 18].

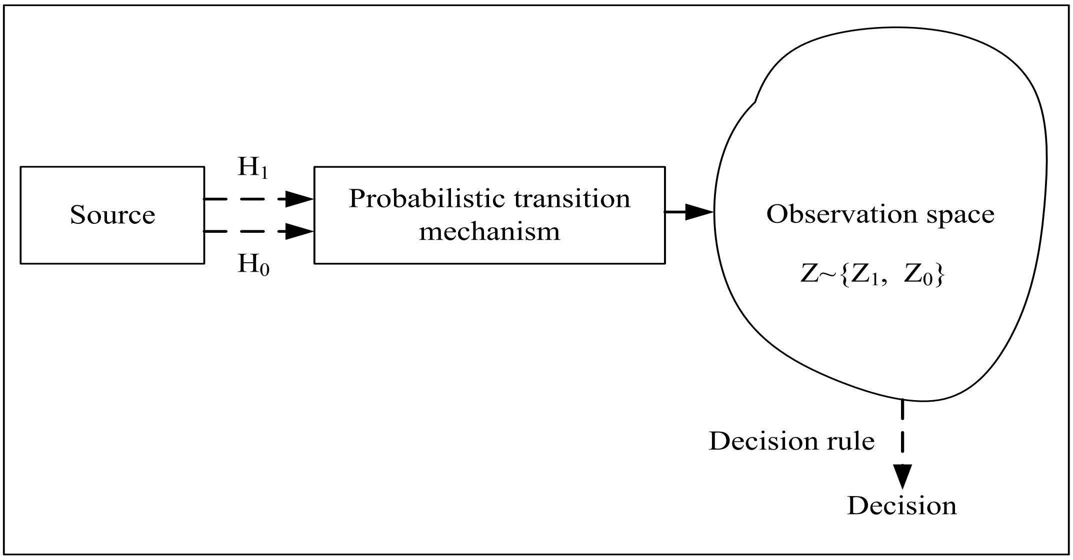

Figure 1.3 : Components of a decision model.

In addition, in Bayesian approach, we recognize two special cases, the first case is when the two hypotheses are likely equal, in this case, the threshold becomes zero which denotes a common situation in digital communication systems. This case denotes minimum probability of error receiver. The second case is when a priori probabilities are unknown. When this arise the decision rule will be based on conditional probabilities since the decision regions can be determined. Based on conditional probabilities, it is possible to find the probability of detection (P_d) (i.e., denotes the presence of the signal when it is), the probability of false alarm (P_{fa}) (i.e., indicates the presence of the signal when it is not), and the probability of miss detection (P_m) (i.e., indicates the absence of the signal when it is present) as follows [17]:

$$P_{fa} = \int_{Z_1} P_{S|H_0}(S \mid H_0) dS \tag{1.1}$$

$$P_d = \int_{Z_1} P_{S|H_1}(S \mid H_1) dS \tag{1.2}$$

$$P_m = \int_{Z_0} P_{S|H_1}(S \mid H_1) dS = 1 - P_d \tag{1.3}$$

- Neyman Pearson test:

In Neyman Pearson test, the assumption is such that the assignment of realistic costs or a priori probabilities are difficult to find due to physical situation, therefore, an alternative way is to work with the conditional probabilities P_{fa} and P_d and optimize the system by making the P_{fa} as small as possible and P_d as large as possible. The solution is obtained by using Lagrange multiplier as follows [17]:

$$F = P_m + \lambda [P_{fa} - \varpi^{'}] \tag{1.4}$$

where F denotes a constrained function and $P_{fa} = \varpi' \leq \varpi$.

The relation between Bayesian criterion and Neyman Pearson criterion is that for both the optimum test is a likelihood ratio test (LRT). In spite of the dimensionality of the observation space, the test is based on comparing a scalar variable LRT with a threshold in order to make a decision. A complete performance of the test is obtained by plotting the receiver operating characteristics (ROC) (i.e., P_d against P_{fa}) as the threshold is varied [17].

- Linear model approach

Another practical method of designing a detector is the use of linear model. It provides mathematical simplicity and general applicability to real world problems. The linear model can be either classical or Bayesian. In classical linear model, the data under H_1 are decribed as follows [19]:

$$\boldsymbol{y} = \boldsymbol{H\theta} + \boldsymbol{w} \tag{1.5}$$

where $\boldsymbol{y}$ is an N×1 vector of observations, $\boldsymbol{H}$ is a known N×K observation matrix with N>K and of rank K, $\boldsymbol{\theta}$ is a K×1 vector or parameters (which may be known or not), and $\boldsymbol{w}$ is an N×1 noise vector with PDF (0, $N_0\boldsymbol{I}$). The decision is made by comparing the test statistic with the threshold (i.e., $T(y) > \lambda \rightarrow H_1$).

In Bayesian linear model, $\boldsymbol{y}$ is an N×1 vector of observation, $\boldsymbol{H}$ is a known N×K observation matrix with N>K, $\boldsymbol{\theta}$ is a P×1 random vector with $\boldsymbol{\theta} \sim \mathcal{N}(0, C_\theta)$, and $\boldsymbol{w}$ is an N×1 noise vector with PDF(0, $N_0\boldsymbol{I}$) and is independent of $\boldsymbol{\theta}$. The decision is made by comparing the test statistics with the predetermined threshold [19].

1.3.2 Classical and Bayesian estimation approaches

In the preceding section, the fundamental of data detection is introduced in which the receiver has to make decision depending on the received signal. In some cases, parameters associated to the received signal may not be known even though the receiver made the true decision, in this case, estimation techniques are required in order to recover efficiently the original transmitted signal. The parameters to be estimated may be random or non random [20].

The estimation of non random signals is referred to as classical estimation (i.e., Figure 1.4) where the data information is summarized by the probability density function (PDF) $p(y;\theta)$, where y is the received signal, θ is the parameter of interest and the PDF is functionally dependent on θ. Therefore, the unknown K×1 parameter vector θ is assumed to be a deterministic constant. The common examples of this type of estimation in literature include Cramer Rao lower bound (CRLB), best linear unbiased estimator (BLUE), maximum likelihood estimator (MLE), least squares estimator (LSE), to name just a few [20].

In situation of random signals, the estimation approach is refered to as Bayesian, in this approach, the data information is described by a priori PDF $p(\theta)$ which specifies the knowledge about the parameter of interest θ as indicated in Figure 1.4. The solution of this approach is based on deriving the joint PDF $p(y,\theta)$ which involves the conditional PDF $p(y/\theta)$ as the data information and a priori PDF $p(\theta)$ as prior information. In literature, common examples of this approach include minimum mean square error (MMSE) estimator, maximum a posteriori (MAP) estimator, linear minimum mean square error (LMMSE) estimator, etc [20].

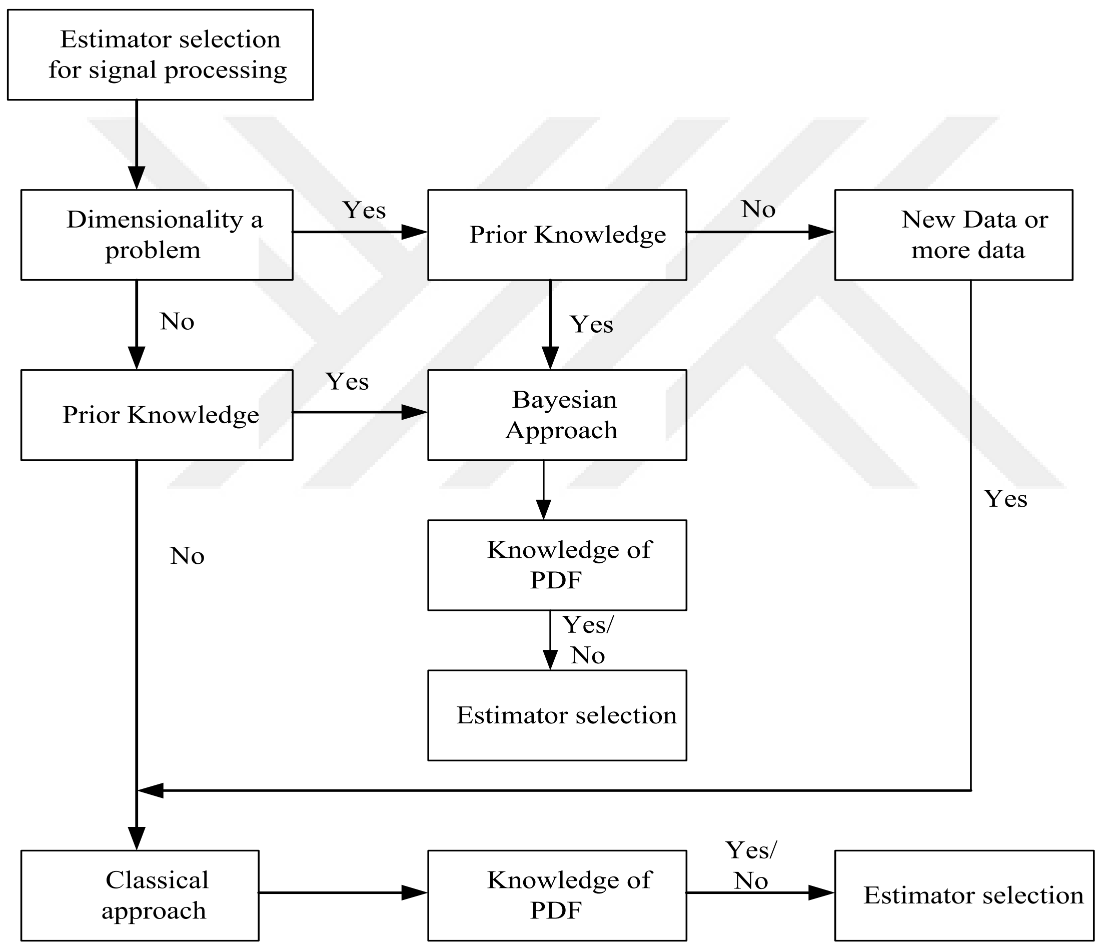

Figure 1.4 : Estimation characterization [20].

1.3.3 Adaptive filtering fundamentals

Adaptive filters find many application in real world application such as digital communications, sonar, seismology among others. The implementation and computation of adaptive filters seek to acheive to the optimum Wiener solution. The important parameters for all adaptive filters are described by the Figure 1.5 that represents the statistical filtering problem [21]:

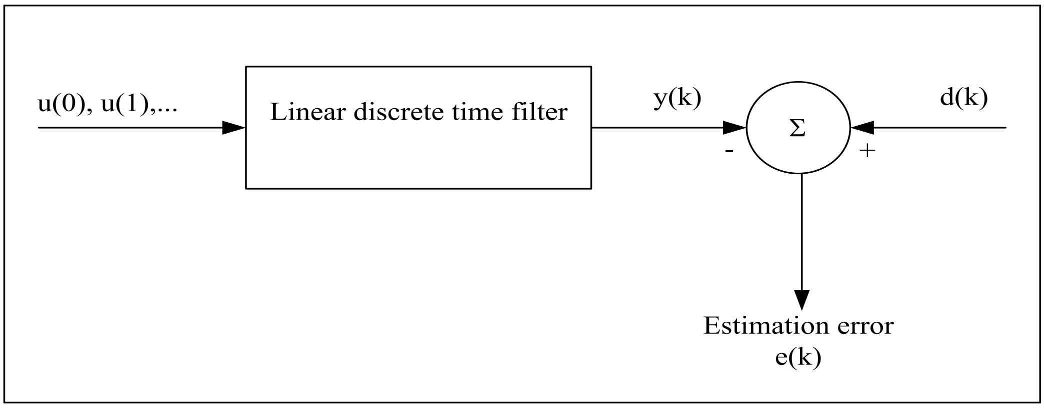

Figure 1.5 : Block diagram of the statistical filtering problem [23].

Various linear adaptive filters have been developed so far with different applications and performances. The choice of adaptive filter over another depends on the consideration of some performance factors such as [21-23]:

- Rate of convergence: This means the number of adaptation cycle required in order to converge to the optimum Wiener solution in the mean square error sense.
- Misadjustement: A parameter that measures the deviation from the Wiener solution.
- Tracking: It means the capability for an algorithm to track time varying parameters particularly in non stationary environment.
- Robustness: An adaptive filter is robust when it can resist to disturbances that cause errors in estimation.
- Computational requirements: It means the number of iteration required to make a complete adaptation cycle of the algorithm, the required memory size and investment needed in order to implement an algorithm.
- Structure and numerical properties: It means the structure of information flow in the program and accuracy of numerical implementation of the algorithm, respectively. An adaptive filtering algorithm is said to be numerically robust if it is insensitive to variations in the wordlength used in its digital implementation.

The common adaptive filters found in literature include:

- Steepest descent algorithm (SDA):

SDA is a recursive adaptive filter that has the tracking capability of time variations in signals statistics compared with Wiener filter. It is an efficient gradient type algorithm, in the sense that it works with the true gradient vector not with an estimate of it. The difficult task of this algorithm is to find the autocorrelation matrix $\boldsymbol{R}$ and cross correlation $\boldsymbol{P}$ when calculating the MSE, therefore this makes it less useful in adaptive filtering algorithm. The SDA updates the tap weights (i.e., W) coefficients in the following general form as [21]:

$$W(k+1) = W(k) - \frac{1}{2}\mu g_W(k) \qquad (1.6)$$

with $g_W(k) = \nabla J(W(k))$

$$W(k+1) = W(k) - \frac{1}{2}\mu \nabla J(W(k)) \qquad (1.7)$$

If the tap input vector $u(k)$ and the desired response $d(k)$ are jointly stationary, then, the mean square error or cost function $J(W(k))$ is given by:

$$J(W(k)) = \sigma_d^2 - 2\boldsymbol{P}^T\boldsymbol{W} + \boldsymbol{W}^T\boldsymbol{R}\boldsymbol{W} \qquad (1.8)$$

where σ_d^2 is the variance of the desired signal. Then, the gradient of $J(W(k))$ is given by:

$$\nabla J(W(k)) = -2\boldsymbol{P} + 2\boldsymbol{R}\boldsymbol{W} \qquad (1.9)$$

The optimal $\boldsymbol{W}_0$ is found by setting the gradient to zero and we have:

$$\boldsymbol{W}_0 = \boldsymbol{R}^{-1}\boldsymbol{P} \qquad (1.10)$$

(1.10) is the Wiener – Hopf equation in matrix form.

Substituting (1.9) in (1.7), we obtain the SDA equation as follows:

$$W(k+1) = W(k) + \mu\left[\boldsymbol{P} - \boldsymbol{R}W(k)\right] \qquad (1.11)$$

where μ denotes the step size parameter.

- Least mean square (LMS) algorithm:

LMS algorithm is a widely used adaptive filter formulated by Widrow and Hoff (1960). It is in the family of stochastic gradient algorithm whereby it uses gradient vector of the filter tap weights to converge to the optimal Wiener solution. The well known feature of the LMS algorithm is its low implentation complexity which have made it the benchmark against other adaptive filters. The calculation of the LMS algorithm involves the substitution of the estimates of the correlation matrix $\boldsymbol{R}$ and the cross correlation vector $\boldsymbol{P}$ in (1.11) as follows [22]:

$$\hat{\nabla}J(W(k)) = -2u(k)d^{H}(k) + 2u(k)u^{H}(k)\hat{W}(k) \tag{1.12}$$

with $\boldsymbol{R}(k) = u(k)u^{H}(k)$ and $\hat{\boldsymbol{P}}(k) = u(k)d^{H}(k)$, then a new recursive relation for updating the tap weight vector is given by:

$$\hat{W}(k+1) = \hat{W}(k) + \mu u(k)\left[d(k) - u^{H}(k)\hat{W}(k)\right] \tag{1.13}$$

Equivalently, the basic computation of the LMS algorithm is:

Filter output: $$y(k) = \hat{W}^{H}(k)u(k) \tag{1.14}$$

Estimation error: $$e(k) = d(k) - y(k) \tag{1.15}$$

Tap weight adaptation: $$\hat{W}(k+1) = \hat{W}(k) + \mu u(k)e^{*}(k) \tag{1.16}$$

- Kalman filters (KF)

KF is a linear optimum filter with some distinctive features such as, mathematical models which are described in terms of state concepts and the solution can be computed recursively, which can be applied without modification to stationary and nonstationary environments. In particular, each updated estimate of the state is computed from the previous estimate and the new input data, so only the previous estimate requires storage. KF algorithm can be described by the following equations [24, 25]:

$$
\begin{cases}
\hat{\boldsymbol{W}}_n(k+1|k) = \hat{\boldsymbol{W}}_n(k|k-1)\boldsymbol{F}(k+1,k) + \boldsymbol{G}_n(k)e_n(k) \\
\boldsymbol{G}_n(k) = \boldsymbol{F}(k+1,k)\boldsymbol{P}_n(k,k-1)u^H(k)\boldsymbol{C}_n(k) \\
\boldsymbol{P}_n(k) = [I - \boldsymbol{F}(k,k-1)\boldsymbol{G}_n(k)u^H(k)]\boldsymbol{P}_n(k,k-1) \\
\boldsymbol{P}_n(k+1,k) = \boldsymbol{F}(k+1,k)\boldsymbol{P}_n(k)\boldsymbol{F}^H(k+1,k) + \boldsymbol{R}_n(k)
\end{cases}
\tag{1.17}
$$

where:

$$
\begin{cases}
\boldsymbol{C}_n(k) = [u^H(k)\boldsymbol{P}_n(k,k-1)u(k) + \boldsymbol{Q}_n(k)]^{-1} \\
e_n(k) = y_n(k) - u^H(k)\hat{h}_n(k|k-1)
\end{cases}
\tag{1.18}
$$

And $\boldsymbol{R}_n$ is the correlation matrix of the process noise, $\boldsymbol{Q}_n$ is the correlation matrix of the measurement noise which has to be estimated, $\boldsymbol{G}_n$ is the Kalman gain, e_n is the error signal, $\boldsymbol{W}_n$ is the channel state vector and $\boldsymbol{F} = \alpha$.

In addition to eliminating the need for storing the entire past observed data, KF computes the estimate directly from all those past data at each step of the filtering process. KF provides a unifying framework for the derivation of the complete family of the recursive least quare (RLS) filter.

- Recursive least squares (RLS) algorithm

RLS algorithm may be viewed as a special case of the Kalman filter on the measurement update equations. RLS algorithm does not require a priori information when used for channel estimation as Kalman filter does, and its computational complexity is less than the Kalman filter. Assuming that the system channel model can be modeled as 1st order autoregressive process. Therefore the standard RLS can be modified to an extended RLS algorithm that is computed as follows [24, 25].

$$
\begin{cases}
\hat{\boldsymbol{W}}_n(k+1|k) = \alpha\hat{\boldsymbol{W}}_n(k|k-1) + \boldsymbol{G}_n(k)e_n^*(k) \\
e_n(k) = y_n(k) - \hat{\boldsymbol{W}}_n^H(k|k-1)u(k) \\
\boldsymbol{G}_n(k) = \alpha\boldsymbol{P}_n(k,k-1)u(k)\boldsymbol{A}_n(k) \\
\boldsymbol{P}_n(k) = \boldsymbol{P}_n(k,k-1) - \boldsymbol{B}_n(k) \\
\boldsymbol{P}_n(k+1,k) = \alpha^2\boldsymbol{P}_n(k) + \boldsymbol{R}_n(k)
\end{cases}
\tag{1.19}
$$

and:

$$
\begin{cases}
\boldsymbol{A}_n(k) = \left[u^H(k)\boldsymbol{P}_n(k,k-1)u(k)+1 \right]^{-1} \\
\boldsymbol{B}_n(k) = \boldsymbol{P}_n(k,k-1)u(k)u^H(k)\boldsymbol{P}_n(k,k-1)\left[1+u^H(k)\boldsymbol{P}_n(k,k-1)u(k) \right]^{-1}
\end{cases}
\tag{1.20}
$$

where $\boldsymbol{R}_n$ means the correlation matrix of the process noise vector.

1.3.4 Classes and applications of adaptive filters

The classes and applications of adaptive filters depend on the structure of signal flow in a certain adaptive filter. Some of the known classes of adaptive filters include identification, inverse modeling, prediction and interference cancellation [21-23].

- Identification:

In this class, the adaptive filter seeks to provide a linear model that matches the unknown plant [21]. The input of the unknown plant is the same as the input of an adaptive filter as represented in Figure 1.6.

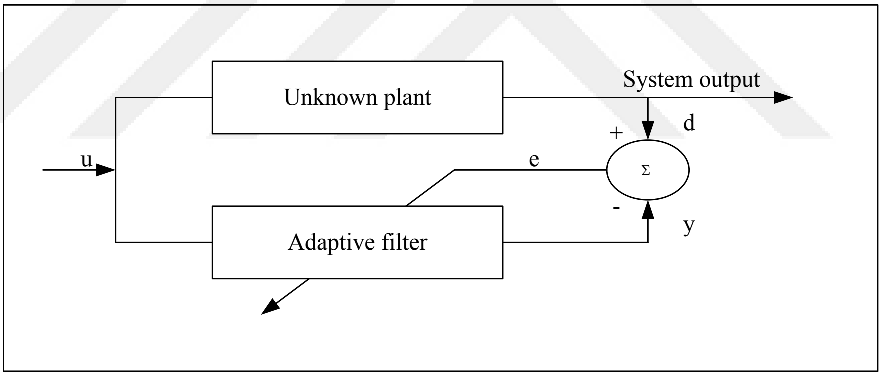

Figure 1.6: Identification model with adaptive filter [22].

This type of class finds many applications such as system identifacation and layered earth modeling. Specifically, for the system identification application, the input is a broadband signal that serves as the input of the unknown system as well as the adaptive filter. When the output mean square error (MSE) is minimized, the adaptive filter represents the unknown system model.

- Inverse modeling:

In this class, an adaptive filter tries to compensate and to provide a linear model that represents the unknown noisy plant as shown in Figure 1.7.

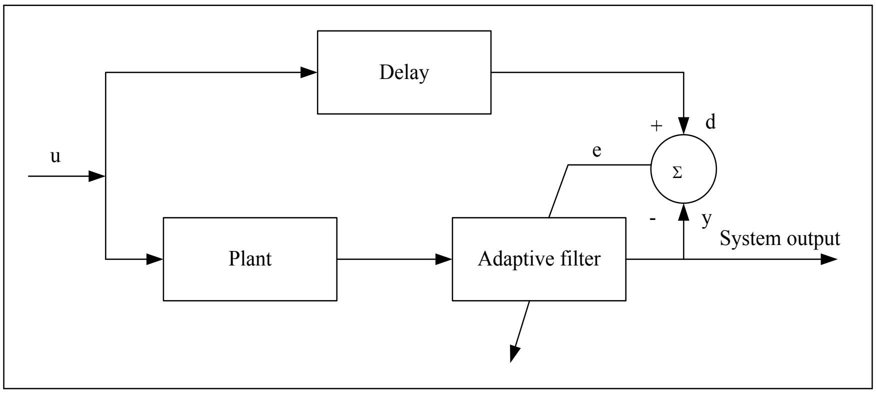

Figure 1.7: Inverse modeling with adaptive filter [23].

The inverse modeling finds various applications in signal processing such as equalization whereby the original transmitted signal distorted by the channel plus environment noise serves as the input to the adaptive filter and the desired signal is the delayed version of the original transmitted signal [23].

- Prediction:

In this class, the function of the adaptive filter is to provide the best prediction of the present value of a random signal. The present value serves as the desired signal of the system, and past values of the signal supply the input of the adaptive filter as represented in Figure 1.8 [23].

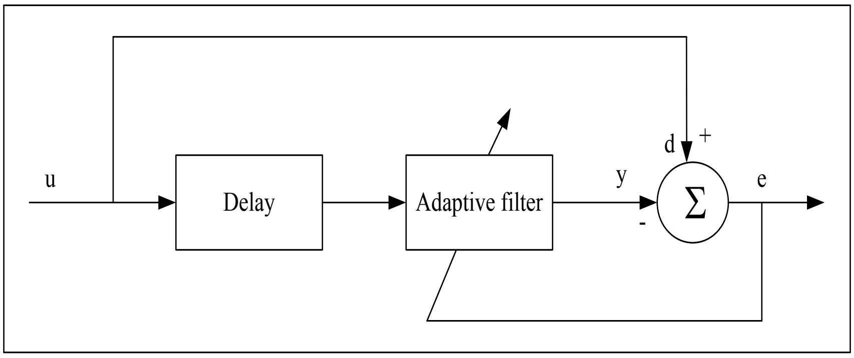

Figure 1.8: Prediction model with adaptive filter [23].

The applications of this class of adaptive filter are signal detection, prediction coding and spectrum analysis.

- Interference cancellation:

The role of adaptive filter in this class is to cancel the unknown interference contained in a primary signal. The primary signal works as the desired signal of the system and the reference signal is used as the input to the filter as shown in Figure 1.9. Noise cancellation is one of the application of this class whereby an adaptive noise canceller is used to substract noise from received signal in order to improve the signal to noise ratio (SNR) [21]. Another application is beamforming which is used in spatial filter where an array of antenna elements has adjustable weights so as to control and cancel interfering signals arriving on the array [23].

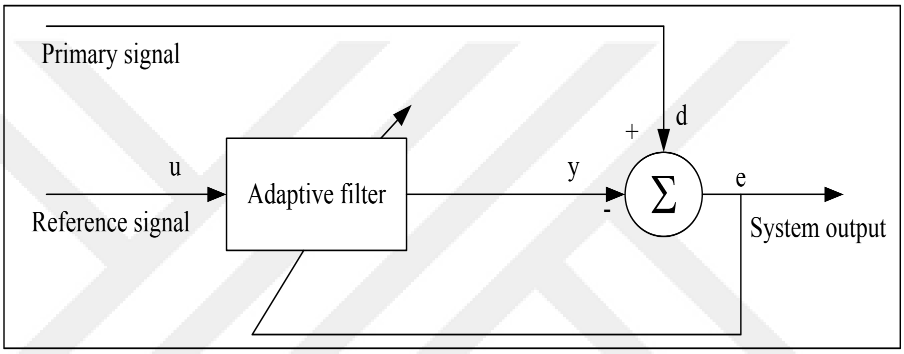

Figure 1.9: Interference cancellation model with adaptive filter [23].

1.4 Parameters of Radio Propagation and Fading Channel Models

1.4.1 Basic radio propagation parameters

In wireless communication networks, the channel between the source and the receiver is experienced by different obstacles such as houses, buildings, trees and other objects that act as reflectors of radio waves. Basically, radio waves are affected by three physical phenomena such as reflection, diffraction and scattering as represented in Figure 1.10 [4, 26].

Reflection is a physical phenomenon that occurs when a propagating electromagnetic wave impings upon an object with very large dimensions compared to the wavelength (i.e., surface of the earth, building,…etc.). Diffraction occurs when the radio path between the transmitter and the receiver is obstructed by a surface that has sharp irregularities like edges. At high frequencies, diffraction like reflection depends on the geometry of object, amplitude, phase and polarization of the incident wave at the point of diffraction. Scattering occurs when the medium through which waves travels consist of objects with dimensions that are small compared with the wavelength, and where the number of obstacles per unit volume is large. Scattered waves are produced by rough surfaces, small objects or by irregularities in the channel [4].

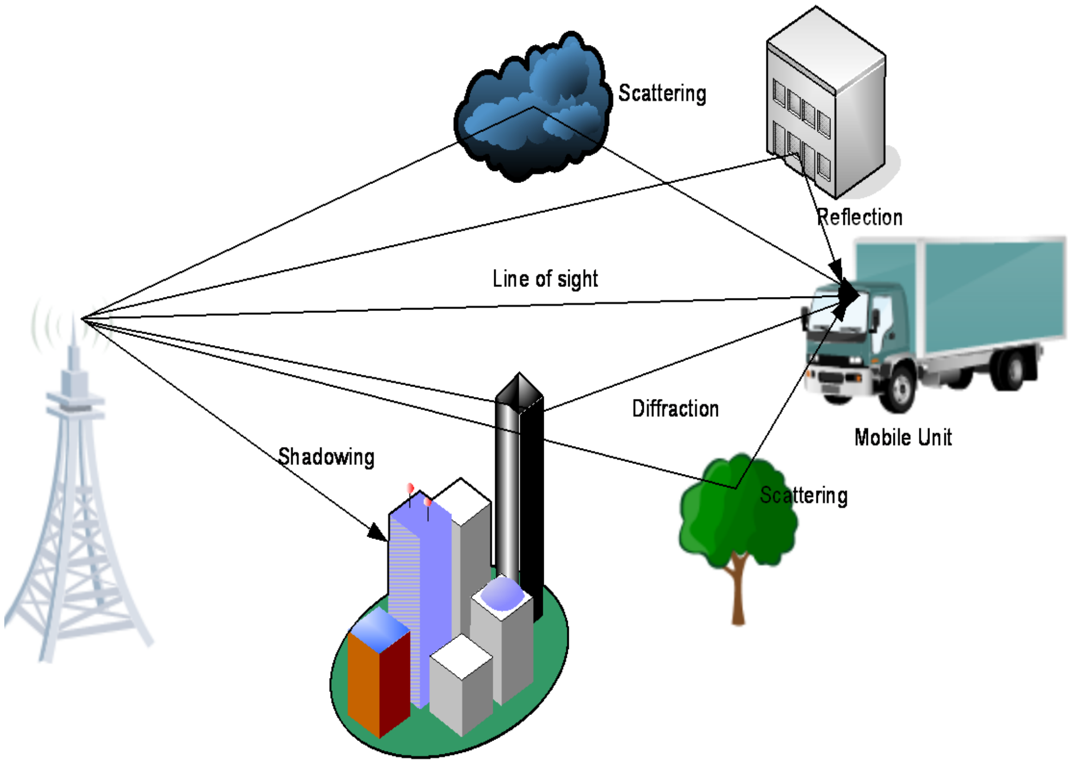

Figure 1.10: Multipath propagation in mobile radio networks.

The difference in times of signal propagation can also cause the signal degradation at the receiver. This is caused by the difference in the arrival time of responses from the longest path and the shortest path which is referred to delay spread. Depending on the arrival time and phase, some interference signals are destructive or constructive. Therefore, if the delay spread is greater than the symbol duration, the original signal is distorted by both the noise and inter-symbol interference (ISI) and the channel undergoes frequency selective fading, otherwise, the channel undergoes frequency flat fading [4].

When a mobile node moves through a large distance, effects occur as large scale fadings. On the other hand when a mobile node moves for short distances, rapid variation of signal levels occur due to the constructive and destructive interference of multiple signal paths such as small scale fading. Therefore, depending on the time variation in the channel and due to mobile speed characterized by the doppler frequency, short term fading can be classified as either fast fading or slow fading [4].

1.4.2 Fading channel parameters

Wireless communication channels are highly affected by channel fading which causes signal variations in amplitude, frequency, phase and delay. Theoretically, the transmitted signals occupy a bandwidth smaller than the channel's coherence bandwidth whereby the channel fading process is correlated. In this case, all spectral components have the same attenuation which is referred to as frequency non selective or frequency flat. On the other hand, if the transmitted signals occupy a bandwidth greater than the channel's coherence bandwith, the phenomenon is refered to as frequency selective fading whereby the spectral components of the transmitted signal faded independently, thus, the received signal spectrum becomes distorted since the relationships between various spectral components are not the same as in the transmitted signal. Depending on the relative extend of multipath fading, the fading frequency of a channel is characterized by frequency selective or frequency flat fading for small scale fading as illustrated in Figure 1.11.

Other sources of signal degradation in response to the channel environment are pathloss and shadowing. Pathloss is due to the signal propagation through space and leads to the reduction of the average received signal power. It is noted that in both theoretical and measurement based propagation models, this average received signal power decreases logarithmically with distance in either outdoor or indoor radio channels. In general form, the path loss is modeled in function of distance and exponent ν parameter as follows [4]:

$$\overline{PL}(ds) \propto \left(\frac{ds}{ds_0}\right)^{\nu} \tag{1.21}$$

where ds_0 is the close-in reference distance and ds indicates the separation distance between the transmitter and the receiver. The path loss exponent ν denotes the rate at which the path loss increases with distance. This parameter changes depending on the environment, in free space, the pathloss is proportional to the second power of the distance, i.e., $\nu = 2$, therefore, by doubling the distance between the transmitter and the receiver, the received power reduces to one fourth of the transmitted power. Depending on the mobile radio environment, the path loss expondent ν varies as presented in Table 1.2 [4].

Table 1.2 : Path loss exponents for different environments [4].

Environment	Path Loss Exponent, v
Free space	2
Urban area cellular radio	2.7 to 3.5
Shadowed urban cellular radio	3 to 5
In building line of sight	1.6 to 1.8
Obstructed in building	4 to 6
Obstructed in factories	2 to 3

Shadowing is caused by obstacles in the wireless channel and affect the received signal by attenuating its power level. Variation in pathloss and shadowing occurs when the mobile device moves through a distance on the order of the cell size and this is refered to as large scale fading [4].

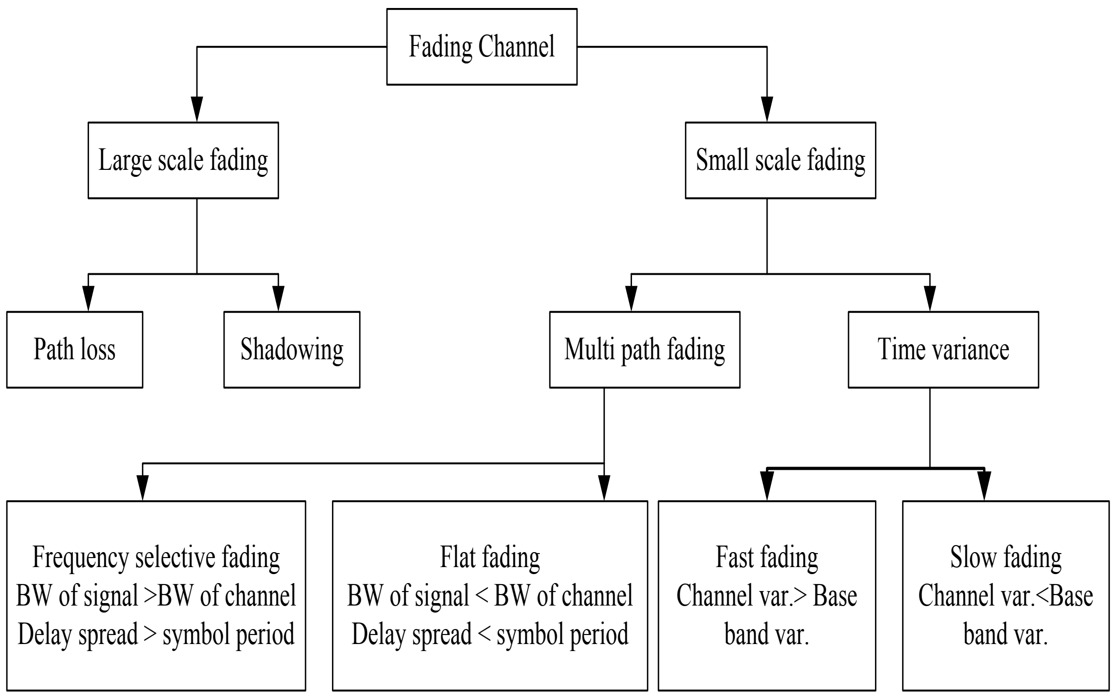

Figure 1.11: Classification of fading channels.

Multipath propagation can be modeled by different statistical models for fading channels and the most common in literature are: Rayleigh, Rician and Nakagami-m fading channels which are described in the following[5, 16].

In Rayleigh fading model, the transmission of a single tone with a constant amplitude is considered. In a typical land wireless network, there is no line of sight (NLOS) between the transmitter and the receiver antennas. Therefore, the radio waves from the transmitter are obstracted in the channel and the receiver receives only reflected radio waves. In this case, according to the central limit theorem, when the number of radio waves is large, two quadrature components of the received signal r are uncorrelated with Gaussian random process with zero mean and variance σ^2. In this process, the envelope of the received signal at anytime instant undergoes a Rayleigh distribution and its phase obeys a uniform distribution between $-\pi$ and π [5]. The probability density function (PDF) and cummulative distribution function (CDF) of the Rayleigh distribution are given respectively by [5]:

$$f_R(r) = \frac{r}{\sigma_r^2} e^{\left(-\frac{r^2}{2\sigma_r^2}\right)}, r \geq 0 \tag{1.22}$$

and ,

$$F_R(r) = 1 - e^{\left(-\frac{r^2}{2\sigma_r^2}\right)}, r \geq 0 \tag{1.23}$$

In Rician fading model, the line of sight (LOS) between the transmitter and the receiver is considered. The received signal is composed by the direct path wave which is a stationary nonfading signal with a constant amplitude and multiple reflected waves that are independent random signals. When the number of reflected signal waves is large, the sum of received signals r is a quadrature components that can be modeled by Gaussian random process with zero mean and variance σ_r^2. The envelope of the reflected signal component has a Rayleigh probability distribution and the sum of the received signal results is Rician envelope distribution [4, 5]. The Rician distribution with the noncentrality parameter ξ has the probability density function (PDF) and cummulative distribution (CDF) given respectively by [16]:

$$f_R(r) = \frac{r}{\sigma_r^2} e^{\left(-\frac{(r^2+\xi)}{2\sigma_r^2}\right)} I_0\left(\frac{\sqrt{\xi} r}{\sigma_r^2}\right), r \geq 0 \tag{1.24}$$

and,

$$F_R(r) = 1 - Q_1\left(\frac{\sqrt{\xi}}{\sigma_r}, \frac{r}{\sigma}\right), r \geq 0 \tag{1.25}$$

where $I_0(.)$ is the zero order modified Bessel function and $Q_1(.,.)$ is the Marcum's Q-function. With $\xi = 0$, we obtain the Rayleigh density function as given in (1.22).

Nakagami-m is another useful fading model that is utilised in multipath fading channels to characterise the statistics of signals transmission. It is very useful since some data realizations do not work well with Rayleigh or Rician fading distribution. Therefore, Nakagami-m becomes a more general method to define some fading distribution with adjustable parameters. For X random variables, the probability density function (PDF) of the Nakagami-m is defined as [5,16]:

$$f_X(x) = \frac{2}{\Gamma(m)}\left(\frac{m}{\eta}\right)^m x^{2m-1} e^{\left(-\frac{mx^2}{\eta}\right)} \tag{1.26}$$

where η is the mean square of X defined as: $\eta = E[X^2]$ and the parameter m is defined as: $m = \frac{\eta^2}{E[(X-\eta)^2]}, m \geq 1/2$ and $E[.]$ is the expectation operator.

1.5 Diversity Parameters

1.5.1 Diversity techniques

In wireless networks, diversity techniques are used to mitigate the effects of multipath fading without additional bandwidth ressources or the transmission power. The basic idea of this technique is that, in multipath propagation environment, signals are faded independently and some signals are highly faded while others are less attenuated. Thus, the use of a proper combination technique decreases the severity of fading and consequently it improves the network performance and reliable transmission. Diversity techniques are particularly useful, since they can be combined with other forms of diversity such as time, frequence and space diversity as described below [4, 26-28]:

The time diversity can be achieved by transmitting symbols of identical message with a separation in time of at least the coherence time of the channel or the reciprocal of the fading rate $1/f_d$. The coherence time is a statistical measure of the period of time over which the channel fading process is uncorrelated. Some methods are used to generate the time diversity such as repetition coding scheme whereby symbols are transmitted over uncorrelated channels and for each stream of symbols appropriate interleave is applied. Time interleaving can cause decoding delays, therefore, it can be more effective in fast fading environment where the coherence time of the channel is small. In slow fading channels, a large interleaver can result to a significant delay which is untolerable for delay sensitive applications such as voice, video and other multimedia transmission [26].

In frequency diversity, a number of different frequencies are used to transmit the same message. The frequency separation should be large enough to ensure independent fading during transmission and to guarantee the uncorrelation of fading statistics for different frequencies. Frequency diversity can be achieved by different techniques of spread spectum such as direct sequence spread spectrum (DSSS), multicarrier modulation and frequency hopping. Spread spectrum techniques are effective when the coherence bandwidth is small, otherwise it becomes ineffective to provide frequency diversity. Frequency diversity can also result in bandwidth inefficiency due to the introduction of redundancy in frequency domain [28].

Space or antenna diversity has been a popular technique in wireless networks for providing diversity gain without additional bandwidth resources. This type of diversity is typically implemented by using multiple antennas for transmission and/or reception. Space diversity can be classified into two categories depending on whether multiple antennas are used for transmission or reception such as receive and transmit diversity [28].

In receive diversity, multiple antennas are arranged at the receiver side in order to receive multiple copies of the transmitted signal. The receiver uses the diversity combining method to combine the replicas of the transmitted signals in order to increase the overall received SNR and mitigate multipath fading.

In transmit diversity, multiple antennas are deployed at the transmitter side and the transmitter processes the message and spread the same message accross multiple antennas. The multiple antennas are separated physically by a proper distance which vary with antenna height, propagation environment and frequency. Typically, a separation of a few wavelength is enough to obtain uncorrelated signals. This type of diversity is very attractive in the current and future generation wireless networks since it does not result in loss of bandwidth as do time and frequency diversity. Two forms of space diversity are met in literature such as polarization and angle diversity. The polarization diversity ensures that signals are uncorrelated without separating antennas far apart, while angle diversity is effective in transmissions with carrier frequency larger than 10 GHz [26-28].

1.5.2 Diversity combining methods

In wireless communication systems, the performance of diversity techniques depends on how multiple signal replicas are combined at the receiver to increase the quality of the received signal. Depending on the complexity and the level of channel state information (CSI) required for improving the performance of the system, there are four main type of combining techniques including selection combining, switched combining, equal gain combining and maximum ratio combining [4, 27, 28].

In selection combining, a simple combination is achieved whereby the signal with the largest instantaneous SNR at every symbol interval is selected as the output, so that the output SNR is corresponding to the best incoming signal [28].

In switched combining, the receiver scans all the diversity branches and selects a particular branch with the SNR larger than the predefined threshold. The selected signal is maintained until it reduces below that threshold. If this happens, the receiver starts again scanning for looking the new branch to switch on. This scheme has less performance compared to selection combining but it is simple in implementation since it does not require simultaneous and continous monitoring of all the diversity branches. Both selection and switched combining do not require the knowledge of the CSI. Therefore, both of the schemes can be implemented in conjuction with coherent and non coherent modulations [27].

Maximum ratio combining (MRC) is a linear combining method whereby the weighting factor of each receiver antenna is chosen to be in proportion to its own signal voltage to noise power ratio. This scheme is optimum since it can maximize the output SNR. Moreover, the maximum SNR output equals the sum of the instantaneous SNRs of the individual signals. Each individual signal must be co phased weighted with its corresponding amplitude and then summed. This scheme requires the knowledge of the CSI on fading amplitude and signal phases. Therefore, it is effective in conjuction with coherent detection and inefficient with non coherent detection [28].

Equal gain combining (EGC) is a suboptimal and simple linear combining method. It does not require the estimation of the fading amplitude for each individual branch. In this scheme, the receiver sets the amplitudes of the weighting factors to be unity and all the received signals are co-phased and then added together with equal gain. The performance of equal gain combining is lower compared to the MRC, but the implementation complexity is less than the one of the MRC [27, 28].

1.6 Performance Metrics

The following metrics play a central role when analyzing the performance of cooperative wireless networks with multipath fadings and time varying channels.

1.6.1 Average error rates

The average error rates can be the instantaneous bit error rate (BER), bit error probability (BEP), symbol error rate (SER) or packet error rate (PER). All these error rates are determined by assuming a given channel realization and average noise power. Their application is very wide for system characterization, particularly the PER is the most important metric in real world systems. The only problem is the derivation of BER and SER expressions, their approximations are usually utilised whereas the closed form of the SER is easily found mathematically [4, 5].

1.6.2 Outage probability

The knowledge of outages are of prime importance in real world systems such as cell dimension since it quantifies the probability that a certain performance can not be met. In other words, outage probability P_{out} is defined as the probability that the received instantaneous SNR (γ_s) falls below a given value corresponding to the maximum allowable probability of error (P_e). Lets γ_0 be the typical minimum SNR required for acceptable performance. Therefore, the outage probability is given by $P_{out} = P(\gamma_s < \gamma_0) = \int_0^{\gamma_0} P_{\gamma_s}(\gamma)d\gamma$, where γ_s is the received SNR when considering AWGN channels. The calculation of outage probability is also very important when the channel does not vary sufficiently fast and this is typically for channel realization, information rates as well as bit, symbol and packet errors [4, 5].

1.6.3 Channel capacity

In wireless communication systems, by considering that the CSI is known at the receiver, there are two ways of defining the channel capacity such as Shannon capacity or ergodic capacity and capacity with outage. Shannon capacity is defined as the maximum data rate that can be transmitted over the AWGN channel with asymptotically small error probability, assuming no constraints on delay or complexity of the encoder and decoder. This capacity is given by $C = B\log_2(1+\gamma)$ where B defines the channel bandwidth and γ is the instantaneous SNR given by $\gamma = P_t/(N_0 B)$, P_t is the transmitted power and N_0 is the power spectral density of noise. Shannon also defined this capacity as the mutual information maximized over all possible input distributions as $C = \max_{p(X)} I(X,Y)$, where X is the input, Y is the output, $p(X)$ is the input distribution and C is the channel capacity expressed in bits per second (bps). The capacity with outage is defined as the maximum rate that can be transmitted over a channel with some outage probability corresponding to the probability that the transmission can not be decoded with negligeable error probability [4, 5].

1.6.4 Receiver operating characteristic (ROC)

ROC is a useful metric that measures the performance of a detector in form of a graph of the probability of detection (P_d) against the probability of false alarm (P_{fa}). For example, the ROC of a LRT depends only on the probability density functions of the observation under the hypotheses H_1 and H_0. In Neyman Pearson test, the slope of the ROC corresponding to any specified value of P_{fa} represents the critical value of the likelihood ratio. In Bayes test, the threshold λ is determined by the a priori probabilities and costs. Consequently, the probabilities of detection and false alarm are determined on the point of the ROC curve at which the tangent has slope λ [16, 19].

1.6.5 Mean square error (MSE) learning curve

The MSE learning curve is another performance metric very useful for evaluating the quality of the received signal in communication systems, since it clarifies the operating characteristics of the estimation (filter) algorithm. It is based on the ensemble averaging of the squared estimation error $|e(k)|^2$. Estimation errors being a real world impairment in communication systems, the learning curve of the mean square estimation error (i.e., $J(k) = E\left[|e(k)|^2\right]$) versus the adaptation cycle k, provides us useful information about the system performance [23].

1.7 Purpose and Scope of the Thesis

The purpose of this thesis is to propose methods or techniques that can recover effectively the original transmitted signal at the receiver in wireless networks with multipath environment. This study focuses on diversity systems in wireless networks, adaptive channel estimation, data detection methods and considering the knowledge of channel state information at the receiver. In order to achieve the purpose of the thesis the set objectives are outlined as follows:

- Identification of existing methods, techniques and their limitations in mitigating the effect of channel impairments in wireless networks and recovering the original transmitted signal at the receiver.
- Investigating different scenarios of implementing relaying cooperation with the purpose of creating diversity environment and enhancing the signal quality at the receiver.
- Deriving and implementing low complexity channel detection method in cooperative wireless communications for both stationary and non stationary environments.
- Deriving and implementing a low complexity adaptive channel estimation and data detection algorithm in cooperative wireless communications for both stationary and non stationary environments.

- Evaluating the performance of the proposed method and technique and comparing the findings with previous findings in literature.

1.8 Original Contributions of the Thesis

The main contributions of this thesis consist of deriving the data detection and channel estimation models based on Bayesian linear model (BLM) detector and least mean square (LMS) algorithm and implementing them in cooperative wireless communications. These contributions are provided throughout the thesis as follows:

- Deriving and implementing Bayesian linear model (BLM) detector in multiple relays based cooperative wireless communications in both stationary and non stationary environments.
- Deriving and implementing the joint least mean square (LMS) algorithm and Bayesian linear model (BLM) detector in multiple relays based cooperative wireless communications in both stationary and non stationary environments.
- Evaluating the performance of the proposed algorithms through simulations by analysing the results and comparing them with previous outcomes in literature.

In our research work, some assumptions and considerations are provided in each part of the work and the obtained results have been published in conferences and journals.

1.9 Organization of the Thesis

In chapter 2, two parts are considered: the first part assumes that the channel state information (CSI) is available at the destination and we propose, derive and implement the Bayesian linear model (BLM) detector in multiple amplify and forward (AF) relays based cooperative wireless communications. In this part, the receiver operating characteristics (ROC), bit error probability and mean square error (MSE) performance parameters are derived and numerical results are obtained through simulations. The effects of relays positions from the source and number of relays are also evaluated.

In the second part, it is assumed that the channel state information is not available at the destination and the joint least mean square (LMS) algorithm and Bayesian linear model (BLM) detector are derived and implemented in multiple AF relays based cooperative wireless communications in order to estimate the channel and detect the original transmitted signal. In this part, the ROC, complementary ROC, MSE learning curve and error probability are derived, numerical results are obtained and compared through simulations. The effects of relays positions, number of relays and gradient step size parameter are also investigated.

In chapter 3, two parts are also considered: the fisrt part assumes that the CSI is available at the destination and assumes time varying channels. Therefore, the performance of the BLM detector is evaluated in multiple relays with time varying channels. In this part, the ROCs, minimum mean square error (MSE) and bit error probability are derived and evaluated through simulation. The obtained results are compared with other existing results in literature. The effects of nodes speeds and number of relays in the network are also evaluated.

In the second part, it is considered that the CSI in not available at the receiver and the unknown channel is varying with time. Therefore, the LMS-BLM receiver is proposed and evaluated in multiple relays networks. The ROCs, bit error probability, MSE learning curve and the minimum MSE are derived and evaluated through simulation analysis. Different parameters are also investigated such as nodes speeds, step size μ and various number of relays in the system.

Finally, chapter 4 concludes the thesis with general conclusions, recommendations and expected future works of the thesis.

1.10 Publications

During the execution of this thesis, the following Journals and conference papers have been published:

1.10.1 Journals

- **Gatera, O., Ilhan, H., Kayran, H., A.** 2016. A novel LMS-BLM Algorithm for AF Relays based Cooperative Wireless Networks. *International Journal of Electronics and Communications* (AEÜ) 70 (2016) 1480-1488.
- **Gatera, O., Ilhan, H., Kayran, H., A.** 2016. Performance Analysis of Differential BLM detector in AF Relay Networks with Time Varying Channels. *International Journal of Computing and Information Sciences*. Vol. 12, N0. 2, December 2016.

1.10.2 Conference papers

- **Gatera, O., Ilhan, H., Kayran, H., A.** 2016. LMS-BLM Receiver in AF Based Cooperative Relay Networks. *18th IEEE Mediterranean Electrotechnical Conference*. April 18-20, 2016, Limassol, Cyprus.
- **Gatera, O., Ilhan, H., Kayran, H., A.** 2016. ROC Analysis of BLM Detection in AF Relays Based Cooperative Wireless Networks. *International Conference on Sustainable Energy, Environment and Information Engineering* (SEEIE 2016) March 20-21, 2016, Bangkok, Thailand, pp:277-281. ISBN: 978-1-60595-337-3.
- **Gatera, O., Ilhan, H., Kayran, H., A.** 2015. BLM Detection in AF Relay Networks. *International Conference on Signal Processing and Communication Systems* (ICSPCS'2015), Cairns, Australia, December, 14-16, 2015.

2. ADAPTIVE CHANNEL ESTIMATION AND DATA DETECTION MODELS FOR COOPERATIVE WIRELESS COMMUNICATIONS IN STATIONARY ENVIRONMENT

2.1 Introduction

In this chapter, a cooperative wireless network that comprises of single source (S), multiple relays (R_M), and single destination/receiver is considered. It is assumed that all nodes are equipped with single antenna and the transmission between nodes is done in half duplex mode. It is also considered that the cooperation and communication between nodes are done in stationary environment whereby all nodes in the network do not move as depicted in Figure 2.1.

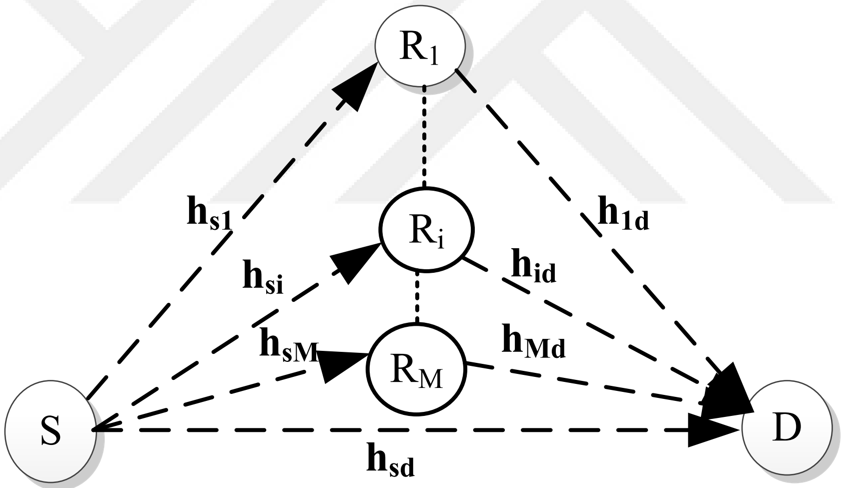

Figure 2.1 : Network model in stationary environment.

In this chapter, two principal sections are considered; in the first section, we assume that the channel state information (CSI) is available at the destination whereas the received signal at the destination is corrupted by noise and other interferences. Therefore, a data detection model based on Bayesian linear model (BLM) detector is proposed for the purpose of recovering the original transmitted signal from noisy signals.

In the second part, it is assumed that the channel state information (CSI) is not available at the receiver and also the received signal is corrupted by noise and other interferences. Therefore, an algorithm that is based on the combination of the least mean square (LMS) and Bayesian linear model (BLM) detector is proposed for the purpose of estimating the channel between the source & destination and the relay & destination and recovering the original transmitted signal at the receiver.

2.2 Bayesian Linear Model (BLM) Detector in Multiple AF Relays Based Cooperative Wireless Networks

2.2.1 Abstract

In this part, the investigation of the performance of Bayesian linear model (BLM) detector in multiple AF relays based cooperative wireless networks is carried out. This part assumes that the channel state information (CSI) is available at the destination and the received signal is corrupted by noise and other interference signals. Therefore, a BLM detector at the receiver is proposed in order to recover the original transmitted signal corrupted by noise and other interferences at the destination. Performance evaluation of the proposed method is examined in terms of receiver operating characteristics (ROC), bit error probability and mean square error (MSE) performance. Computer simulations and results analysis are developed in order to assess the effectiveness of the proposed algorithm.

2.2.2 Related work

In literature, studies on signal detection were addressed in various research works. The most popular study on detection theory is investigated in [29] where the author consider deterministic signals of uknown structure in Gaussian noise. This work is extended for random amplitude signals with different fading channels such as Rayleigh, Nakagami and Rician distribution [30]. In [31], closed form expressions of the detection probability (P_d) are derived over Rayleigh, Nakagami and Rician fading channels with different diversity schemes such as equal gain combining (EGC), selection combining (SC) and switch & stay combining (SSC). The same analysis is done in [32] for low complexity diversity schemes such as square law combining (SLC) and square law selection (SLS). Other methods are utilised to evaluate the probability of detection such as moment generating function (MGF) by considering the maximum ratio combining (MRC) detector at the receiver [33].

The assessment of signal detection is also addressed in cooperative relay networks, the upper and lower bound expressions of the average probability of detection for fixed gain relay networks are derived in [34]. In order to improve the energy detection for low SNR, multihop cooperative diversity network over independent and identically distributed (IID) Rayleigh fading channels is proposed in [35]. The probability of detection is also determined by using the method of Marcum Q-function [36].

Based on the above literature review, this part use an alternative method based on Bayesian linear model (BLM) detector in order to enhance the detection performance at the receiver. The main contributions of this part include:

- Deriving and implementing the BLM detector in multiple amplify and forward (AF) relays based cooperative wireless communications.
- Determining the test statistic of the system with BLM detection approach.
- Deriving the probabilities of detection, false alarm, miss detection and error of the BLM detector.
- Deriving and evaluating the performance of the proposed algorithms in terms of receiver operating characteristics (ROC) , minimum mean square error (MSE) and bit error probability.
- Evaluating the effects of relays positions from the source and number of relays on the system performance.
- Comparing the obtained results of the proposed method with other existing methods in literature.

2.2.3 Bayesian linear model (BLM) detector description in M-relays networks

The receiver based on BLM detector contains a combiner and detector as represented in Figure 2.2. The scheme comprises of the received signals (i.e., $y_{sd}, y_{1d}, ..., y_{id}, ..., y_{Md}$), tap weights (i.e., $W_{sd}, W_{1d}, ..., W_{id}, ..., W_{Md}$) and detection parameters such as test statistic $T(y)$, threshold λ, and test hypotheses H_0 and H_1.

As indicated before, the receiver decision based on hypotheses tests decides the presence of the signal under hypothesis H_1 when the test statistic is greater than the threshold that means the received signal is composed of the original transmitted signal and corrupted by noise due to transmission medium. The receiver may also decides the absence of the signal when the test statistic is less than the predefined threshold which means that the received signal is only composed by the noise. It may also happen that the receiver provides the wrong decision whereas there is a presence of signal or absence of the signal.

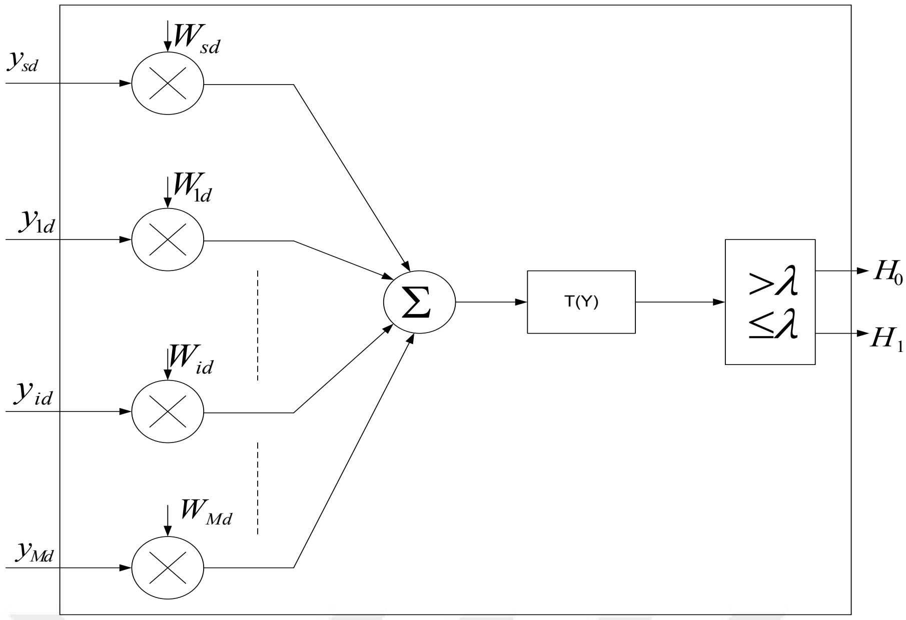

Figure 2.2: Block diagram of the BLM detector in M-relays networks.

As represented in Figure 2.2, the received signals from the source and various relays at the destination are combined and the detector computes the test statistic which is compared with the predetermined threshold in order to decide on the received signal according to test hypotheses H_0 and H_1.

2.2.4 System and channel models

As illustrated in the Figure 2.1, coefficients h_{sd}, h_{si} and h_{id} are channels between the source & destination, the source & relays and the relays & destination. The system signal processing comprises of two phases, in the first phase, the received signals from the links between the source & destination and the source & relays are respectively given by:

$$y_{sd}(k) = \sqrt{P_s} h_{sd} u(k) + w_{sd}(k) \tag{2.1}$$

$$y_{si}(k) = \sqrt{P_s} h_{si} u(k) + w_{si}(k) \tag{2.2}$$

where P_s is the power of the source, $u(k)$ is the signal generated by the source and transmitted to relays and destination. Coefficients $w_{sd}(k)$ and $w_{si}(k)$ are assumed to be complex additive white Gaussian noise with zero mean and variance N_0. During the second phase, the source is silent and each relay multiplies the received signal $y_{si}(k)$ with the amplification factor G_i and forwards it to the destination. In this case, orthogonal transmission is required in order to transmit N[th] symbol at each relay in the network. This can be realized by using time division multiple access (TDMA) or frequency division multiple access (FDMA) [4,5]. Therefore, the received signal $y_{id}(k)$ at the destination is given by:

$$y_{id}(k) = \sqrt{P_i} G_i h_{id} y_{si}(k) + w_{id}(k) \tag{2.3}$$

The expression (2.3) can be simplified as:

$$y_{id}(k) = \sqrt{P_i} h_{id} u_{id}(k) + w_{id}(k) \tag{2.4}$$

where $u_{id}(k) = G_i y_{si}(k)$ indicates the generated signal at each relay in the network, $w_{id}(k)$ is the complex additive white Gaussian noise with zero mean and variance N_0 and P_i is the power at each relay. The amplification factor G_i is expressed as [15]:

$$G_i \leq \sqrt{\frac{1}{E(|h_{si}|^2)P_s + N_0}} \tag{2.5}$$

where E (.) represents the expectation operator. In matrix form, the system input output can be represented as follows:

$$\begin{bmatrix} y_{sd} \\ y_{1d} \\ \cdots \\ y_{id} \\ \cdots \\ y_{Md} \end{bmatrix} = \begin{bmatrix} \sqrt{P_s} h_{sd} & 0 & \cdots & 0 \\ 0 & \sqrt{P_1} h_{1d} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \sqrt{P_i} h_{id} & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & \sqrt{P_M} h_{Md} \end{bmatrix} \begin{bmatrix} u_{sd} \\ u_{1d} \\ \cdots \\ u_{id} \\ \cdots \\ u_{Md} \end{bmatrix} + \begin{bmatrix} w_{sd} \\ w_{1d} \\ \cdots \\ w_{id} \\ \cdots \\ w_{Md} \end{bmatrix} \tag{2.6}$$

Assuming that the received signals at the destination are independent and identically distributed (i.i.d), and can be analyzed in linear model. Therefore, the matrix in (2.6) can be represented by a linear equation as follows:

$$\boldsymbol{y} = \boldsymbol{Hu} + \boldsymbol{w} \tag{2.7}$$

where $\boldsymbol{y}$ indicates the column vector of the received signal, $\boldsymbol{H}$ indicates the channel matrix, $\boldsymbol{u}$ indicates the column vector of the transmitted signal and $\boldsymbol{w}$ indicates the column vector of the received noise at the destination.

2.2.5 Mathematical models

2.2.5.1 Receiver operating characteristics (ROC)

In general, the decision problem between the presence and absence of the signal in non fading environment is governed by the following two hypotheses [16]:

$$\boldsymbol{y} = \begin{cases} \boldsymbol{w} : \ H_0 \\ \boldsymbol{Hu} + \boldsymbol{w} : \ H_1 \end{cases} \tag{2.8}$$

The received signal may be the noise only or absence of the signal which corresponds to the hypothesis H_0. Otherwise, the received signal is a combination of the transmitted signal and the noise which corresponds to the hypothesis H_1 that indicates the presence of the signal. The receiver decision is usually probabilistic according to the hypotheses H_0 and H_1. Considering the BLM detection approach, the probabilities of density function (PDFs) of (2.8) are expressed respectively as follows:

$$f_Y(y) = \begin{cases} \dfrac{1}{(2\pi)^{N/2}\det^{1/2}(N_0\boldsymbol{I})}\exp\left[-\dfrac{1}{2(N_0\boldsymbol{I})}\boldsymbol{y}^T\boldsymbol{y}\right]: & H_0 \\ \dfrac{1}{(2\pi)^{N/2}\det^{1/2}(C_u + N_0\boldsymbol{I})}\exp\left[-\dfrac{1}{2(C_u + N_0\boldsymbol{I})}\boldsymbol{y}^T\boldsymbol{y}\right]: & H_1 \end{cases} \tag{2.9}$$

where $\boldsymbol{y}$ is an $N\times 1$ vector of observations, $\boldsymbol{H}$ is a known $N\times p$ observation matrix with $N > P$, $\boldsymbol{u}$ is an $P\times 1$ random vector with $\boldsymbol{u(}N(0,C_u))$, $\boldsymbol{w}$ is an $N\times 1$ noise vector with PDF $N(0,N_0\boldsymbol{I})$ and is independent of $\boldsymbol{u}$ and C_u is the covariance of the source signal $\boldsymbol{u}$. In non fading environment, the signal energy detection is simply realized such that the received signal $y(k)$ passes the process of filtering, squaring, integrating and the decision statistic is given by [33]:

$$T = A\int |y(k)|^2\, dk \tag{2.10}$$

where A is a constant. The decision statistic is seen to be a sum of squares of Gaussian random variables whose distribution is a non central chi-square under H_1 and central chi square under H_0. Thus, the PDF of T under H_0 and H_1 can be written as:

$$f_T(T) = \begin{cases} \dfrac{1}{2^c \Gamma(c) N_0{}^p} T^{c-1} \exp\left[-\dfrac{1}{2(N_0)} T\right]: & H_0 \\ \dfrac{1}{2N_0}\left(\dfrac{T}{2\gamma}\right)^{\frac{c-1}{2N_0}} \exp\left[-\dfrac{2\gamma+T}{2N_0}\right] I_{c-1}\left(\dfrac{\sqrt{2\gamma T}}{N_0}\right): & H_1 \end{cases} \tag{2.11}$$

where $\Gamma(.)$ is the Gamma function and $I_c(.)$ is the c^{th} order modified Bessel functions of the first kind. The parameter c depends on the time bandwidth product [33]. The instantaneous signal to noise ratio (SNR) is defined by $\gamma = \left|h_{ij}\right|^2 P_s / N_0$ (from node i to node j) where P_s is the power of the source and N_0 is the noise power spectral density.

When the receiver decides the presence of the signal under hypothesis H_1, the detection performance is evaluated in terms of probability of detection (P_d), and when the receiver provides wrong decision under H_0, it implies the probability of false alarm (P_{fa}). Otherwise the receiver decides the absence of the signal or noise only which corresponds to the probability of non detection (P_n). It may happen that the receiver decides the absence of the signal whereas there is; this case indicates the probability of missed detection (P_m).

Theoretically, the probabilities of detection and non detection are respectively defined as [16, 19]:

$$P_d = \mathrm{P}\ (T(y) > \lambda \ \ | H_1) \tag{2.12}$$

and,

$$P_n = \mathrm{P}\ (T(y) < \lambda \ \ | H_0) \tag{2.13}$$

In (2.12), the probability of detection exists when the obtained test statistic is greater than the predetermined threshold; in this case the receiver is allowed to process the received information signal from the transmitter. In (2.13) the test statistic is less than the predetermined threshold, therefore there is an absence of the signal or only the noise is present. In some cases the receiver may make error decisions. Theoretically, error decision probabilities of the receiver such as P_{fa} and P_m are defined respectively by:

$$P_{fa} = P(T(y) > \lambda \ | H_0) \tag{2.14}$$

and,

$$P_m = P(T(y) < \lambda \ | H_1) \tag{2.15}$$

The relation between the probabilities of detection and missed detection is given by:

$$P_m = 1 - P_d \tag{2.16}$$

where $T(y)$ is the test statistic of the receiver and λ is the predetermined threshold.

Then, the closed form of the probabilities of detection (P_d) and false alarm (P_{fa}) are defined respectively by [32]:

$$P_d = Q_c\left(\frac{\sqrt{2\gamma}}{\sigma}, \frac{\sqrt{\lambda}}{\sigma}\right) \tag{2.17}$$

and

$$P_{fa} = \frac{\Gamma(c, \lambda / 2\sigma^2)}{\Gamma(c)} \tag{2.18}$$

where, $\Gamma(.,.)$ is the upper incomplete Gamma function defined as $\Gamma(a,x) = \int_x^\infty t^{a-1} e^{-t} dt$ [16]. The parameter c is the time bandwidth product of the observed signal which signifies the number of observed samples $c = N/2$ with N defines the degree of freedoms (DOFs) and λ is the detection threshold. $Q_c(.,.)$ is the c^{th} order generalized Marcum Q-function defined as [16]:

$$Q_c(a,b) = \int_b^\infty \frac{x^c}{a^{c-1}} \exp\left(-\frac{x^2+a^2}{2}\right) I_{c-1}(ax)dx \tag{2.19}$$

The expression (2.19) can be simplified as:

$$Q_c(a,b) = \sum_{n=0}^{\infty} \exp\left(-\frac{a^2}{2}\right) \frac{(a^2/2)^n}{n!} \sum_{k=0}^{n+c-1} \exp\left(-\frac{b^2}{2}\right) \frac{\left(b^2/2\right)^k}{k!} \tag{2.20}$$

Using the equation (2.20) and the relation in [16, Eq.8.352], equation (2.17) becomes:

$$Q_c\left(\frac{\sqrt{2\gamma}}{\sigma}, \frac{\sqrt{\lambda}}{\sigma}\right) = \sum_{n=0}^{\infty} \exp\left(-\frac{\gamma}{\sigma^2}\right) \frac{\left(\gamma/\sigma^2\right)^n}{n!} \frac{\Gamma\left(n+c, \lambda/(2\sigma^2)\right)}{\left(n+c-1\right)!} \tag{2.21}$$

In addition, we can mention that the threshold λ is commonly determined by solving the probability of false alarm in (2.18) as follows [19, 37]:

$$\frac{\Gamma(c; \lambda/2\sigma^2)}{\Gamma(c)} = \exp\left(-\frac{\lambda}{2\sigma^2}\right) \sum_{k=0}^{c-1} \frac{\left(\frac{\lambda}{2\sigma^2}\right)^k}{k!} \tag{2.22}$$

where c are even valued. Therefore, using (2.18) and (2.22) the threshold can be derived iteratively as follows [19]:

$$\lambda_{k+1}^{'} = -\ln p_{fa} + \ln\left[1 + \sum_{r=1}^{c-1} \frac{\left(\lambda_k^{'}\right)^r}{r!}\right] \tag{2.23}$$

where $\lambda^{'} = \lambda/2\sigma^2$. Analytically, using the BLM detection approach, the test statistic $T(y)$ is derived as follows [19]:

$$T(y) = \boldsymbol{y}^T \boldsymbol{H}\boldsymbol{C}_u\boldsymbol{H}^T (\boldsymbol{H}\boldsymbol{C}_u\boldsymbol{H}^T + N_0\boldsymbol{I})^{-1} \boldsymbol{y} \tag{2.24}$$

The receiver decides the presence of the signal when the test statistic is greater than the threshold ($T(y) > \lambda$) for the hypothesis H_1 that indicates the presence of the signal. Otherwise, the receiver decides the absence of the signal according to the hypothesis H_0. In (2.24), the covariance matrix $\boldsymbol{C}_u$ and the noise variance $N_0\boldsymbol{I}$ are represented by the following diagonal matrix:

$$\boldsymbol{C}_u = \begin{bmatrix} \sigma_{sd}^2 & 0 & \dots & 0 \\ 0 & \sigma_{1d}^2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & \sigma_{Md}^2 \end{bmatrix} \tag{2.25}$$

where, σ_{sd}^2 and σ_{Md}^2 are the variances of the signal generated by the source and relays respectively.

$$N_0\boldsymbol{I} = \begin{bmatrix} N_0 & 0 & \dots & 0 \\ 0 & N_0 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & N_0 \end{bmatrix} \tag{2.26}$$

The test statistic $T(y)$ is evaluated by substituting the channel covariance matrix and the noise variance matrix values in (2.24), after doing some variable changing, we obtain the following expression:

$$T(y) = \left(\frac{|h_{sd}|^2 \sigma_{sd}^2}{|h_{sd}|^2 \sigma_{sd}^2 + N_0} \right) |y_{sd}|^2 + \sum_{i=1}^{M} \left(\frac{|h_{id}|^2 \sigma_{id}^2}{|h_{id}|^2 \sigma_{id}^2 + N_0} \right) |y_{id}|^2 \tag{2.27}$$

The test statistic (2.27) under test hypotheses is described as follows:

$$\begin{cases} H_0 & : T(y) = \dfrac{\gamma_{sd}}{\gamma_{sd}+1} N_0 \left| \dfrac{y_{sd}}{\vartheta_{sd(0)}} \right|^2 + \displaystyle\sum_{i=1}^{M} \dfrac{\gamma_{id}}{\gamma_{id}+1} N_0 \left| \dfrac{y_{id}}{\vartheta_{id(0)}} \right|^2 \\ H_1 & : T(y) = \dfrac{\gamma_{sd}}{\gamma_{sd}+1} (\kappa_{sd}^2 \sigma_{sd}^2 + N_0) \left| \dfrac{y_{sd}}{\vartheta_{sd(1)}} \right|^2 + \displaystyle\sum_{i=1}^{M} \dfrac{\gamma_{id}}{\gamma_{id}+1} (\kappa_{id}^2 \sigma_{id}^2 + N_0) \left| \dfrac{y_{id}}{\vartheta_{id(1)}} \right|^2 \end{cases} \tag{2.28}$$

where $\gamma_{sd} = |h_{sd}|^2 \sigma_{sd}^2 / N_0$, $\bar{\gamma}_{sd} = \kappa_{sd}^2 \sigma_{sd}^2 / N_0$, $\gamma_{id} = |h_{id}|^2 \sigma_{id}^2 / N_0$, $\bar{\gamma}_{id} = \kappa_{id}^2 \sigma_{id}^2 / N_0$, $\vartheta_{sd(1)}^2 = E\left[|y_{sd}|^2 \right] = (\kappa\sigma_{sd}^2 + N_0)$, $\vartheta_{id(1)}^2 = E\left[|y_{id}|^2 \right] = (\kappa\sigma_{id}^2 + N_0)$, $\vartheta_{sd(0)}^2 = N_0$ and $\vartheta_{id(0)}^2 = N_0$

The expression in (2.28) can be simplified as follows:

$$\begin{cases} H_0 & :T(y) = \alpha_{(0)}\chi^2_{2(sd)} + \sum_{i=1}^{M} \beta_{i(0)}\chi^2_{2(rd)}(i) \\ H_1 & :T(y) = \alpha_{(1)}\chi^2_{2(sd)} + \sum_{i=1}^{M} \beta_{i(1)}\chi^2_{2(rd)}(i) \end{cases} \tag{2.29}$$

where: $\alpha_{(0)} = \frac{\gamma_{sd}}{\gamma_{sd}+1}N_0$, $\beta_{i(0)} = \frac{\gamma_{id}}{\gamma_{id}+1}N_0$, $\alpha_{(1)} = \frac{\gamma_{sd}}{\gamma_{sd}+1}(\kappa^2_{sd}\sigma^2_{sd} + N_0)$,

$\beta_{i(1)} = \frac{\gamma_{id}}{\gamma_{id}+1}(\kappa^2_{id}\sigma^2_{id} + N_0)$, $\chi^2_{2(sd)}$ and $\chi^2_{2(rd)}(i)$ are independent and identically distributed Chi-squared random variables with two degree of freedom for the source & destination and relay & destination respectively.

The probabilities density functions (PDFs) of the test statistic $T(y)$ in (2.29) are determined as follows [19]:

$$\begin{cases} P(T;H_0) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \phi_{T_{H_0}}(\omega)\exp(-j\omega T)d\omega \\ P(T;H_1) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \phi_{T_{H_1}}(\omega)\exp(-j\omega T)d\omega \end{cases} \tag{2.30}$$

It is shown that $P(T;H_0)$ and $P(T;H_1)$ are obtained from the inverse fourrier transforms of the characteristic functions of $T(y)$ according to the hypotheses H_0 and H_1 that are given by:

$$\begin{cases} \phi_{T_{H_0}} = \frac{1}{1-2j\omega\alpha_{(0)}} + \prod_{i=1}^{M} \frac{1}{1-2j\omega\beta_{i(0)}} \\ \phi_{T_{H_1}} = \frac{1}{1-2j\omega\alpha_{(1)}} + \prod_{i=1}^{M} \frac{1}{1-2j\omega\beta_{i(1)}} \end{cases} \tag{2.31}$$

where, $\prod_{i=1}^{M} \frac{1}{1-2j\omega\beta_{i(0)}} = \sum_{i=1}^{M} \frac{L_i}{1-2j\omega\beta_{i(0)}}$, with $L_i = \prod_{l=1,l\neq i}^{M} \frac{1}{1-\beta_{l(0)}/\beta_{i(0)}}$, and where

$\prod_{i=1}^{M} \frac{1}{1-2j\omega\beta_{i(1)}} = \sum_{i=1}^{M} \frac{R_i}{1-2j\omega\beta_{i(1)}}$, with $R_i = \prod_{l=1,l\neq i}^{M} \frac{1}{1-\beta_{l(1)}/\beta_{i(1)}}$

Substituting (2.31) in (2.30), the PDFs for dual hop (2 segments) relays network are given by:

$$\begin{cases} P(T;H_0)=\frac{1}{2}\int_{-\infty}^{\infty}\frac{1}{\left(1-2j\omega\alpha_{(0)}\right)}\exp(-j\omega T)\frac{d\omega}{2\pi}+\frac{1}{2}\sum_{i=1}^{M}\int_{-\infty}^{\infty}\frac{L_i}{(1-2j\omega\beta_{i(0)})}\exp\left(-j\omega T\right)\frac{d\omega}{2\pi} \\ P(T;H_1)=\frac{1}{2}\int_{-\infty}^{\infty}\frac{1}{\left(1-2j\omega\alpha_{(1)}\right)}\exp(-j\omega T)\frac{d\omega}{2\pi}+\frac{1}{2}\sum_{i=1}^{M}\int_{-\infty}^{\infty}\frac{R_i}{(1-2j\omega\beta_{i(1)})}\exp\left(-j\omega T\right)\frac{d\omega}{2\pi} \end{cases} \tag{2.32}$$

After deriving (2.32) and making some variable changing, we obtain:

$$\begin{cases} P(T;H_0)=\frac{1}{4\alpha_{(0)}}\exp\left(-\frac{T}{2\alpha_{(0)}}\right)+\sum_{i=1}^{M}\frac{L_i}{4\beta_{i(0)}}\exp\left(-\frac{T}{2\beta_{i(0)}}\right) \\ P(T;H_1)=\frac{1}{4\alpha_{(1)}}\exp\left(-\frac{T}{2\alpha_{(1)}}\right)+\sum_{i=1}^{M}\frac{R_i}{4\beta_{i(1)}}\exp\left(-\frac{T}{2\beta_{i(1)}}\right) \end{cases} \tag{2.33}$$

The probabilities of false alarm and detection can be determined as follows [19]:

$$P_{fa}=\int_{\lambda}^{\infty}P(T;H_0)dT=\frac{1}{2}\exp\left(-\frac{\lambda}{2\alpha_{(0)}}\right)+\frac{1}{2}\sum_{i=1}^{M}L_i\exp\left(-\frac{\lambda}{2\beta_{i(0)}}\right) \tag{2.34}$$

and

$$P_{d}=\int_{\lambda}^{\infty}P(T;H_1)dT=\frac{1}{2}\exp\left(-\frac{\lambda}{2\alpha_{(1)}}\right)+\frac{1}{2}\sum_{i=1}^{M}R_i\exp\left(-\frac{\lambda}{2\beta_{(1)}}\right) \tag{2.35}$$

2.2.5.2 Bit error probability performance analysis

The bit error probability (BEP) of a system that transmits with equal likely probability is given by the following expression [38]:

$$BEP=\frac{1}{2}(1-P_d+P_{fa}) \tag{2.36}$$

By substituting (2.34) and (2.35) in (2.36), the BEP is given by:

$$BEP = \frac{1}{2} - \frac{1}{4}\left[\exp\left(-\frac{\lambda}{2\alpha_{(1)}}\right) - \exp\left(-\frac{\lambda}{2\alpha_{(0)}}\right) - \sum_{i=1}^{M}\left\{R_i \exp\left(-\frac{\lambda}{2\beta_{i(1)}}\right) - L_i \exp\left(-\frac{\lambda}{2\beta_{i(0)}}\right)\right\}\right] \quad (2.37)$$

2.2.5.3 MSE performance analysis

The minimum mean square error (MMSE) estimator with Bayesian linear model approach is given by [19]:

$$\hat{\boldsymbol{s}} = \boldsymbol{H}\boldsymbol{C}_u\boldsymbol{H}^T(\boldsymbol{H}\boldsymbol{C}_u\boldsymbol{H}^T + N_0\boldsymbol{I})^{-1}\boldsymbol{y} \quad (2.38)$$

Substituting (2.25) and (2.26) into (2.38), we obtain:

$$\hat{s}_i = \begin{cases} \dfrac{P_s\,|\,h_{sd}\,|^2\,\sigma_s^2}{P_s\,|\,h_{sd}\,|^2\,\sigma_s^2 + N_0}\,y_{sd} \\ \dfrac{P_1\,|\,h_{1d}\,|^2\,\sigma_s^2}{P_1\,|\,h_{1d}\,|^2\,\sigma_s^2 + N_0}\,y_{1d} \\ \cdots \\ \dfrac{P_i\,|\,h_{id}\,|^2\,\sigma_s^2}{P_i\,|\,h_{id}\,|^2\,\sigma_s^2 + N_0}\,y_{id} \end{cases} \quad (2.39)$$

Since, the transmission of signals is orthogonal and all signals are independently transmitted from the relays, the overall estimate is the summation of independent estimation by using the following property: The MMSE estimator of s based on i uncorrelated data vectors, assuming jointly Gaussian statistics is given by [16]:

$$\hat{s} = E\left(s\,|\,y_1, y_2, ..., y_i\right) = E\left(s\,|\,y_1\right) + E\left(s\,|\,y_2\right) + ... + E\left(s\,|\,y_i\right) = \sum_{i=1}^{M} E\left(s\,|\,y_i\right) \quad (2.40)$$

Therefore, the MMSE estimate $\hat{\boldsymbol{s}}$ becomes:

$$\hat{\boldsymbol{s}} = \frac{P_s\,|\,h_{sd}\,|^2\,\sigma_s^2}{P_s\,|\,h_{sd}\,|^2\,\sigma_s^2 + N_0}\,y_{sd} + \sum_{i=1}^{M}\frac{P_i\,|\,h_{id}\,|^2\,\sigma_s^2}{P_i\,|\,h_{id}\,|^2\,\sigma_s^2 + N_0}\,y_{id} \quad (2.41)$$

Then, the MSE is given by:

$$MSE(\boldsymbol{s}) = E[|(\boldsymbol{s} - \hat{\boldsymbol{s}})|^2] \quad (2.42)$$

2.2.6 Numerical results

In this study, simulation results are presented in order to investigate the performance of the BLM detector through the ROCs, bit error probability and minimum MSE. Four scenarios are considered; the first scenario evaluates the probability of detection of the BLM detector with various number of relays, and compares it with the upper and lower bounds of probability of detection given in [34]. The second scenario evaluates the probability of detection and bit error probability for various positions of relays with different number of relays. The third scenario evaluates the everage probability of error with different number of relays. The fourth scenario evaluates the mean square error (MSE) of the BLM detector with various number of relays.

It is considered that the variance of channel fading coefficient between nodes (i.e: σ_h^2) is found by using path loss model equivalent to $\sigma_h^2 = d_{ij}^{-\nu}$ with ν which indicates the path loss exponent, here we take $\nu = 3$ which corresponds to the shadowed urban cellular radio environment [4], and d_{ij} which denotes the distance between two nodes in the network and the distance between the source and the destination equals to one whereas the distance between the source & relay and the relay & destination varies according to the relation: $d_{sd} = d_{sr} + d_{rd}$.

During simulation, the signal is generated at the source and modulated with QPSK and sent to all relays and destination node in the network. The channels between the source & destination, source & relays, and relays & destination are generated with Rayleigh fading distribution. Each relay amplifies the received signal from the source only and forwards it to the destination. The amplification is done by only multiplying the received signal with the amplification factor or gain which is given by the expression in (2.5). At the destination node, the BLM detector computes the signal energy for each link, combines all received signal energies from different links and then determines the test statistic which is compared with the predetermined threshold. The threshold is determined by solving the probability of false alarm given by the expression (2.18). The probability of false alarm (P_{fa}) is taken between 0 and 1 and the bandwidth product c equals to 2.

In Figure 2.3, the ROC is evaluated in M-relays (R=2, R=3 and R=4) with BLM detector at the destination. The results show that the probability of detection increases when the number of relays increase and the BLM detector results outperform the results of the upper and lower bound of probability of detection for the number of relays higher than 2. In Figure 2.4, the ROCs of the BLM detector is also analyzed in M-relays (R=2, R=3 and R=4) located at different distances from the source and destination. The results show that the probability of detection increases as the number of relays increases and when relays are closer to the source. The same observation about the improved performance when relays are closer to the source is observed in [39, 40]. In Figure 2.5, the error probability is investigated with M- relays (R=4, R=3 and R=4). The obtained results show that the error probability decreases when the number of relays increases in the system and the Figure 2.6 shows that the bit error probability improves much more when the relay is closer to the source than the relay closer to the destination. In Figure 2.7, the MSE of the BLM detector is investigated in M-relays and the results show that the MSE decreases as the number of relays increases.

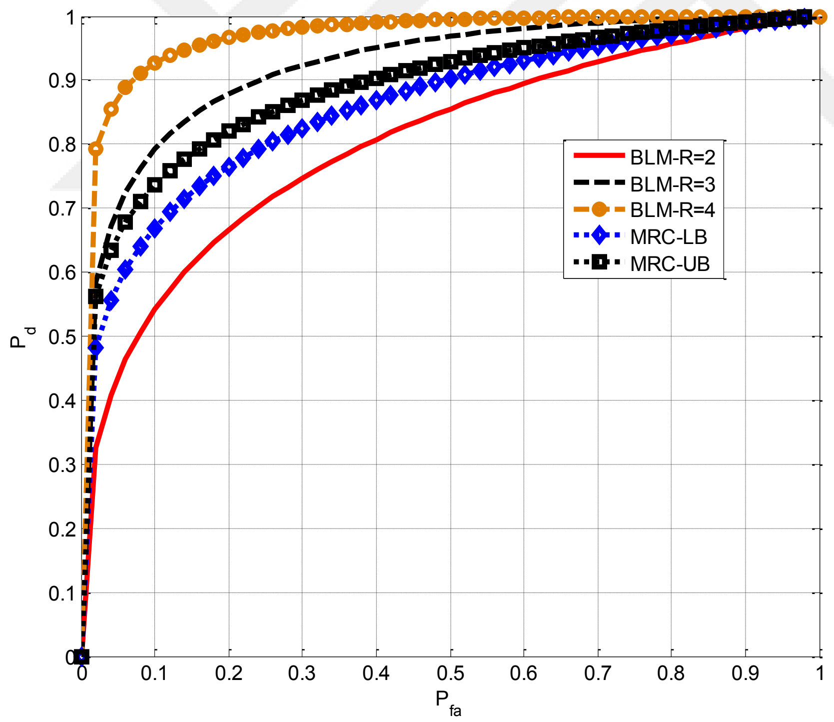

Figure 2.3 : ROCs of the BLM detector with the upper & lower bounds.

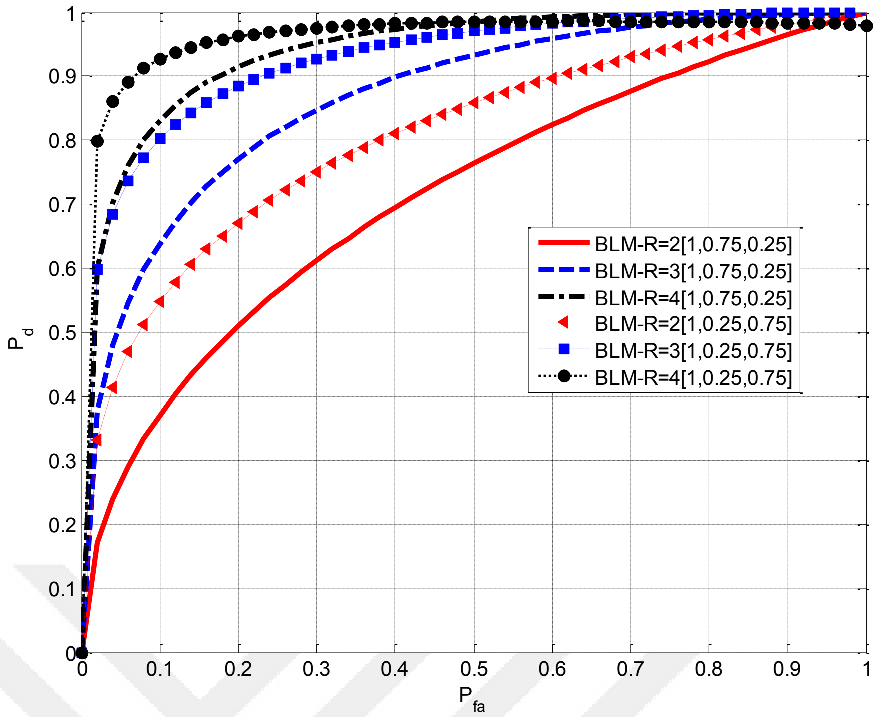

Figure 2.4 : ROCs of the BLM detector with various relays positions.

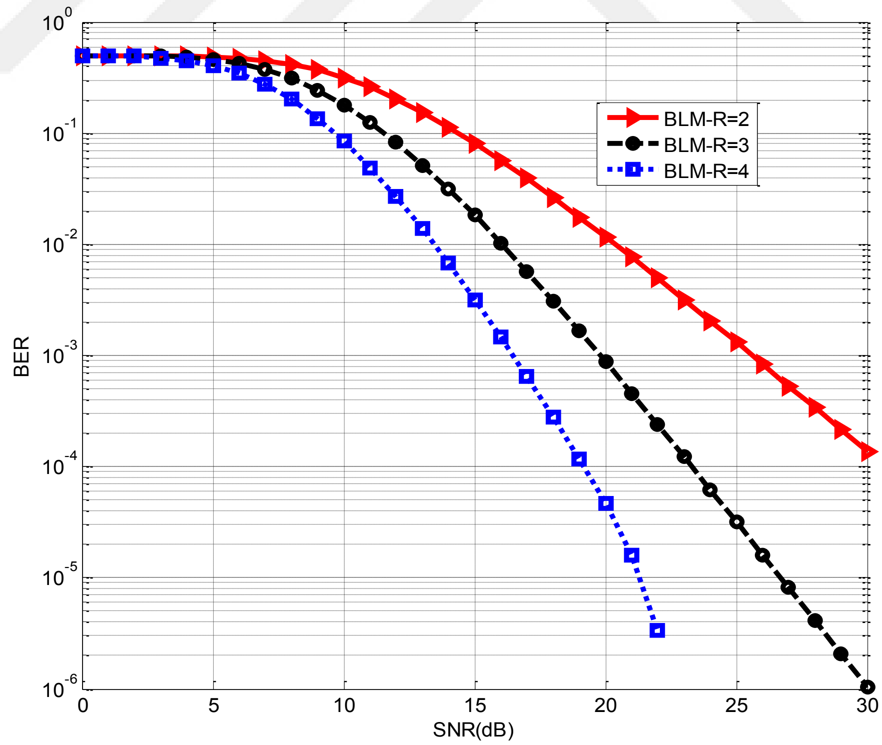

Figure 2.5 : Average error probability of the BLM detector in M-Relays network.

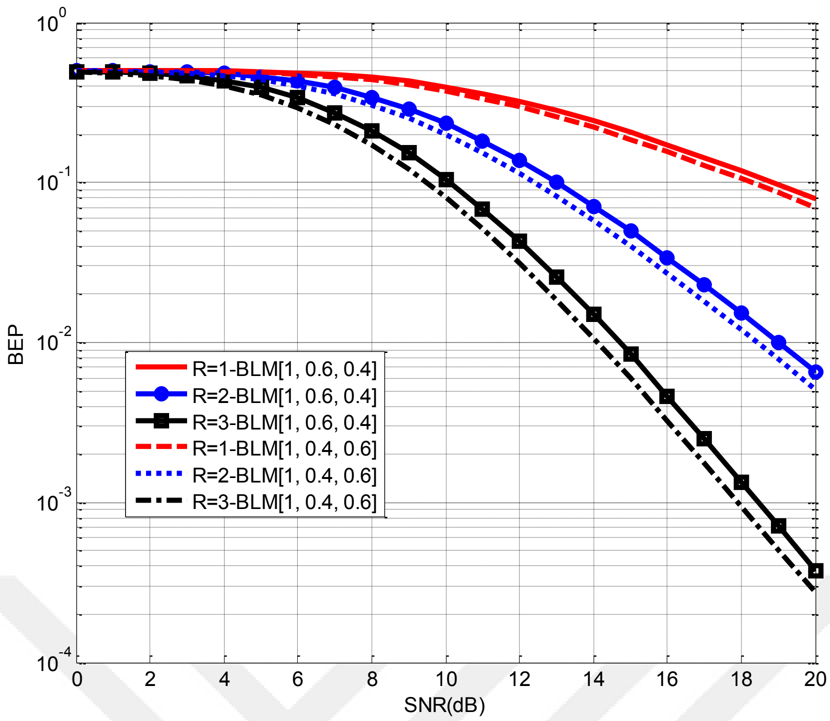

Figure 2.6 : BEP of the BLM detector with various relays positions.

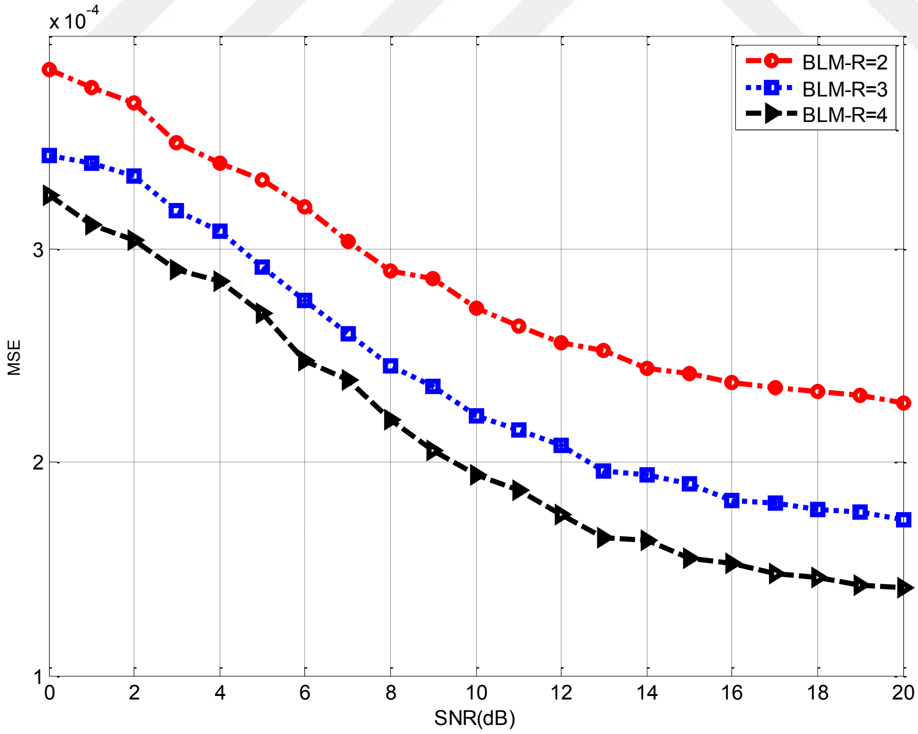

Figure 2.7 : MSE of the BLM detector in M-Relays network.

2.2.7 Summary

In this study, the Bayesian linear model (BLM) detector in amplify and forward (AF) multiple relays network is proposed. It is also assumed that the CSI is available at the destination and the network system is operating over independent and identically distributed Rayleigh fading channels. Four scenarios are considered; the first scenario is based on evaluating the receiver operating characteristics (ROC) and comparing it with the upper and lower bound of the probability of detection (i.e., Figure 2.3). The second scenario evaluates the ROC and bit error rate in various number of relays and different locations of the relays (i.e., Figure 2.4 and Figure 2.5). The third scenario evaluates the BER in various number of relays (i.e., Figure 2.6). The last scenario evaluates the minimum mean square error (MSE) of the BLM detector with various number of relays (i.e., Figure 2.7).

The simulation results of the ROCs show that the bayesian linear model (BLM) detector provides better detection performance than the upper and lower bound of the probability of detection, and the detection performance increases when the number of relays increases and when relays are closer to the source. The results of error probability show that signal errors in the system decreases when the number of relays increases in the system and when the distance between the source and relays is reduced. Similarly, the results of MSEs show that the system performance improves gradually as the number of relays increases in the network. The distance between the source and relay is an important factor that determines the performance of the system in a network that use multiple relays. In summary, the overall results have shown that the BLM detector is effective in M-relays based cooperative communications and can recover efficiently the original transmitted signal as the number of relays increases in the network.

2.3 A Novel LMS-BLM Algorithm for AF Relays Based Cooperative Wireless Networks

2.3.1 Abstract

In this section, multiple AF relays based cooperative wireless networks are considered. A number of studies in literature on wireless networks assume perfect channel state information at the receiver (CSIR), but in reality, due to the nature of wireless channels, little information is known on both the channel state information (CSI) and original transmitted signal at the receiver. Therefore, the main contribution in this work is based on proposing a novel algorithm that combines the least mean square (LMS) and Bayesian linear model (BLM) detector for the purpose of estimating the channel and recovering the original transmitted signal at the receiver. Analytical and theoretical simulations on receiver operating characteristics (ROC), complementary ROC, mean square errors (MSE) learning curves and probability of error are presented. The assessment of the effects of gradient step size and number of relays on both the detection performance and the MSE learning curve are carried out.

The main advantages of the proposed algorithm are low implementation complexity, linear computation and can improve the detection performance of the receiver [23-25].

2.3.2 Related work

In literature, most of the existing studies focus on either signal or energy detection [29-34] and assume perfect CSI at the receiver or the transmitter or both [41-47]. In [41], authors consider pilot symbol aided channel estimation for cooperation diversity systems and focus on sub optimal linear minimum mean square estimator (LMMSE) design. A complete study on training based channel estimation for relay networks with AF transmission scheme is done in [42] and new estimation scheme that directly estimates the overall channels from the source to the destination is studied on both linear least square (LS) and minimum mean square error (MMSE) estimators. In [43], a wireless network with AF relays is studied where an autoregressive model is used to characterise the time varying channels and Kalman filter is utilised for channel estimation. In [44], the expectation-maximization (EM) algorithm is used to obtain the channel estimates in an iterative way. Space-alternating generalized expectation – maximization (SAGE) algorithm is used to perform code-aided iterative channel estimation from the broadcasting signals with AF protocol [45]. The problem of data detection and channel estimation is investigated in [46] by proposing a combination of generalized likelihood ratio test (GLRT) and least mean square (LMS) algorithm in DF relay networks. Iterative channel estimation and data detection based on parallel interference cancellation (PIC) at the receiver is proposed in [47].

In this study, by considering that the CSI is not available at the receiver and the original transmitted signal is corrupted by unwanted signals, a novel algorithm is proposed which combines the LMS algorithm and the BLM detector with the purpose of recovering the desired signal. Therefore, the main contribution of this part is based on implementing the proposed algorithm in cooperative wireless networks with AF relays and examining the following performance metrics:

- Deriving the test statistic of the proposed algorithm.
- Deriving the probability densit functions of the test statistic.
- Deriving the probabilities of false alarm, detection and error of the receiver.
- Performing simulations for the mean square error (MSE) learning curve.
- Performing simulations for the theoretical and analytical receiver operating characteristics (ROCs) of the system.
- Evaluating the effects of gradient step size and number of relays on the ROCs.
- Evaluating the effects of gradient step size and number of relays on the MSE learning curve.

The advantages of the proposed algorithm are based on simple matrix computations of the BLM detector, low implementation complexity and feasibility of the LMS algorithm compared to other existing adaptive algorithms such as RLS algorithm and Kalman filters. The complexity of the LMS algorithm follows linear law whereas the one of the RLS follows square law. Moreover, the use of the Kalman filters for channel estimation requires the knowledge of some a priori information of the channel availability at the receiver which is not the case when using the RLS algorithm. Therefore, the computation complexity of the LMS and RLS becomes less than the one of the Kalman filter [23-25]. In this part, simulation results show that the obtained analytical results are in agreement with the theoretical results and the system can provide satisfactory results of the ROCs that are different from previous studies [29-34].

2.3.3 System model

As represented the network model depicted in Figure 2.1, the channel estimation is realized between the source and destination, and the relay and destination. We assume that each relay forwards the received signal from the source only and does not add additional traffic on the transmitted signal.

In this system model, pilot assisted estimation is considered and there is no any assumption on the channel distribution characteristics instead the theoretic channel during implementation is considered. Two phases of data transmission are considered; in the first phase the source broadcasts the signal to the destination and relays in the network. In the second phase, the source is silent and relays amplify and forward the signal to the destination. The transmitted signals obey orthogonal transmission which can be acheived by using time division multiple access (TDMA) or frequency division multiple access (FDMA) [4]. Therefore, the destination/receiver is equipped with LMS-BLM receiver for channel estimation and data detection as described in Figure 2.8.

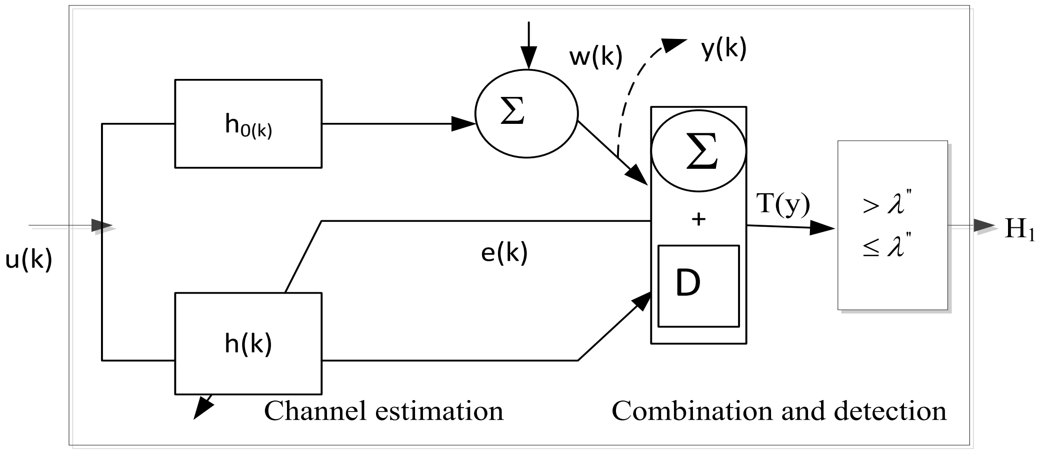

Figure 2.8 : Block diagram representing the LMS- BLM Receiver.

In the above scheme, the block diagram comprises of two main parts, the first part is about channel estimation based on LMS algorithm and the second part comprises of combiner and data detection with BLM detection approach. The overall test statistic is compared with predetermined threshold which is derived from the expression (2.18).

2.3.4 Mathematical and performance metric models

In reality, CSI is not available at the receiver and need to be estimated. In this context, the source sends additional pilot symbols and the corresponding received signal to the destination which are used to obtain the channel estimate. Therefore, the proposed algorithm that is based on least mean square (LMS) algorithm for channel estimation and Bayesian linear model (BLM) detector at the receiver is implemented in wireless relays network in order to enhance the original transmitted signal recovery. The LMS algorithm is a linear adaptive filtering algorithm that consists of two basic processes such as filtering and adaptive processes. In filtering, given the input signal, the output of the linear filter is computed and then the estimation error is generated by comparing this output and the desired response. In adaptive process, the automatic adjustment of the parameters of the filter is done in accordance with the estimation error. From Figure 2.8, the observed signals at the destination can be represented as:

$$\begin{cases} y_{sd}(k) = u(k)h_{0(sd)}(k) + w(k) \\ y_{1d}(k) = u_{1d}(k)h_{0(1d)}(k) + w(k) \\ \cdots \\ y_{id}(k) = u_{id}(k)h_{0(id)}(k) + w(k) \\ \cdots \\ y_{Md}(k) = u_{Md}(k)h_{0(Md)}(k) + w(k) \end{cases} \tag{2.43}$$

Assuming that the received signals can be modeled as linear form and all unknown channels are independent random variables where each individual realization of the channel path is independent for all time step *k*. Therefore, the linear form of the received signal vector $\boldsymbol{y}$ at symbol time *k* can be written as:

$$\boldsymbol{y}(k) = \boldsymbol{H}(k)\boldsymbol{u}(k) + \boldsymbol{w}(k) \tag{2.44}$$

where $\boldsymbol{H}$ denotes the channel matrix, $\boldsymbol{u}$ is the symbol vector simultaneously transmitted by the source and $\boldsymbol{w}$ assumed to be the additive white Gaussian noise vector with zero mean and covariance matrix $N_0\boldsymbol{I}$. Therefore, the LMS algorithm is computed in the following recursion equations:

$$\begin{cases} \boldsymbol{d}(k) = \hat{\boldsymbol{H}}(k)\boldsymbol{u}^H(k) \\ \boldsymbol{e}(k) = \boldsymbol{y}(k) - \boldsymbol{d}(k) \\ \hat{\boldsymbol{H}}(k+1) = \hat{\boldsymbol{H}}(k) + \mu \boldsymbol{e}^*(k)\boldsymbol{u}(k) \end{cases} \tag{2.45}$$

The channel estimate $\hat{\boldsymbol{H}}(k+1)$ is updated according to the estimation errors $\boldsymbol{e}(k)$, μ is the step size and $\boldsymbol{u(}k)$ is the transmitted signal at time step *k*. The mean square error (MSE) is given by: $E[\boldsymbol{e}^2(k)] = E[(\boldsymbol{y}(k) - \boldsymbol{d}(k))^2]$. After obtaining the channel estimates, the BLM detector combines the received signals and computes the test statistic as given in the following [19]:

$$\hat{T}(y) = \boldsymbol{y}^T \hat{\boldsymbol{H}}\boldsymbol{C}_u \hat{\boldsymbol{H}}^T (\hat{\boldsymbol{H}}\boldsymbol{C}_u \hat{\boldsymbol{H}}^T + N_0 \boldsymbol{I})^{-1} \boldsymbol{y} \tag{2.46}$$

The test statistic $\hat{T}(y)$ in (2.46) can be defined as the total signal energy received at the receiver due to the combination of the energy signals between the source and destination, and the relay and destination links. In order to decide about the presence or absence of the signal, the test statistic is compared with the threshold λ that is derived from the closed form expression given in (2.18). In equation (2.46), the covariance matrix equals $\boldsymbol{C}_u = diag[\sigma_{sd}^2, \sigma_{1d}^2, ..., \sigma_{id}^2, ..., \sigma_{Md}^2]$ and the noise variance equals to $N_0\boldsymbol{I} = diag[N_0, ..., N_0]$.

The test statistic (2.46) is evaluated by substituting the values of covariance matrix of the transmitted signal and the noise variance matrix, after doing some variable changing, we obtain the following expression:

$$\hat{T}(y) = \left(\frac{\hat{h}_{sd}^2 \sigma_{sd}^2}{\hat{h}_{sd}^2 \sigma_{sd}^2 + N_0} \right) y_{sd}^2 + \sum_{i=1}^{M} \left(\frac{\hat{h}_{id}^2 \sigma_{id}^2}{\hat{h}_{id}^2 \sigma_{id}^2 + N_0} \right) y_{id}^2 \tag{2.47}$$

In (2.47) y_{sd}^2 and y_{id}^2 are i.i.d random variables with N(0,1). According to the hypotheses H_0 and H_1, the $\hat{T}(y)$ can be derived as follows:

$$\begin{cases} H_0 : \hat{T}(y) = \left(\dfrac{\hat{h}_{sd}^2 \sigma_{sd}^2 N_0}{\hat{h}_{sd}^2 \sigma_{sd}^2 + N_0} \right) \left(\dfrac{y_{sd}}{\upsilon_{(0)}} \right)^2 + \sum_{i=1}^{M} \left(\dfrac{\hat{h}_{id}^2 \sigma_{id}^2 N_0}{\hat{h}_{id}^2 \sigma_{id}^2 + N_0} \right) \left(\dfrac{y_{id}}{\upsilon_{i(0)}} \right)^2 \\ H_1 : \hat{T}(y) = \hat{h}_{sd}^2 \sigma_{sd}^2 \left(\dfrac{y_{sd}}{\upsilon_{(1)}} \right)^2 + \sum_{i=1}^{M} \hat{h}_{id}^2 \sigma_{id}^2 \left(\dfrac{y_{id}}{\upsilon_{i(1)}} \right)^2 \end{cases} \tag{2.48}$$

where $\upsilon_{(0)}^2 = N_0$, $\upsilon_{i(0)}^2 = N_0$, $\upsilon_{(1)}^2 = \hat{h}_{sd}^2 \sigma_{sd}^2 + N_0$ and $\upsilon_{i(1)}^2 = \hat{h}_{id}^2 \sigma_{id}^2 + N_0$. The relation (2.48) can be written again as follows:

$$\begin{cases} H_0 : \hat{T}(y) = \hat{\alpha}_{(0)sd} \chi_{sd}^2 + \sum_{i=1}^{M} \hat{\beta}_{i(0)} \chi_{rd}^2(i) \\ H_1 : \hat{T}(y) = \hat{\alpha}_{(1)} \chi_{sd}^2 + \sum_{i=1}^{M} \hat{\beta}_{i(1)} \chi_{rd}^2(i) \end{cases} \tag{2.49}$$

where: $\hat{\alpha}_{(0)} = \dfrac{\hat{h}_{sd}^2 \sigma_{sd}^2}{\hat{h}_{sd}^2 \sigma_{sd}^2 + 1}$, $\hat{\beta}_{i(0)} = \dfrac{\hat{h}_{id}^2 \sigma_{id}^2}{\hat{h}_{id}^2 \sigma_{id}^2 + 1}$, $\hat{\alpha}_{(1)} = \hat{h}_{sd}^2 \sigma_{sd}^2$, $\beta_{i(1)} = \hat{h}_{id}^2 \sigma_{id}^2$, $N_0 = 1$, χ_{sd}^2 and $\chi_{rd}^2(i)$ are independent and identically distributed Chi-squared random variables with one degree of freedom for the source and destination, and relay and destination links respectively.

$$\begin{cases} P(\hat{T}; H_0) = \dfrac{1}{2\pi} \int_{-\infty}^{\infty} \phi_{\hat{T}_{H_0}}(\omega) \exp(-j\omega \hat{T}) d\omega \\ P(\hat{T}; H_1) = \dfrac{1}{2\pi} \int_{-\infty}^{\infty} \phi_{\hat{T}_{H_1}}(\omega) \exp(-j\omega \hat{T}) d\omega \end{cases} \tag{2.50}$$

It is shown that $P(\hat{T}; H_0)$ and $P(\hat{T}; H_1)$ are the inverse fourier transforms of the characteristic functions of $\hat{T}(y)$ according to the hypotheses H_0 and H_1. The characteristic functions are given by:

$$\begin{cases} \phi_{\hat{T}_{H_0}} = \dfrac{1}{\sqrt{1 - 2j\omega \hat{\alpha}_{(0)}}} + \prod_{i=1}^{M} \dfrac{1}{\sqrt{1 - 2j\omega \hat{\beta}_{i(0)}}} \\ \phi_{\hat{T}_{H_1}} = \dfrac{1}{\sqrt{1 - 2j\omega \hat{\alpha}_{(1)}}} + \prod_{i=1}^{M} \dfrac{1}{\sqrt{1 - 2j\omega \hat{\beta}_{i(1)}}} \end{cases} \tag{2.51}$$

for,

$$\prod_{i=1}^{M}\frac{1}{\sqrt{1-2j\omega\hat{\beta}_{i(0)}}}=\sum_{i=1}^{M}\frac{\hat{L}_i}{\sqrt{1-2j\omega\hat{\beta}_{i(0)}}}\ \text{ with } \hat{L}_i=\prod_{l=1,l\neq i}^{M}\frac{1}{\sqrt{1-\hat{\beta}_{l(0)}/\hat{\beta}_{i(0)}}}$$

and for,

$$\prod_{i=1}^{M}\frac{1}{\sqrt{1-2j\omega\hat{\beta}_{i(1)}}}=\sum_{i=1}^{M}\frac{\hat{R}_i}{\sqrt{1-2j\omega\hat{\beta}_{i(1)}}}\ \text{ with } \hat{R}_i=\prod_{l=1,l\neq i}^{M}\frac{1}{\sqrt{1-\hat{\beta}_{l(1)}/\hat{\beta}_{i(1)}}}$$

Substituting (2.51) in (2.50), the PDFs for dual hop networks are derived as follows:

$$\begin{cases} P(\hat{T};H_0)=\frac{1}{2}\int_{-\infty}^{\infty}\frac{1}{\left(1-2j\omega\hat{\alpha}_{(0)}\right)^{1/2}}\exp(-j\omega\hat{T})\frac{d\omega}{2\pi}+\frac{1}{2}\sum_{i=1}^{M}\int_{-\infty}^{\infty}\frac{\hat{L}_i}{(1-2j\omega\hat{\beta}_{i(0)})^{1/2}}\exp\left(-j\omega\hat{T}\right)\frac{d\omega}{2\pi} \\ P(\hat{T};H_1)=\frac{1}{2}\int_{-\infty}^{\infty}\frac{1}{\left(1-2j\omega\hat{\alpha}_{(1)}\right)^{1/2}}\exp(-j\omega\hat{T})\frac{d\omega}{2\pi}+\frac{1}{2}\sum_{i=1}^{M}\int_{-\infty}^{\infty}\frac{\hat{R}_i}{(1-2j\omega\hat{\beta}_{i(1)})^{1/2}}\exp\left(-j\omega\hat{T}\right)\frac{d\omega}{2\pi} \end{cases} \tag{2.52}$$

Using [16, 19] and [48], the PDFs of the test statistic (2.52) can be derived as follows:

$$P(\hat{T};H_0)=\frac{\hat{T}^{-1/2}}{\sqrt{2\pi\hat{\alpha}_{(0)}}}\exp(-\frac{\hat{T}}{2\hat{\alpha}_{(0)}})+\sum_{i=1}^{M}\hat{L}_i\frac{\hat{T}^{-1/2}}{\sqrt{2\pi\hat{\beta}_{i(0)}}}\exp(-\frac{\hat{T}}{2\hat{\beta}_{i(0)}}) \tag{2.53}$$

and,

$$P(\hat{T};H_1)=\frac{\hat{T}^{-1/2}}{\sqrt{2\pi\hat{\alpha}_{(1)}}}\exp(-\frac{\hat{T}}{2\hat{\alpha}_{(1)}})+\sum_{i=1}^{M}\hat{R}_i\frac{\hat{T}^{-1/2}}{\sqrt{2\pi\hat{\beta}_{i(1)}}}\exp(-\frac{\hat{T}}{2\hat{\beta}_{i(1)}}) \tag{2.54}$$

Using the solutions found in (2.53) and (2.54), the probabilities of false alarm and detection are respectively derived as follows [49, Sec.5.3. Eq. 21]:

$$\hat{P}_{fa}=\int_{\lambda}^{\infty}P(\hat{T};H_0)d\hat{T}=\frac{1}{\sqrt{\pi}}\Gamma\left(\frac{1}{2},\frac{1}{2\hat{\alpha}_{(0)}}\lambda\right)+\sum_{i=1}^{M}\frac{\hat{L}_i}{\sqrt{\pi}}\Gamma\left(\frac{1}{2},\frac{1}{2\hat{\beta}_{i(0)}}\lambda\right) \tag{2.55}$$

and,

$$\hat{P}_{d}=\int_{\lambda}^{\infty}P(\hat{T};H_1)d\hat{T}=\frac{1}{\sqrt{\pi}}\Gamma\left(\frac{1}{2},\frac{1}{2\hat{\alpha}_{(1)}}\lambda\right)+\sum_{i=1}^{M}\frac{\hat{R}_i}{\sqrt{\pi}}\Gamma\left(\frac{1}{2},\frac{1}{2\hat{\beta}_{i(1)}}\lambda\right) \tag{2.56}$$

Using the solutions (2.55) and (2.56), it is likely to design a receiver with minimum probability of error (minPe). Therefore, the average probability of error ($\bar{P}_e$) is defined as follows [16]:

$$\bar{P}_e = P(H_0 / H_1)P(H_1) + P(H_1 / H_0)P(H_0) \tag{2.57}$$

Assuming equal prior probabilities of signal transmission, we can write:

$$P(H_1) = P(H_0) = 1/2 \tag{2.58}$$

Therefore, the $\bar{P}_e$ becomes:

$$\begin{aligned} \bar{P}_e &= \frac{1}{2}P(H_0 / H_1) + \frac{1}{2}P(H_1 / H_0) \\ &= \frac{1}{2}\hat{P}_{fa} + \frac{1}{2}(1 - \hat{P}_d) \end{aligned} \tag{2.59}$$

By substituting (2.55) and (2.56) in (2.59), the average probability of error ($\bar{P}_e$) becomes:

$$\bar{P}_e = \frac{1}{2} - \frac{1}{2\sqrt{\pi}}\Gamma\left(\frac{1}{2}, \frac{\lambda}{2\hat{\alpha}_{(1)}}\right) + \frac{1}{2\sqrt{\pi}}\Gamma\left(\frac{1}{2}, \frac{\lambda}{2\hat{\alpha}_{(0)}}\right) + \sum_{i=1}^{M}\left\{\frac{\hat{L}_i}{2\sqrt{\pi}}\Gamma\left(\frac{1}{2}, \frac{\lambda}{2\hat{\beta}_{i(0)}}\right) - \frac{\hat{R}_i}{2\sqrt{\pi}}\Gamma\left(\frac{1}{2}, \frac{\lambda}{2\hat{\beta}_{i(1)}}\right)\right\} \tag{2.60}$$

2.3.5 Numerical results

In this study, simulation results are presented in order to investigate the performance of the LMS-BLM receiver. Three scenarios are considered; the first scenario compares the probabilities of detection of the LMS-BLM receiver for different number of relays and the upper & lower bounds of probability of detection as given in [34]. The second scenario evaluates the effects of variable number of relays and step size on the learning curve of the LMS-BLM receiver. The third scenario evaluates the probability of error for different number of relays. In the process of channel estimation using LMS algorithm, it is assumed that both CSI and original transmitted signal are not known at the receiver. In this case, a training signal $u(k)$ is generated and sent to the destination and producing the output $u^*(k) = h_0(k) \times u(k)$. It is also assumed that the unknown filter $h_0(k)$ is a FIR filter with order P. In the presence of noise, the observation $y(k)$ can be expressed by $y(k) = u^*(k) + w(k)$ where the noise $w(k)$ is assumed to be white. In practice, when the length of the filter $h_0(k)$ is unknown, a large value of P can be chosen in order to make sure that it is overestimated. In this case, it is assumed that the length of P is known. For all deemed scenarios, the average SNR is identical for each link $\overline{SNR} = \overline{\gamma}_{sd} = \overline{\gamma}_{si} = \overline{\gamma}_{id}$.

At the source, the signal is generated and transmitted to all relays and destination node. The relay amplifies the received signal from the source only and forwards it to the destination. The amplification is done by only multiplying the received signal with the amplification factor or gain. At the destination terminal, the channels between the source and destination, the relays and destination are estimated using the LMS algorithm. This is followed by the BLM detector for detecting the original signal from noise. The BLM detector is based on detecting the signal energy for each link and then computing the test statistic which is compared with the predefined threshold as represented in Figure 2.8. The threshold is determined by using the expression (2.18) that represents an ideal detection condition in wireless network. In this formula, the P_{fa} is taken between 0 and 1 and the bandwidth product u is 2.

In the first scenario, there are three cases: in the first case, it is assumed that less information is known about CSI and original transmitted signal at the receiver. In this case, the LMS-BLM receiver is used for channel estimation and data detection between the source and destination, and the relay and destination links. In the second case, the upper and lower bounds of the probability of detection are plotted for comparison purposes. The results in Figure 2.9 show that with one and five relays (R=1 and R=5) the proposed algorithm provides higher detection performance comparing with the upper & lower bounds of the probability of detection. The probabilities of missed detection of the LMS-BLM algorithm with one and five relays indicate better results than the results of the upper and lower bounds in [34] as presented in Figure 2.10. The results in Figure 2.11 show that the analytical probability of detection of the LMS-BLM method is slightly equivalent to the upper bound of the probability of detection which justify the higher performance of our proposed algorithm. The theoretical probability of detection provides higher performance than the upper and lower bounds of probability of detection in [34] and marks a 10% difference with analytical results due to some formula approximation.

In the second scenario, the evaluation of the effect of step size and number of relays on the MSE learning curve is carried out. During simulation, the theoretical channel h is chosen such that its length corresponds to the order value of the FIR filter with number of steps equal to $P = 10$. In this scenario, we investigate the effect of variable gradient step size of values equal to $\mu = 0.002$ and $\mu = 0.004$ and variable number of relays from R=1 and R=5 on the MSE learning curve of the LMS-BLM receiver. The results in Figure 2.12 shows that when the value of step size and the number of relays increases, the MSE decreases faster. The gradient step size for the LMS algorithm is very important since it determines the convergence of the algorithm and therefore the accuracy of the estimation errors.

In the third scenario, the probability of error is found analytically and plotted in Figure 2.13. In this scenario, we propose different number of relays from R=1, 5 and 8 and consider a range of SNR from -10dB to 10dB. The results show that the probability of error improves when the number of relays increases which proves the accuracy of the analytical results.

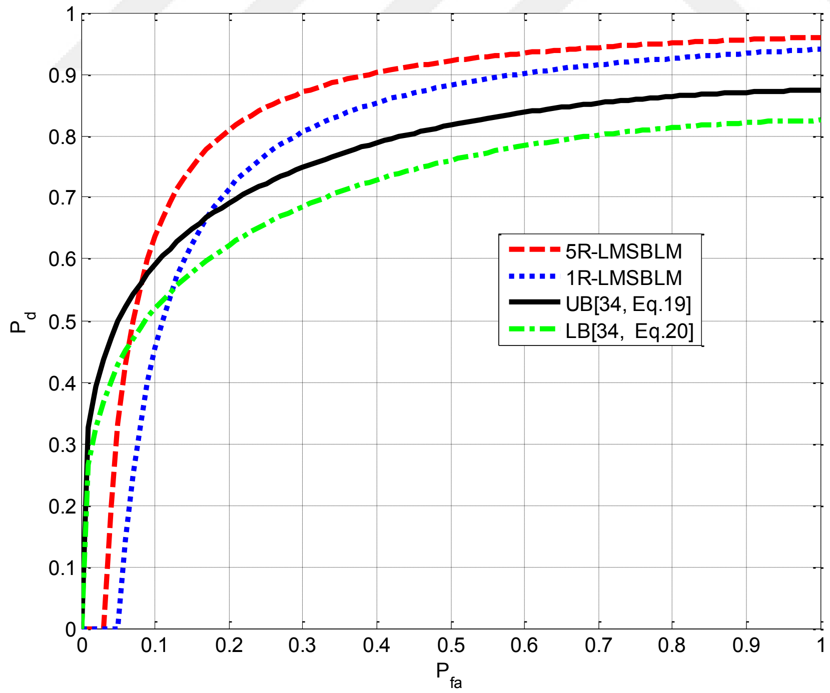

Figure 2.9 : ROCs of the LMS-BLM algorithm with the upper & lower bounds.

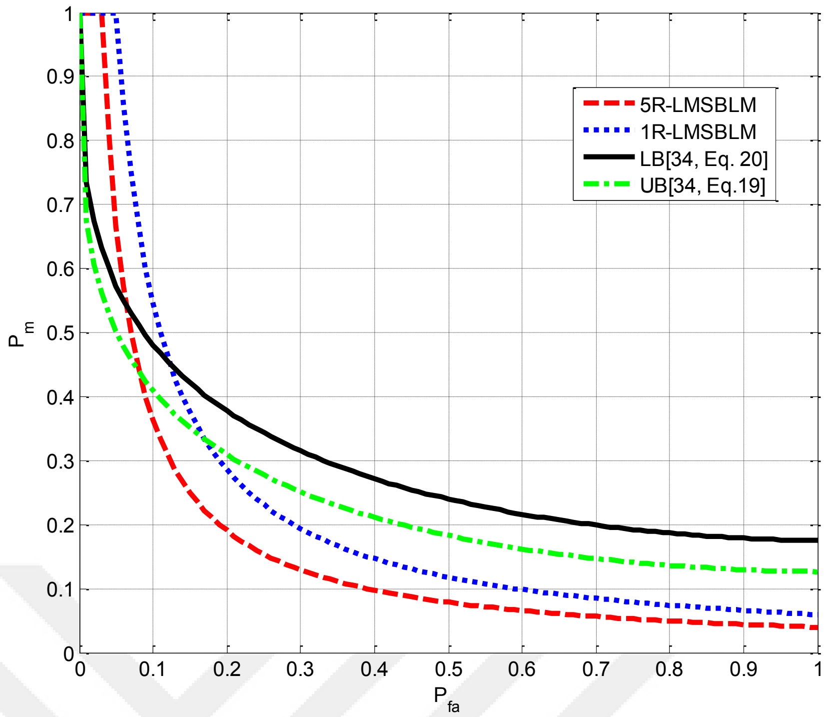

Figure 2.10 : C-ROCs of the receiver with the upper & lower bounds.

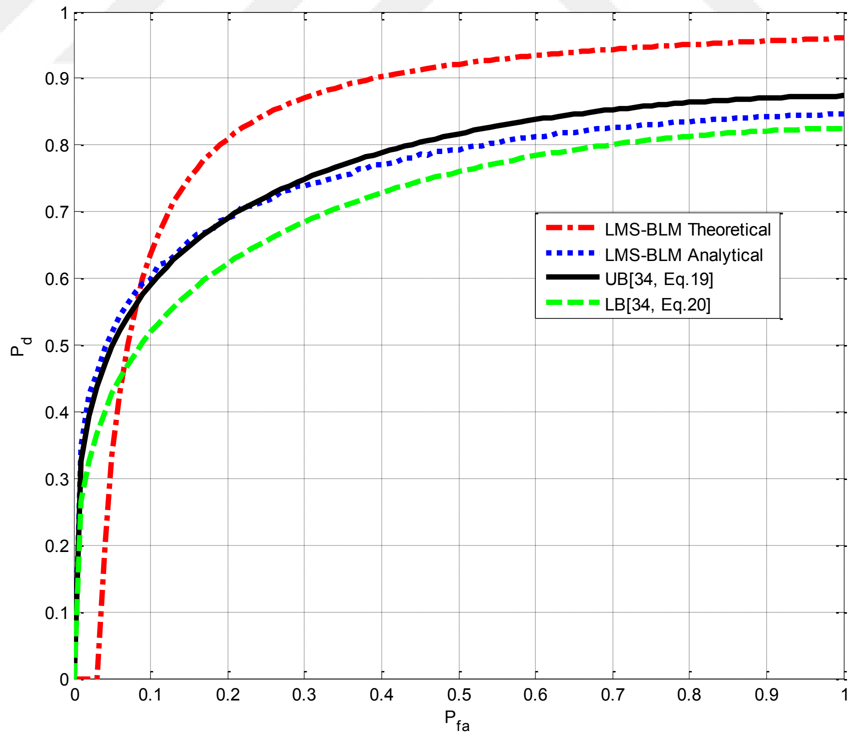

Figure 2.11 : ROC of the LMS-BLM Algorithm with the upper & lower bounds.

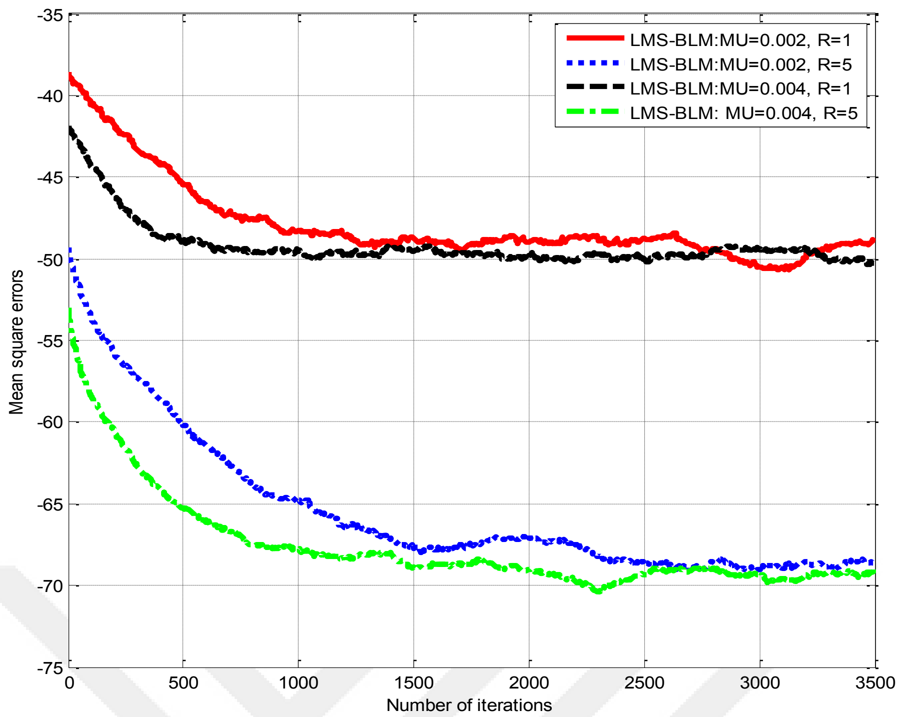

Figure 2.12 : MSE Learning curve with various step size (μ) and M-relays.

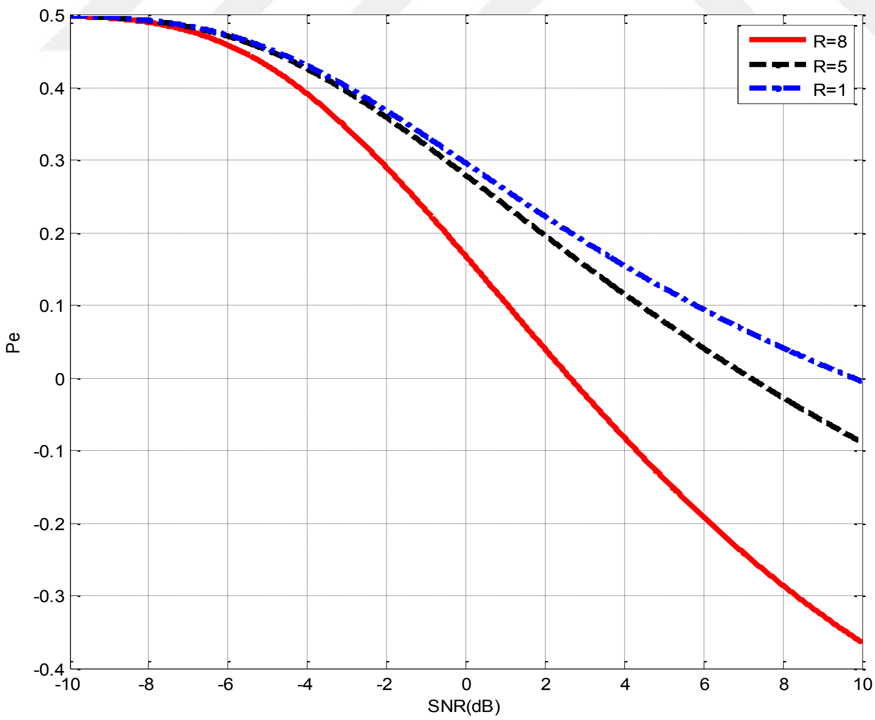

Figure 2.13 : Probability of error of the LMS-BLM receiver.

2.3.6 Summary

In this section, a novel LMS-BLM receiver was proposed and its performance was evaluated by considering a wireless network employing multiple relays strategy. The main contribution in this paper was to propose an effective tool that can recover the original transmitted signal from noise at the receiver. Simulation results were presented through three different scenarios. The first scenario assumed that little information is known on CSI and original transmitted signal at the receiver. The investigation was carried out on the probability of detection for different number of relays and compared with the upper and lower bounds of the probability of detection as given in [34]. The second scenario investigated the effects of variable step size μ and various number of relays on the MSE learning curve of the system. The results showed that the higher the number of active relays available in the network the higher the probability of detection. The higher the gradient step size, the higher the LMS algorithm's descent speed. The third scenario investigated the probability of error and the results showed that the probability of error decreases as the number of relays increases. The results of the receiver operating characteristics (ROCs) and the MSE learning curve of the receiver showed that the proposed algorithm is effective. The proposed algorithm can be applied in the current or future generation wireless networks where cooperative communications with relays strategy is applicable.

3. ADAPTIVE CHANNEL ESTIMATION AND DATA DETECTION MODELS FOR COOPERATIVE WIRELESS NETWORKS IN NON STATIONARY ENVIRONMENT

3.1 Introduction

This chapter considers a typical wireless communication system consisting of a single source (S), multiple mobile relays (R_M) and single mobile destination as depicted in Figure 3.1. An example of this scenario could be a cellular network with fixed base station communicating with mobile terminals and other mobile terminals acting as relay stations. Therefore, due to the mobility of mobile terminals, the channel gain between nodes in the network varies with time.

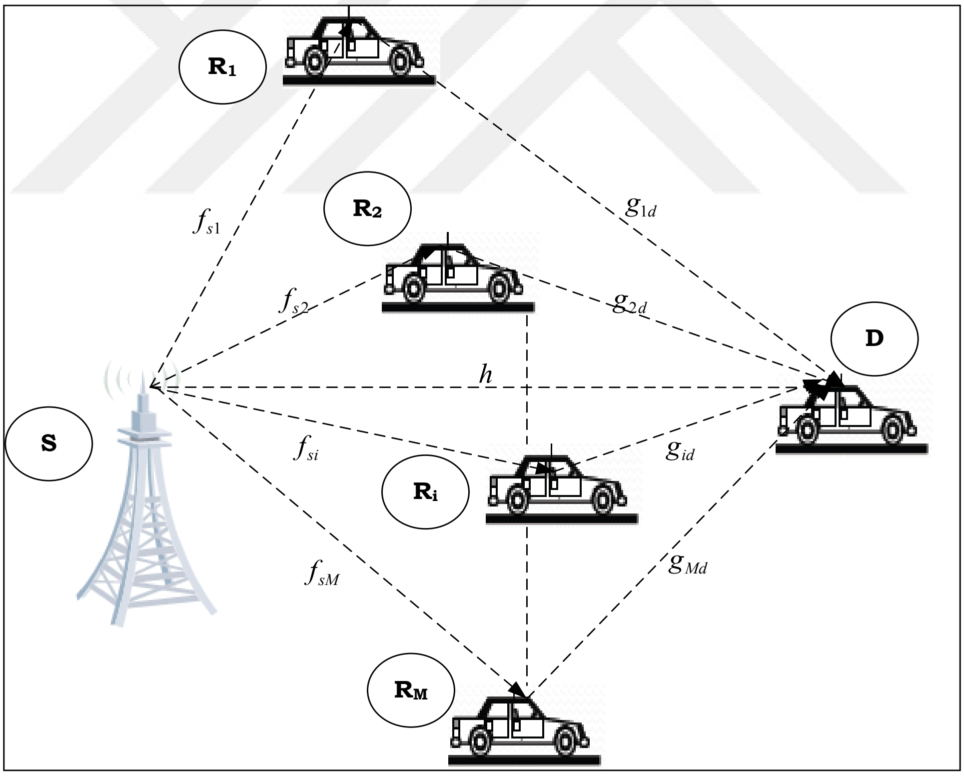

Figure 3.1 : Network model with mobile terminals.

In this model, the transmission is considered to be done in two phases and half duplex mode. In the first phase, the source broadcasts the signal to relays and destination. In the second phase, the source is silent and relays amplify or demodulate the received signal from the source only and forward it to the destination. In this case, orthogonal transmission is required in order to transmit N symbols without interfering each other. This can be realized by using time division multiple access (TDMA) or frequency division multiple access (FDMA) [4].

In this chapter, we have two principal sections, in the first section, we assume that the CSI is available at the destination but the original transmitted signal is unknown due to noise and other interference signals. Therefore, the performance of the BLM detector is investigated in order to assess its ability to recover the original transmitted signal in time varying channels.

In the second part, it is assumed that the CSI is not available at the destination and the unknown channels between communicating links is varying with time. Therefore, the performnace of the LMS-BLM receiver is investigated in cooperative wireless network with time varying channels.

3.2 Bayesian Linear Model (BLM) Detector in Cooperative Wireless Networks with Time Varying Channels

3.2.1 Abstract

Time-varying channels are the fundamental phenomenon that affect the performance of signal transmissions in wireless networks. Fading caused by channel variations can be classified as slow or fast fading depending on the mobility of nodes in the networks. Therefore, multiple relays are considered in this paper for their ability to create diversity environment that can directly mitigate the effects caused by multipath fadings in wireless networks. In this part, a wireless network with mobile terminals is investigated and it is assumed that the channel state information (CSI) is available at the destination, and original transmitted signal is corrupted by noise and other interferences. Therefore, the main contributions are based on implementing multiple amplify and forward (AF), and demodulate and forward (DaF) relays, and proposing the Bayesian linear model (BLM) detector for recovering the original transmitted signal at the receiver. The performance investigation is done through analytical and numerical analysis in terms of receiver operating characteristics (ROC), minimum mean square error (MSE) and bit error probability over n*Rayleigh fading channels. The results have shown that the proposed method is effective in recovering the original signal in time varying channels, the performance can be improved by increasing the number of relays in the network and the performance decreases when the Rayleigh cascading order increases. The proposed method can be applied in the current or future wireless networks (e.g., 4G/LTE wireless networks, 5G wireless networks, etc.) that allow multiple relays, use of high carrier frequencies and low symbol periods.

3.2.2 Related work

In literature, the problem of detection was initially discussed on energy detection of deterministic and random signals [29-34] without considering the time varying issues.

The investigation of time varying channels is studied in [51-59], by evaluating their effects and proposing solutions in wireless communication networks. In [51,52], they consider multiple AF relays based cooperative system with maximum ratio combining (MRC) at the destination and investigate the effects of both the mobile cooperating nodes speeds, and the receivers' channel state information (CSI) estimation rates on the system outage performance. The fading links are considered to be frequency-flat time varying Rayleigh fading and modeled by a first-order autoregressive process (AR-1). They found that the results experience asymptotic floor due to time varying channels and these can be elimanated by a well designed fast tracking loops at the receiver. In [53], they investigate the effect of time varying channels on the bit error rate (BER) performance. In this study, the performance of different reception methods, including cooperative maximum likelihood detection, maximum likelihood detection, Alamouti's receiver, zero forcing detection and decision feedback detection are also evaluated. They found that time varying nature contributes to the error flooring effect. In [54, 55], they study on dual-hop AF relaying over time varying Rayleigh fading channels with differential M-PSK modulation and non-coherent detection. A first order time series model is utilized to characterize the time varying nature of the cascaded channel in two symbol detection systems**.** The results in this paper have shown that error floor and performance degradation occur at high SNR and fast fading.

In [56], the effect of mobile velocity on communications fading channels is investigated and an analytical model to evaluate it in a multipath fading channel is presented. A Markov process is used to characterize the effect of velocity which captures the correlated nature of the channel. Different schemes are considered such as closed loop power control, channel coding, and finite interleaving in order to evaluate their sensitivity on the mobile velocity. In [57], they investigate the performance degradation due to rapidly time varying channels in a repetition based coherent cooperative system. They found that the mobility of the source affects the system performance more than the mobility of the destination for both the AF and the demodulate and forward (DaF) relays. In this paper, they developed a ML detection rules for a variety of mobile scenarios. In [58], they investigate the performance of differential amplify and forward (D-AF) relaying for multi-node wireless communications over time varying Rayleigh fading channels. They use a first order auto-regressive model to characterize the time varying nature of the channels. They develop and propose a new set of combining weights for signal detection at the destination and compare them with the conventional combining scheme through simulations. They also derive the pairwise probabilty (PEP) that is used to obtain the approximate total average BER. They found that the system performance is related to the autocorrelation of the direct and cascaded channels and an irreducible error floor exists at high signal to noise ratio (SNR) in time varying channels**.** In [59], the modulation and detection for simple receivers in rapidly time varying channels are evaluated. They use first order autoregressive (AR-1) channel model and various performance metrics to evaluate the advantages of each modulation scheme. Due to the mobility of two communicating nodes, different research papers suggested n*Rayleigh fading channel, because the time varying channel between those nodes results in two or more independent Rayleigh fading process generated by independent group of scatterers around those nodes in motion [60, 61].

Therefore, based on the above literature review, new results are derived by proposing the Bayesian linear model (BLM) detector in multiple relays networks with time varying channels. The main contributions are described as follows:

- Investigating on existing solutions and their limitations in literature about time varying channels in wireless communication networks.
- Implementing the BLM detector in multiple AF and DaF relays based cooperative wireless networks with time varying channels.
- Deriving the probabilities of detection and false alarm, bit error probability and minimum mean square error (MSE) of the system.
- Evaluating the performance of the BLM detector in terms of receiver operating characteristics (ROCs), bit error probability and minimum MSE performance over n*Rayleigh fading channels.
- Performing computer simulations, evaluating the performance of the proposed system through different scenarios and compare the obtained results with the existing ones in literature.

3.2.3 System and mathematical models

As depicted in Figure 3.1, h, f_{ij}, g_{ij} are the channels between the source and destination, the source and relays, and the relays and destination, respectively, from i^{th} to j^{th} node. In this paper, we consider two kinds of channel fading distribution; the classical Rayleigh fading channel and the n*Rayleigh fading channel. In classical Rayleigh fading channel, the probability density function (PDF) is given by [5, 62]:

$$f_{\gamma_{ij}}(\gamma) = \frac{1}{\bar{\gamma}} \exp\left(-\frac{\gamma}{\bar{\gamma}} \right) \tag{3.1}$$

then, the corresponding cumulative distribution function (CDF) is given by:

$$F_{\gamma_{ij}}(\gamma) = 1 - \exp\left(-\frac{\gamma}{\bar{\gamma}} \right) \tag{3.2}$$

The second channel fading distribution considered in this paper is n*Rayleigh fading channel with the PDF defined by [60]:

$$f_{\gamma_{ij}}(\gamma) = \frac{\kappa^{\xi} \gamma^{\rho-1}}{n\Gamma(\xi)} \exp\left(-\kappa \gamma^{1/n} \right) \tag{3.3}$$

and its CDF is given by:

$$F_{\gamma_{ij}}(\gamma) = \frac{\kappa^{(\xi-\rho n)}}{\Gamma(\xi)} \Gamma\left(\rho n, \kappa \gamma^{1/n} \right) \tag{3.4}$$

where γ represents the instantaneous SNR of the channel between node i and node j (i.e., node denotes source, relay or destination stations) and its average is $\bar{\gamma}$, $\kappa = 2\xi / \eta \bar{\gamma}^{1/n}$, $\xi = 0.6102 * n + 0.4263$ and $\eta = 0.6102 * n + 0.4263$ are parameters defined in [60], $\rho = \xi / n$ where n is the cascading order, $\Gamma(.)$ is the gamma function and $\Gamma(.,.)$ is the incomplete gamma function.

As discussed before, the signal transmission is done in two phases. Therefore, the received signals at the destination and relays in both phases are represented as:

$$y_{sd}(k) = \sqrt{P_s} h(k) u(k) + w_{sd}(k) \tag{3.5}$$

$$y_{si}(k) = \sqrt{P_s} f_{si}(k) u(k) + w_{si}(k) \tag{3.6}$$

$$y_{id}^{AF}(k) = \sqrt{P_i} G_i g_{id}(k) y_{si}(k) + w_{id}(k) \tag{3.7}$$

(3.7) can be simplified as:

$$y_{id}^{AF}(k) = \sqrt{P_i} g_{id}(k) u_{id}^{AF}(k) + w_{id}(k) \tag{3.8}$$

where P_s is the power of the source, P_i is the power of the relay, $u(k)$ is the signal generated and encoded differentially by the source and transmitted to the destination and relays, $w_{sd}(k)$, $w_{si}(k)$ and $w_{id}(k)$ are zero mean circular symmetric complex Gaussian (ZMCSCG) noises with variance N_0, $u_{id}^{AF}(k) = G_i y_{si}(k)$ indicates the generated signal at each relay, and G_i is the amplification gain with AF relaying strategy.

In time varying channels, the amplification factor is related to the Jakes' autocorrelation model. When the CSI is avalaible at the relay, the amplification factor is given by [15]:

$$G_i^2 = \frac{1}{E\left(\left|f_{si}(k)\right|^2\right) P_s + N_0} \tag{3.9}$$

where $E\left(\left|f_{si}(k)\right|^2\right) = a_{si}^{2(k-1)} \left|f(1)\right|^2 + \left(1 - a_{si}^{2(k-1)}\right) \delta_{si}^2$. It is noted that the performance of the AF relay networks highly depends on the proper choice of the amplification gain.

In DaF relaying scheme, the received signal from the source is detected by each relay according to symbol by symbol basis as represented by the following expression [15]:

$$u_{id}^{DaF}(k) = Sgn\left(\Re\left\{f_{si}^* y_{si}(k)\right\}\right) \tag{3.10}$$

where, $u_{id}^{DaF}(k)$ is the generated signal at each relay by using DaF protocol, $Sgn(.)$ is the sign function and $\Re$ indicates the real function. The $Sgn(.)$ function can be defined as:

$$Sgn(x) = \begin{cases} 1, & if\ x > 0, \\ 0, & if\ x = 0, \\ -1, & if\ x < 0 \end{cases} \tag{3.11}$$

After demodulating/modulating the signal, each relay forwards the modulated signal to the destination and the received signal is given by:

$$y_{id}^{DaF}(k) = \sqrt{P_i} g_{id} u_{id}^{DaF}(k) + w_{id}(k) \tag{3.12}$$

As mentioned before, in this model, we consider fixed base station (BS), mobile stations (MSs) and other MSs that act as relay stations (RSs). Due to the mobility of nodes, the channel link between nodes in the network is modeled by first order autoregressive (AR-1) model process in order to characterize the time varying nature of links. The channel link between the source & destination, the source & relay, and the relay & destination are defined as follows [51, 59]:

$$h(k) = a_{sd} h(k-1) + \sqrt{1-a_{sd}^2}\, \varepsilon_{sd}(k) \tag{3.13}$$

$$f_{si}(k) = a_{si} f_{si}(k-1) + \sqrt{1-a_{si}^2}\, \varepsilon_{si}(k) \tag{3.14}$$

$$g_{id}(k) = a_{id} g_{id}(k-1) + \sqrt{1-a_{id}^2}\, \varepsilon_{id}(k) \tag{3.15}$$

where $\varepsilon_{sd}(k), \varepsilon_{si}(k)$ and $\varepsilon_{id}(k)$ are varying components that obey circular symmetric complex Gaussian (ZMCSCG) noises processes with $CN(0,\delta_{sd}^2), CN(0,\delta_{si}^2)$ and $CN(0,\delta_{id}^2)$, a_{sd} , a_{si} and a_{id} are the temporal correlation coefficients with values between 0 and 1. The temporal correlation is related to the channel variation rate, when a_{ij}=0, the channel realization becomes independent and identically distributed (i.i.d), and when a_{ij}=1, the channel becomes quasi static fading. The relationship between the Doppler shift and temporal correlation is governed by the approximation known on Jakes' autocorrelation model as follows [56, 57]:

$$a_{ij} = E\left[h_{ij}(k+\tau) h_{ij}^*(k) \right] = J_0(2\pi f_d T_s) \tag{3.16}$$

where $J_0(.)$ is the zero order Bessel function of the first kind, $f_D = f_c \upsilon / c = \upsilon / \lambda$ is the Doppler frequency due to the mobility of nodes. The Jakes' autocorrelation of the source and destination, source and relays, and relays and destination links are respectively given by: $a_{sd} = J_0(2\pi f_d T_s), a_{si} = J_0(2\pi f_i T_s)$ and $a_{id} = J_0(2\pi f_i T_s) J_0(2\pi f_d T_s)$. Assuming that the relays and destination accurately estimate the CSI and all channels estimates are the same despite some channel variation. Therefore, the channel gains knowledge can be described as circularly complex Gaussian random processes. Considering the transmission of the first symbol of the Nth length block, the channel gains knowledge $h'(k), f'_{si}(k), g'_{id}(k)$ can be described as follows [51, 52]:

$$h'(k) \sim CN\left(a_{sd}^{k-1} h(1), (1 - a_{sd}^{2(k-1)})\delta_{sd}^2\right) \tag{3.17}$$

$$f_{si}^{'}(k) \sim CN\left(a_{si}^{k-1} f_{si}(1), (1 - a_{si}^{2(k-1)})\delta_{si}^2\right) \tag{3.18}$$

$$g_{id}^{'}(k) \sim CN\left(a_{id}^{k-1} g_{id}(1), (1 - a_{id}^{2(k-1)})\delta_{id}^2\right) \tag{3.19}$$

Due to time varying channels, the density knowledge statistics of the received signals for each link are given by:

$$y'_{sd}(k) \sim CN\left(u(k) a_{sd}^{k-1} h(1), P_s u^2(k)(1 - a_{sd}^{2(k-1)})\delta_{sd}^2 + N_0\right) \tag{3.20}$$

$$y'_{si}(k) \sim CN\left(u(k) a_{si}^{k-1} f_{si}(1), P_s u^2(k)(1 - a_{si}^{2(k-1)})\delta_{si}^2 + N_0\right) \tag{3.21}$$

$$y'_{id}(k) \sim CN\left(u_{id}(k) a_{id}^{k-1} g_{id}(1), P_i u_{id}^2(k)(1 - a_{id}^{2(k-1)})\delta_{id}^2 + N_0\right) \tag{3.22}$$

From equation (3.20), (3.21) and (3.22), the average SNR for the source and destination, source and relays, and relays and destination links are respectively given by:

$$\overline{\gamma}_{sd} = \frac{E_s a_{sd}^{2(k-1)}}{E_s (1 - a_{sd}^{2(k-1)})\delta_{sd}^2 + N_0} \tag{3.23}$$

$$\overline{\gamma}_{si} = \frac{E_s a_{si}^{2(k-1)}}{E_s (1 - a_{si}^{2(k-1)})\delta_{si}^2 + N_0} \tag{3.24}$$

$$\bar{\gamma}_{id} = \frac{E_s a_{id}^{2(k-1)}}{E_s(1-a_{id}^{2(k-1)})\delta_{id}^2 + N_0} \tag{3.25}$$

The average SNR for each link is obtained by assuming that: $E[|h(1)|^2] = E[|f_{si}(1)|^2] = E[|g_{id}(1)|^2] = 1$, where $E[.]$ denotes the expectation operator and $P_s = P_i = 1$. The received signals (3.5), (3.6) and (3.8) can be grouped in matrix form as follows:

$$\begin{bmatrix} y_{sd} \\ y_{1d} \\ \cdots \\ y_{id} \\ \cdots \\ y_{Md} \end{bmatrix} = \begin{bmatrix} \sqrt{E_s} h_{sd} & 0 & \cdots & 0 \\ 0 & \sqrt{E_1} g_{1d} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \sqrt{E_i} g_{id} & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & \sqrt{E_M} g_{Md} \end{bmatrix} \begin{bmatrix} u_{sd} \\ u_{1d} \\ \cdots \\ u_{id} \\ \cdots \\ u_{Md} \end{bmatrix} + \begin{bmatrix} w_{sd} \\ w_{1d} \\ \cdots \\ w_{id} \\ \cdots \\ w_{Md} \end{bmatrix} \tag{3.26}$$

where y_{id} in (3.26) refers to the received signal with AF relays network or DaF relays network (i.e., $y_{id} \approx \{y_{id}^{AF}\} or \{y_{id}^{DaF}\}$ and $u_{id} \approx \{u_{id}^{AF}\} or \{u_{id}^{DaF}\}$). Assuming that signals are transmitted orthogonally, therefore, the received signals at the destination can be represented by: $\boldsymbol{y} = \boldsymbol{Hu} + \boldsymbol{w}$, where $\boldsymbol{y}$ indicates the column vector of the received signals with AF or DaF, $\boldsymbol{H}$ denotes the channel matrix, $\boldsymbol{u}$ is the column vector of the transmitted signal generated by the source and relays and $\boldsymbol{w}$ refers to the noise vector received at the destination.

3.2.4 Performance metrics analyses

In this section, the performance analysis is done in terms of the receiver operating characteristics (ROC), bit error probability and minimum mean square error (MSE).

3.2.4.1 Receiver operating characteristic (ROC)

Theoretically, the ROC is defined as the detection performance of the receiver evaluated by plotting the curve of the probability of detection (P_d) against the probability of false alarm (P_{fa}) which are given in (2.12) and (2.14), respectively.

The exact closed form expressions of the probabilities of detection and false alarm over AWGN are also given in (2.17) and (2.18), respectively.

Analytically, assuming that the CSI is available at the receiver,by using the Bayesian linear model (BLM) detection approach the test statistic in time varying channels is given by [19]:

$$T^{V}(y) = \boldsymbol{y}^{T}\boldsymbol{H}\boldsymbol{C}_{u}\boldsymbol{H}^{T}(\boldsymbol{H}\boldsymbol{C}_{u}\boldsymbol{H}^{T} + N_{0}\boldsymbol{I})^{-1}\boldsymbol{y} \tag{3.27}$$

In (3.27), the covariance matrix $C_u = diag[\sigma_{sd}^2, \sigma_{s1}^2, ..., \sigma_{sM}^2]$ and the noise variance matrix $N_0\boldsymbol{I} = diag[N_0, ..., N_0]$. Therefore, by substituting the covariance and noise variance values in (3.27), the test statistic in time varying channels is derived as:

$$T^{V}(y) = \frac{\sigma_{sd}^{2}\left|h_{sd}\right|^{2}}{\left|h_{sd}\right|^{2}\sigma_{sd}^{2} + N_{0}}\left|y_{sd}\right|^{2} + \sum_{i=1}^{M}\frac{\sigma_{id}^{2}\left|h_{id}\right|^{2}}{\left|h_{id}\right|^{2}\sigma_{id}^{2} + N_{0}}\left|y_{id}\right|^{2} \tag{3.28}$$

According to the hypotheses H_0 and H_1, the test statistic is represented as follows:

$$\begin{cases} H_0 : T^{V}(y) = \dfrac{\sigma_{sd}^{2}(1-a_{sd}^{2(k-1)})\delta_{sd}^{2}N_0}{\sigma_{sd}^{2}(1-a_{sd}^{2(k-1)})\delta_{sd}^{2} + N_0}\left|\dfrac{y_{sd}}{\vartheta_{(0)}}\right|^{2} + \displaystyle\sum_{i=1}^{M}\dfrac{\sigma_{id}^{2}(1-a_{id}^{2(k-1)})\delta_{id}^{2}N_0}{\sigma_{id}^{2}(1-a_{id}^{2(k-1)})\delta_{id}^{2} + N_0}\left|\dfrac{y_{id}}{\vartheta_{i(0)}}\right|^{2} \\ H_1 : T^{V}(y) = \sigma_{sd}^{2}(1-a_{sd}^{2(k-1)})\delta_{sd}^{2}\left|\dfrac{y_{sd}}{\vartheta_{(1)}}\right|^{2} + \displaystyle\sum_{i=1}^{M}\sigma_{id}^{2}(1-a_{id}^{2(k-1)})\delta_{id}^{2}\left|\dfrac{y_{id}}{\vartheta_{i(1)}}\right|^{2} \end{cases} \tag{3.29}$$

where, $\vartheta_{(0)}^2 = N_0$, $\vartheta_{i(0)}^2 = N_0$, $\vartheta_{(1)}^2 = \sigma_{sd}^2(1-a_{sd}^{2(k-1)})\delta_{sd}^2 + N_0$ and $\vartheta_{i(1)}^2 = \sigma_{id}^2(1-a_{id}^{2(k-1)})\delta_{id}^2 + N_0$. The expression (3.29) can be simplified as follows:

$$\begin{cases} H_0 : T^{V}(y) = \alpha_{(0)}\chi_{2(sd)}^{2} + \displaystyle\sum_{i=1}^{M}\beta_{i(0)}\chi_{2(rd)}^{2} \\ H_1 : T^{V}(y) = \alpha_{(1)}\chi_{2(sd)}^{2} + \displaystyle\sum_{i=1}^{M}\beta_{i(1)}\chi_{2(rd)}^{2} \end{cases} \tag{3.30}$$

where, $\alpha_{(0)} = \dfrac{\sigma_{sd}^2(1-a_{sd}^{2(k-1)})\delta_{sd}^2 N_0}{\sigma_{sd}^2(1-a_{sd}^{2(k-1)})\delta_{sd}^2 + N_0}$, $\beta_{i(0)} = \dfrac{\sigma_{id}^2(1-a_{id}^{2(k-1)})\delta_{id}^2 N_0}{\sigma_{id}^2(1-a_{id}^{2(k-1)})\delta_{id}^2 + N_0}$, $\alpha_{(1)} = \sigma_{sd}^2(1-a_{sd}^{2(k-1)})\delta_{sd}^2$ and $\beta_{i(1)} = \sigma_{id}^2(1-a_{id}^{2(k-1)})\delta_{id}^2$. It is also shown that the parameters $\chi^2_{2(sd)}$ and $\chi^2_{2(rd)}(i)$ are independent and identically distributed Chi-squared random variables with two degree of freedom for the source & destination and the relay & destination respectively. The probability density functions (PDFs) of the test statistics in (3.30) are determined as follows:

$$\begin{cases} P(T^V;H_0) = \dfrac{1}{2\pi}\displaystyle\int_{-\infty}^{\infty}\phi_{T_{H_0}}(\omega)\exp(-j\omega T^V)d\omega \\ P(T^V;H_1) = \dfrac{1}{2\pi}\displaystyle\int_{-\infty}^{\infty}\phi_{T_{H_1}}(\omega)\exp(-j\omega T^V)d\omega \end{cases} \tag{3.31}$$

The characteristic functions of $T^V(y)$ according to the hypotheses H_0 and H_1 in $P(T^V;H_0)$ and $P(T^V;H_1)$ are given by [32, 33]:

$$\begin{cases} \phi_{T^V_{H_0}} = \dfrac{1}{1-2j\omega\alpha^V_{(0)}} + \displaystyle\prod_{i=1}^{M}\dfrac{1}{1-2j\omega\beta^V_{i(0)}} \\ \phi_{T^V_{H_1}} = \dfrac{1}{1-2j\omega\alpha^V_{(1)}} + \displaystyle\prod_{i=1}^{M}\dfrac{1}{1-2j\omega\beta^V_{i(1)}} \end{cases} \tag{3.32}$$

where, $\displaystyle\prod_{i=1}^{M}\frac{1}{1-2j\omega\beta^V_{i(0)}} = \sum_{i=1}^{M}\frac{\psi_i}{1-2j\omega\beta^V_{i(0)}}$ and, $\psi_i = \displaystyle\prod_{l=1,l\neq i}^{M}\frac{1}{1-\beta^V_{l(0)}/\beta^V_{i(0)}}$ and where, $\displaystyle\prod_{i=1}^{M}\frac{1}{1-2j\omega\beta^V_{i(1)}} = \sum_{i=1}^{M}\frac{\xi_i}{1-2j\omega\beta^V_{i(1)}}$ and, $\xi_i = \displaystyle\prod_{l=1,l\neq i}^{M}\frac{1}{1-\beta^V_{l(1)}/\beta^V_{i(1)}}$; substituting (3.32) in (3.31), the PDFs for dual hop (2 segments) relays network are derived as follows:

$$\begin{cases} P(T^V;H_0) = \dfrac{1}{2}\displaystyle\int_{-\infty}^{\infty}\frac{1}{\left(1-2j\omega\alpha^V_{(0)}\right)}\exp(-j\omega T^V)\frac{d\omega}{2\pi} + \frac{1}{2}\sum_{i=1}^{M}\int_{-\infty}^{\infty}\frac{\psi_i}{(1-2j\omega\beta^V_{i(0)})}\exp\left(-j\omega T^V\right)\frac{d\omega}{2\pi} \\ P(T^V;H_1) = \dfrac{1}{2}\displaystyle\int_{-\infty}^{\infty}\frac{1}{\left(1-2j\omega\alpha^V_{(1)}\right)}\exp(-j\omega T^V)\frac{d\omega}{2\pi} + \frac{1}{2}\sum_{i=1}^{M}\int_{-\infty}^{\infty}\frac{\xi_i}{(1-2j\omega\beta^V_{i(1)})}\exp\left(-j\omega T^V\right)\frac{d\omega}{2\pi} \end{cases} \tag{3.33}$$

(3.33) is the inverse fourrier transformation, therefore the PDFs are derived as follows:

$$\begin{cases} P(T^V;H_0) = \dfrac{1}{4\alpha_{(0)}^V}\exp\left(-\dfrac{T^V}{2\alpha_{(0)}^V}\right) + \sum_{i=1}^{M}\dfrac{\psi_i}{4\beta_{i(0)}^V}\exp\left(-\dfrac{T^V}{2\beta_{i(0)}^V}\right) \\ P(T^V;H_1) = \dfrac{1}{4\alpha_{(1)}^V}\exp\left(-\dfrac{T^V}{2\alpha_{(1)}^V}\right) + \sum_{i=1}^{M}\dfrac{\xi_i}{4\beta_{i(1)}^V}\exp\left(-\dfrac{T^V}{2\beta_{i(1)}^V}\right) \end{cases} \tag{3.34}$$

The probabilities of false alarm and detection of the BLM detector can be determined as follows:

$$P_{fa} = \int_{\lambda}^{\infty} P(T^V;H_0)dT^V = \frac{1}{2}\exp\left(-\frac{\lambda}{2\alpha_{(0)}^V}\right) + \frac{1}{2}\sum_{i=1}^{M}\psi_i \exp\left(-\frac{\lambda}{2\beta_{i(0)}^V}\right) \tag{3.35}$$

and,

$$P_d = \int_{\lambda}^{\infty} P(T^V;H_1)dT^V = \frac{1}{2}\exp\left(-\frac{\lambda}{2\alpha_{(1)}^V}\right) + \frac{1}{2}\sum_{i=1}^{M}\xi_i \exp\left(-\frac{\lambda}{2\beta_{i(1)}^V}\right) \tag{3.36}$$

3.2.4.2 Minimum mean square error (MSE) and bit error probability (BEP) performance analysis

The BER is a metric that describes the nature of the system behavior and the quality of the signal detected at the receiver. In our network model, the receiver is equipped with BLM detector, whereby the minimum mean square error (MMSE) estimate of the transmitted signal is given by [19]:

$$\hat{\boldsymbol{s}}^V = \boldsymbol{H}\boldsymbol{C}_u\boldsymbol{H}^T(\boldsymbol{H}\boldsymbol{C}_u\boldsymbol{H}^T + N_0\boldsymbol{I})^{-1}\boldsymbol{y} \tag{3.37}$$

Using (3.26) and associated covariance and noise matrix values, (3.37) is derived as follows:

$$\hat{\boldsymbol{s}}^V = \frac{P_s|h_{sd}|^2\sigma_{sd}^2}{P_s|h_{sd}|^2\sigma_{sd}^2 + N_0}y_{sd} + \sum_{i=1}^{M}\frac{P_i|h_{id}|^2\sigma_{id}^2}{P_i|h_{id}|^2\sigma_{id}^2 + N_0}y_{id} \tag{3.38}$$

Then, this can be simplified as:

$$\hat{s}^V = \frac{P_s(1-\rho_{sd}^{2(k-1)})\delta_{sd}^2\sigma_{sd}^2}{P_s(1-\rho_{sd}^{2(k-1)})\delta_{sd}^2\sigma_{sd}^2 + N_0}y_{sd} + \sum_{i=1}^{M}\frac{P_i(1-\rho_{id}^{2(k-1)})\delta_{id}^2\sigma_{id}^2}{P_i(1-\rho_{id}^{2(k-1)})\delta_{id}^2\sigma_{id}^2 + N_0}y_{id} \tag{3.39}$$

The mean square error can be derived as follows:

$$MSE_{\hat{s}} = E\{\left|(s-\hat{s}^{V})\right|^{2}\} \tag{3.40}$$

The bit error probability (BEP) can be evaluated by using the expression (2.38) given in [38].

Substituting (3.35) and (3.36) in (2.38), we obtain:

$$BEP^{V} = \frac{1}{2} - \frac{1}{4}\left\{\exp\left(-\frac{\lambda}{2\alpha_{(1)}^{V}}\right) - \exp\left(-\frac{\lambda}{2\alpha_{(0)}^{V}}\right)\right\} - \frac{1}{4}\sum_{i=1}^{M}\left\{\xi_i \exp\left(-\frac{\lambda}{2\beta_{i(1)}^{V}}\right) - \psi_i \exp\left(-\frac{\lambda}{2\beta_{i(0)}^{V}}\right)\right\} \tag{3.41}$$

3.2.5 Numerical results

The BLM detector is proposed in multiple relays cooperative wireless network with time varying channels. Simulation results are presented in order to investigate the performance of the BLM detector in terms of ROCs, bit error probability and minimum MSE. Six scenarios are considered; the first scenario investigates the receiver operating characteristics (ROCs) with different number of relays and various nodes speeds. The second scenario evaluates the ROCs of the BLM detector over n*Rayleigh fading channels. The third scenario compares the BER performance of the BLM detector with the one of the MRC detector. The fourth scenario investigates the effects of mobility of the relays only or destination only on the detection performance. The fifth scenario investigates the detection performance of the BLM detector in multiple AF and DaF relays networks. The sixth scenario evaluates the bit error probability (BEP) performance in multiple AF relays.

During signal transmission, we consider two phases as discussed before: in the first phase, the source generates and modulates the signal in differential QPSK, where $u(k) = \psi(k)u(k-1)$ with $\psi(k) = \{e^{j2\pi k/N}, k = 0,..,N-1\}$ which denotes the set of M-PSK symbols and $u(0) = 1$ as initial reference symbol. The modulated signal is broadcasted to all relays and destination. During the second phase, the source is silent and each relay amplifies or demodulates the received signal from the source only and forwards it to the destination. The destination uses the BLM detector to combine and to compute the test statistic that is compared with the predetermined threshold. The receiver decides the presence of the signal when the test statistic is greater than the threshold, otherwise it decides the absence of the signal.

During simulations, different parameters are utilised such as the carrier frequency equals to 2GHz and the symbol period equals to 0.1 ms which represents the parameters used in the current wireless technologies. Various velocities are calculated in Table 3.1, in normal circumstances, the value of 75 km/h is assumed to be a typical vehicle speed as claimed in literature and high speeds are also common in vehicles and trains [55]. Depending on the node speed, the associated fading is classified as slow fading for very low speed node and fast fading for high speed node as decribed in Table 3.1.

In Figure 3.2, the ROCs of the BLM detector are analyzed in multiple relays (R=2, R=3 and R=4) and various node speeds (i.e., 27 km/h and 108km/h) which correspond to slow fading and fast fading channels. The results show that the probability of detection increases when the number of relays increases. Figure 3.3 depicts the detection performance of the BLM detector between the Rayleigh and 2*Rayleigh fading channel (n=2). The results show that the system performance decreases as the number of cascading n increases and this can be compansated by providing high diversity gain in the network or increasing the number of relays.

Table 3.1 : Doppler frequencies and associated nodes speeds.

$f_D(Hz)$	$T_s(ms)$	$f_D T_s$	$f_c(GHz)$	$\upsilon = \frac{cf_D}{f_c}(km/h)$	Type of fading
0	0.1	0	2	0	Slow fading
50	0.1	0.005	2	27	Slow fading
100	0.1	0.01	2	54	Fast fading
200	0.1	0.02	2	108	Fast fading
400	0.1	0.04	2	216	Fast fading
600	0.1	0.06	2	324	Fast fading

Figure 3.4 depicts the BER results between the BLM detector and the MRC detector in multiple relays (R=1, R=2 and R=4) with slow fading channels (i.e. 27km/h). The results have shown that the BER performance of the BLM detector is almost equivalent to the MRC detector given in [58], and the BER performance improves when the number of relays increases. The purpose of comparing the BLM detector with the MRC detector is described in literature whereby, the MRC detector has been proven to be an ideal combining technique and signal detector in wireless networks with multipath environment. Therefore, this comparison provides to us useful information about the performance of the BLM detector.

Figure 3.5 represents the effect of the mobility of the relays and destination on the system performance. The results show that the mobility of relays affects the detection performance more than the mobility of destination, therefore, this should put into account when designing a wireless network. Figure 3.6 depicts the comparison of the detection performance of the BLM detector between the amplify and forward (AF) and demodulate and forward (DaF). The results show that the DaF outperforms the AF for higher number of relays, but for low number of relays AF performs better than DaF. Therefore, DaF requires sufficient number of relays for the receiver to provide better performance. Figure 3.7 depicts the bit error probability performance of the BLM detector. The results show that the performance improves when the number of relays increases.

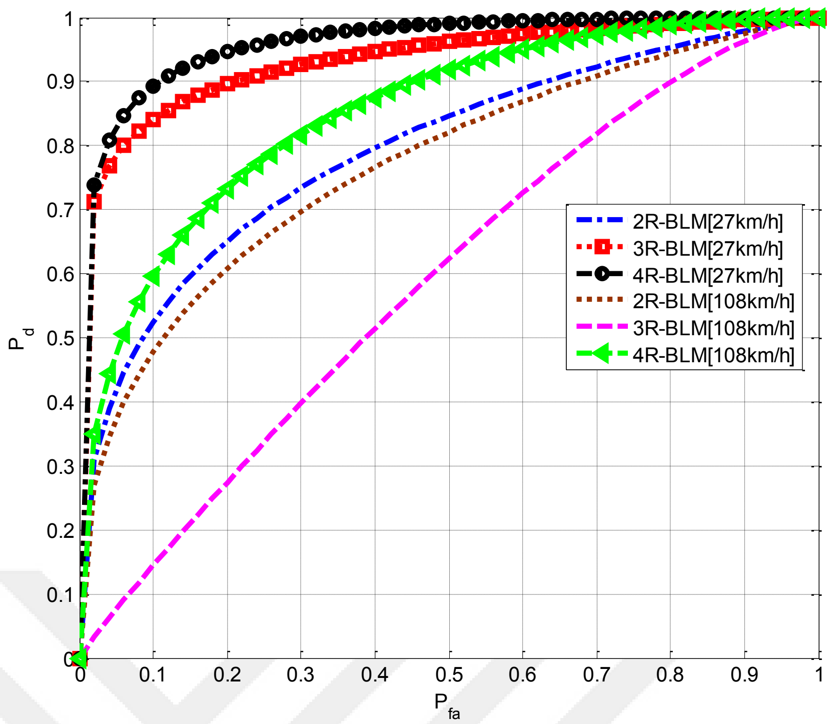

Figure 3.2 : ROC of the BLM detector for various nodes speeds and relays.

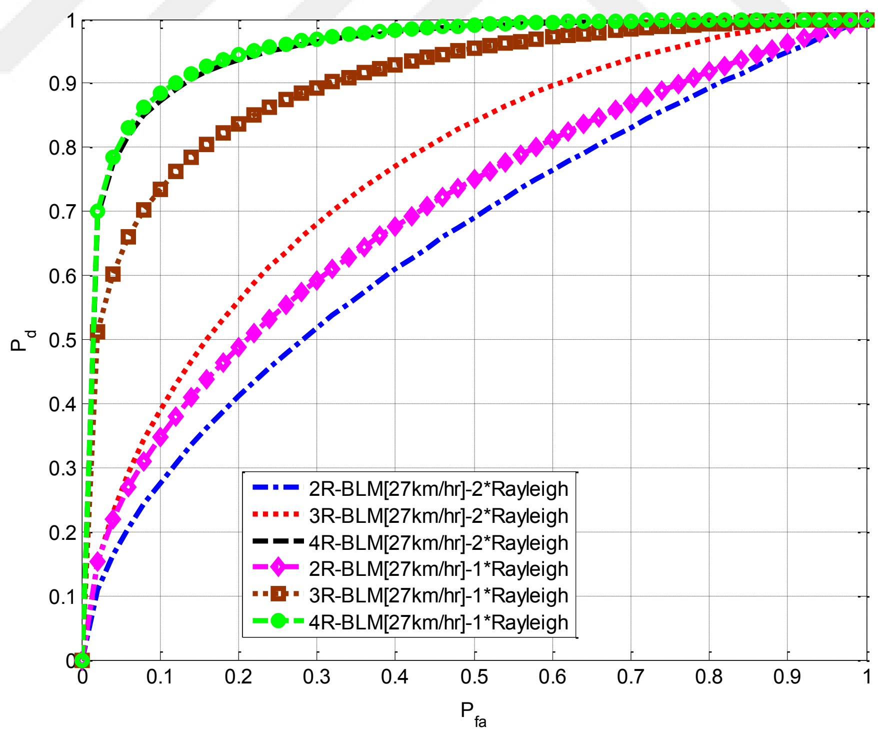

Figure 3.3: ROCs of the BLM detector with n*Rayleigh fading channels.

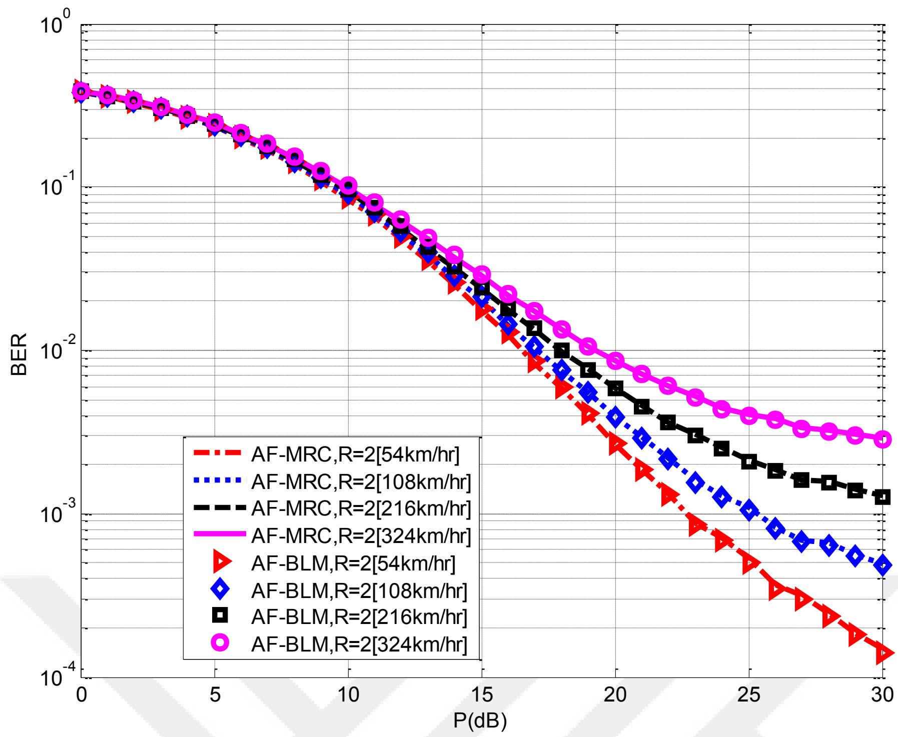

Figure 3.4: BER analysis in M-Relays with BLM detector and MRC detector.

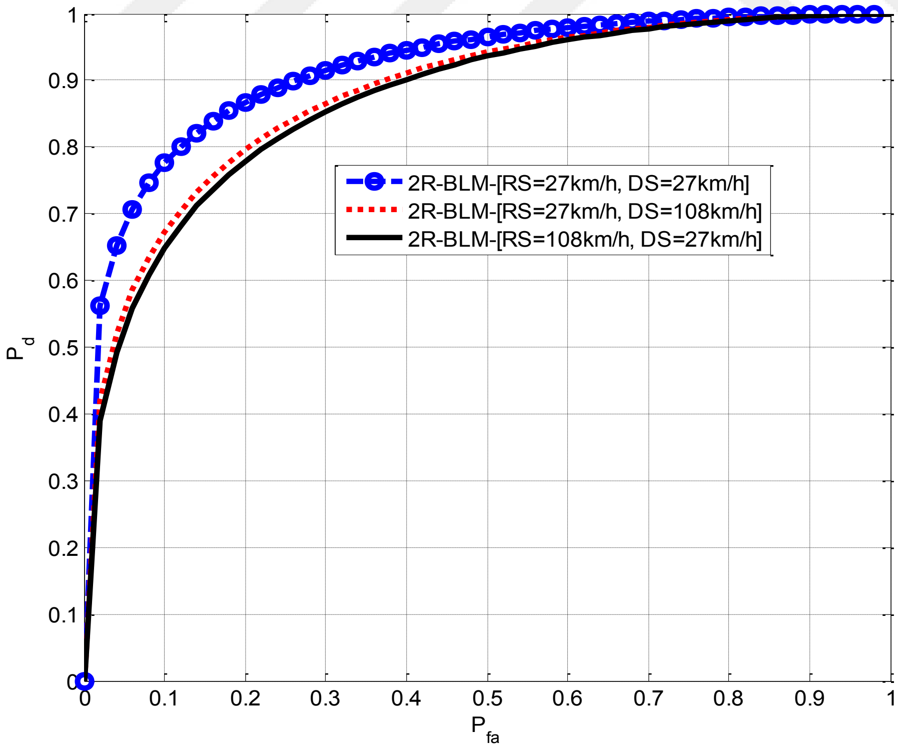

Figure 3.5 : Effect of nodes speeds on the BLM detection performance.

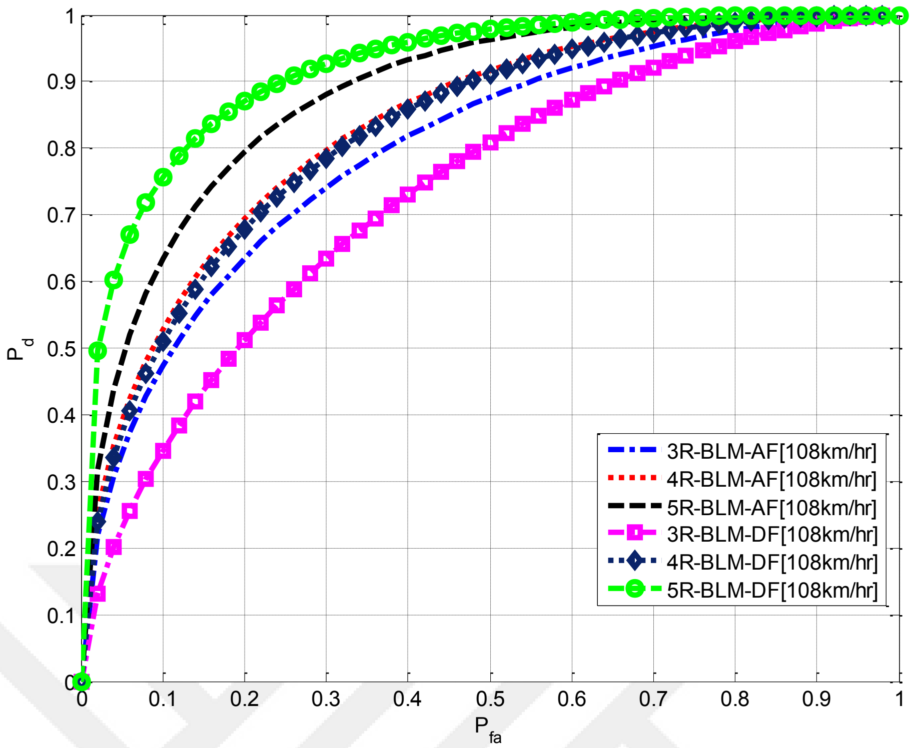

Figure 3.6: BLM detection performance in AF and DF relays with nodes speeds.

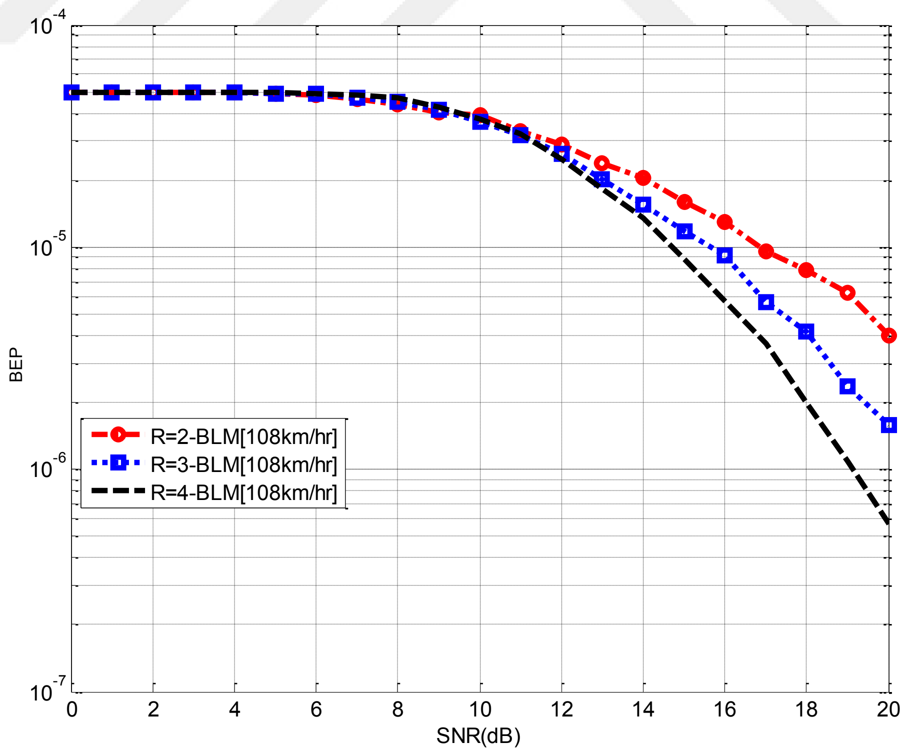

Figure 3.7: BEP results of the BLM detector in AF M-relays with nodes speeds.

3.2.6 Summary

The performance of the BLM detector in multiple relays with time varying channels was investigated. Six scenarios were considered; the first scenario investigated the receiver operating characteristics (ROCs) with various number of relays and nodes speeds (i.e., Figure 3.2). The findings showed that the high speed of nodes affects the system performance, particularly, when the network has few number of relays. The second scenario evaluated the ROCs over n*Rayleigh fading channels. The findings showed that the detection performance decreases when the Rayleigh cascading order n increases (i.e., Figure 3.3 for n=1 and n=2). The third scenario compared the BER performance of the BLM detector with the MRC detector. The findings showed that the BLM detector results are roughly closer to the ones of the MRC detector (i.e., Figure 3.4). The purpose of this comparison was that in literature, the MRC detector has proven to be an ideal combining technique and detector in wireless networks with multipath channels. Therefore, these results provided us with useful information about the effectiveness of the proposed method. The fourth scenario investigated the effects of the mobility of relays only or destination only on the detection performance (i.e., Figure 3.5). The results showed that the mobility of relays affects the receiver detection performance more than the mobility of the destination. Therefore, the speeds of relays must be put into account when designing a wireless network with multiple relays. The fifth scenario investigated the detection performance of the BLM detector in multiple AF and DaF relays network (i.e., Figure 3.6). The results showed that DaF outperformed AF for higher number of relays and for low number of relays AF performed better than DaF. The sixth scenario evaluated the bit error probability (BEP) performance in multiple AF relays (i.e., Figure 3.7). The results showed that it is beneficial to increase the number of relays in the network in order to minimise the error rates at the receiver. The simulation parameters utilised in this study and the obtained results demonstrated that the BLM detector can be utilised in the current and future wireless networks that use carrier frequency in the range of 2 Ghz and multiple relays in the network.

3.3 Joint LMS-BLM Receiver for Cooperative Wireless Networks with Time Varying Channels

3.3.1 Abstract

In non stationary environment, transmitted signals are mostly challenged by multipath time varying channels. In most of studies, diversity techniques have been proven to mitigate the effects of channel impairments in wireless networks including fading caused by time varying channels. In this study, multiple relays are considered in order to create diversity environment that can compensate the loss of signal during transmission. Futhermore, it is assumed that the dynamic channel state information (CSI) and original transmitted signal are unknown at the receiver; therefore, the main contributions are based on proposing the joint least mean square (LMS) algorithm and Bayesian linear model (BLM) detector for the purpose of estimating the channel and evaluating its performance in recovering the original transmitted signal in time varying channels. Analytical and numerical analyses on receiver operating characteristics (ROC), mean square errors (MSE) learning curves, minimum mean square error (MSE) and bit error probability are presented. The results have shown that the proposed algorithm is effective in tracking the time varying channels and its performance can be improved by increasing the number of relays in the network, and choosing the appropriate step size for the stability and convergence of the algorithm. The proposed algorithm can be applied in the current and future wireless networks that use carrier frequencies in the range of 2GHz and multiple relays.

3.3.2 Related work

In literature, different studies have investigated the time varying channels and their effects in wireless networks [51, 52, 55-59, 63]. Their findings have shown that most of the results experience error floors due to time varying channels and which can be eliminated by well designed fast tracking loops at the receivers. Although channel estimation and data detection are known from the past years in different studies, they are still largely unexplored particulary in wireless networks with time varying channels. The most common studies on data detection only focus on signal energy detection [29-36, 38] and channel estimation using common estimation methods [41, 42].

In cooperative diversity systems, [46] proposed a new adaptive algorithm for estimating the channel between the relay and destination in DF relay networks when the presence of an input training sequence is probabilistic and obeys Bernoulli random variable. The proposed algorithm combines the generalized likelihood ratio test (GLRT) detector and the classical least mean square (LMS) channel estimator. The effect of autocorrelation channels and channel estimation based on linear minimum mean square error (LMMSE) estimator are evaluated in [63, 64] for a wide range of scenarios, including different gain and mobility conditions of relays. In [65], they investigate the channel estimation in time varying multiple relay cooperative network. In [66], data detection and channel estimation are investigated in OFDM-based AF cooperative vehicular communication system with multiple relays. In [67], the performance of adaptive gain multiple relays AF cooperative system with both conventional relaying (CR) and best relay selection (BR) scheme is investigated. They found that the mobility of source and the destination affects the system performance, and the BR provides higher asymptotic error limit than CR scheme. In [68], AF protocol in time varying Rice fading are considered and the MAP estimation is derived in time varying channels is derived. In [69], an autoregressive model for the combined AF time varying relay channel is presented and then a causal iterative channel estimation method based on Kalman filter is derived for time varying channels. The findings have shown that the mobility of relays has a significant impact on the BER performance and has to be considered in practical system design. In [70], AF wireless relay networks are considered; then, an iterative channel estimation and data detection based on interference cancellation (PIC) at the receiver is proposed. In [71-75], stationarity and non stationarity of the LMS algorithm are investigated for different scenarios of wireless network systems.

Based on the above literature review, none of the works reported has studied the performance of the LMS-BLM receiver in multiple relays network with time varying channels. In addition, most of the studies assume perfect CSI at the receiver but in practical conditions, channel estimation schemes are always indispensable in wireless networks. Therefore, the main contributions in this section are based on considering no CSI at the receiver and performing the following tasks:

- Investigating the LMS-BLM receiver in multiple AF relays based cooperative wireless networks with time varying channels.

- Deriving and evaluating the performance of the LMS-BLM receiver in terms of receiver operating characteristics (ROCs), MSE learning curve, bit error probability and MSE performance in multiple relays with time varying channels.
- Performing computer simulations, results analysis based on the derived performance metrics and evaluating the effect of node velocities and step size parameter on the system performance.

3.3.3 System model

As represented the network model depicted in Figure 3.1, the channel estimation is realized between the source and destination, and the relay and destination. It is also assumed that the relay can forwards the received signal from the source only and do not add additional traffic on the transmitted signal.

In this system model, pilot assisted estimation is considered and there is no any assumption on the channel distribution characteristics instead we consider theoretic channel during implementation. Two phases of data transmission are considered; in the first phase the source broadcasts the signal to the destination and to relays in the network. In the second phase, the source is silent, relays amplify and forward the signal to the destination. The transmitted signals obey orthogonal transmission which can be achieved by using time division multiple access (TDMA) or frequency division multiple access (FDMA) [51, 52]. Therefore, the destination/receiver is equipped with LMS-BLM receiver for channel estimation and data detection which are described in the following sections.

In Figure 3.8, the LMS-BLM receiver scheme is presented; two main parts are shown: in the first part, the LMS algorithm is used to estimate the unknown channel $\boldsymbol{h}_0(k)$ and the second part comprises of combiner and data detector using the BLM detection approach. The receiver is composed by N tap transversal adaptive filter, the input sequence $\boldsymbol{u}(k)=\left[u(k),u(k-1),...,u(k-N+1)\right]^T$ is considered to be known stationary input vector, the coefficients $\boldsymbol{h}_0(k)=\left[h_{0(sd)}(k),h_{0(1d)}(k),...,h_{0(id)},...,h_{0(Md)}(k)\right]^T$ are considered to be unknown time varying channels, $w(k)$ is unknown independent and identically distributed (i.i.d) observation noise which is assumed to be white, $d(k)$ is the desired output signal and $y(k)$ is the observation with time varying model. In these models k denotes the time index and N indicates the data length.

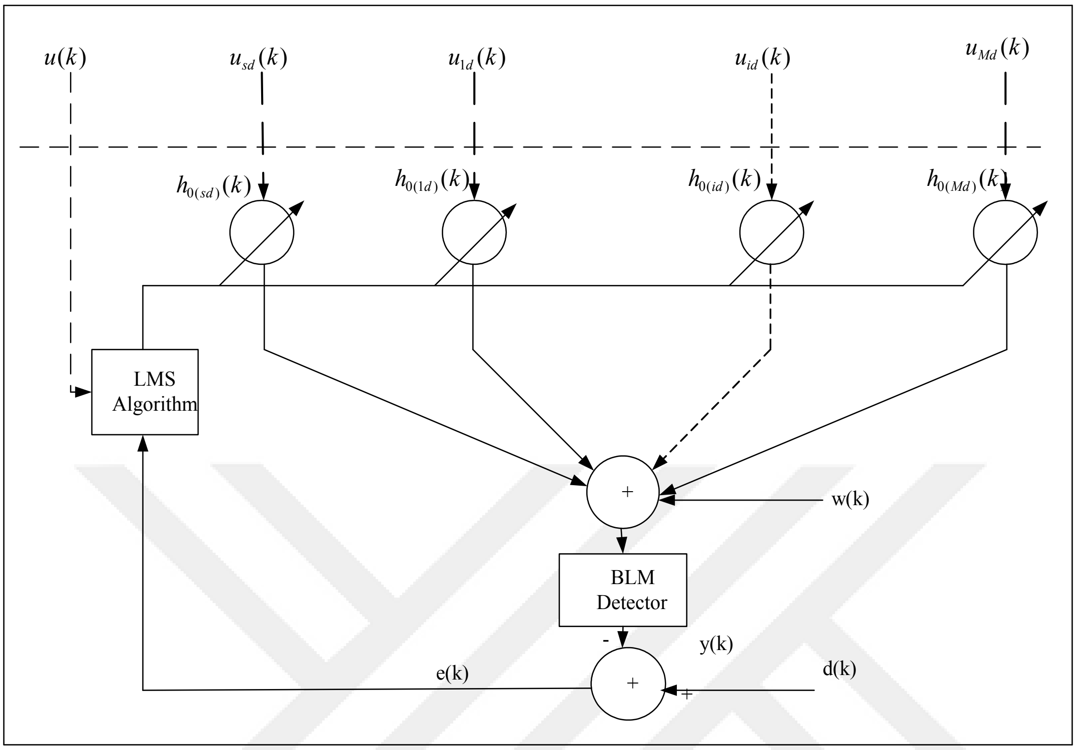

Figure 3.8 : Block diagram representing the LMS- BLM Receiver.

3.3.4 Mathematical models

In real world application, it is obvious to consider a non stationary environment in which the transmitters and/or the receivers are assumed to have a certain motion. In literature, the cause of non stationarity can be classified in two ways: the first cause is when the source supplying the desired response is both noisy and time varying. In this case, the correlation matrix of the tap inputs of the adaptive filtering algorithm remains fixed whereas the crosscorrelation vector between the tap inputs and the desired response is assumed to be time varying form. The second cause arises when the stochastic source of tap inputs applied to the algorithm is non stationary. In this case, both the correlation matrix of the tap inputs and their cross correlation vectors with the desired response assume time varying forms.

In this analysis, we consider pilot assisted estimation and we do not put any assumption on the channel distribution characteristics instead we consider theoretic channel during implementation. We also assume channel identification problem for identifying the dynamic channel system, whereby the training signal $\boldsymbol{u}(k)$ is sent to the unknown time varying channel $\boldsymbol{h}_0(k)$ which is considered as finite impulse response (FIR) filter with unknown length P. Since the unknown channel $\boldsymbol{h}_0(k)$ is considered to be time varying, without loss of generality, it is modeled by first order Markovian non stationary as follows [51, 74]:

$$\boldsymbol{h}_0(k) = \rho \boldsymbol{h}_0(k-1) + \sqrt{1-\rho^2}\,\Omega(k) \tag{3.42}$$

where ρ denotes a temporal parameter approximated by Jakes' autocorrelation model as defined before as $\rho = J_0(2\pi f_d T_s)$ and $\Omega(k) \sim N(0,\delta^2)$ is a non stationary unknown noise with zero mean, independent and identically distributed (i.i.d) process independent of $\boldsymbol{u}(k)$ and $w(k)$.

Assuming that the receiver accurately estimated the unknown channel $\boldsymbol{h}_0(k)$, therefore, the channel knowledge of (3.42) is given by:

$$\boldsymbol{h}_0^{'}(k) \sim N(\rho^{k-1}\boldsymbol{h}_0(1), (1-\rho^{2(k-1)})\delta^2) \tag{3.43}$$

The observation is considered to be time varying with the following expression [42, 43]:

$$y(k) = \boldsymbol{h}_0(k) * \boldsymbol{u}(k) + w(k) \tag{3.44}$$

where $w(k)$ is unknown i.i.d observation noise which assumed to be white with density knowledge ($w(k) \sim N(0, N_0)$). The density knowledge of the observation is given by:

$$\boldsymbol{y}'(k) \sim N(\boldsymbol{u}(k)\rho^{k-1}\boldsymbol{h}_0(1), \boldsymbol{u}^2(k)(1-\rho^{2(k-1)})\delta^2 + N_0) \tag{3.45}$$

Generally, the estimation in time varying channels can be a challenging task due to random parameters and system's time evolution experiences asymptotic floor which can be eliminated by well designed tracking loops at the receivers [51,76]. Therefore, the LMS algorithm is proposed for estimating an unknown dynamic channel. The algorithm computes the update equation as follows:

$$\begin{cases} d(k) = \hat{\boldsymbol{h}}(k)\boldsymbol{u}^T(k) \\ e(k) = y(k) - d(k) \\ \hat{\boldsymbol{h}}(n+1) = \rho\hat{\boldsymbol{h}}(k) + \mu e^*(k)\boldsymbol{u}(k) \end{cases} \tag{3.46}$$

The channel estimate is updated according to the temporal autocorrelation parameter ρ and the constant step size parameter μ. The step size μ must be choosen in the interval of $0 < \mu < 2/\zeta_{\max}$, where $\zeta_{\max}$ is the maximum eigenvalue of the input signal autocorrelation matrix $\boldsymbol{R}$. In order to ensure the stability of the LMS algorithm, the $\zeta_{\max}$ is upper bounded, and μ is best choosen in the interval of $0 < \mu < 1/tr[\boldsymbol{R}]$, where $tr[.]$ denotes the trace operator. Note that the adaptation is only happened when the detector decides the presence of the signal according to the hypothesis H_1, otherwise, the detector decides the absence of the signal according to the hypothesis H_0 described as follows:

$$\begin{cases} H_0 : y(k) = w(k) \\ H_1 : y(k) = \boldsymbol{u}(k)\boldsymbol{h}_0(k) + w(k) \end{cases} \tag{3.47}$$

3.3.4.1 Receiver operating characteristic (ROC)

Theoretically, the ROC is defined as the detection performance of the receiver evaluated by plotting the curve of the probability of detection (P_d) against the probability of false alarm (P_{fa}) which are given in (2.12) and (2.14), respectively. The exact closed form expressions of the probabilities of detection and false alarm over AWGN are given in (2.17) and (2.18), respectively.

The detection decision is made by comparing the test statistic and the predetermined threshold λ and the detector decides the presence of the signal when the test statistic is greater than the threshold λ ($T(y) \geq \lambda$). Therefore, the observation signal received at the destination from the source and each relay in the network (i.e., Figure 3.8) can be written as follows:

$$\begin{cases} y_{sd}(k) = u(k)h_{0(sd)}(k) + w(k) \\ y_{id}(k) = u_{id}(k)h_{0(id)}(k) + w(k) \\ \quad \cdots \\ y_{iM}(k) = u_{iM}(k)h_{0(iM)}(k) + w(k) \end{cases} \tag{3.48}$$

where $u_{id}(k) = G_i * y_{si}$, the amplification gain is $G_i = \{E_i / (E[|h_{0(si)}|^2]E_s + N_0\}^{1/2}$, E_i denotes the energy of each relay, E_s is the energy of the source and $y_{si} = u(k)h_{0(si)}(k) + w(k)$ is the received signal at the relay. Assuming that the observation (3.48) can be written in linear form as $\boldsymbol{y} = \boldsymbol{Hu} + \boldsymbol{w}$, the BLM detector computes the test statistic using the following expression [19]:

$$\hat{T}^V(y) = \boldsymbol{y}^T \hat{\boldsymbol{H}}\boldsymbol{C}_u \hat{\boldsymbol{H}}^T (\hat{\boldsymbol{H}}\boldsymbol{C}_u \hat{\boldsymbol{H}}^T + N_0 \boldsymbol{I})^{-1} \boldsymbol{y} \tag{3.49}$$

where the covariance matrix $\boldsymbol{C}_u = diag[\sigma_0^2, \sigma_1^2, ..., \sigma_i^2]$ and the noise variance $N_0 \boldsymbol{I} = diag[N_0, ..., N_0]$. The closed form expression of the test statistic is given by:

$$\hat{T}^V(y) = \left(\frac{\hat{h}_{sd}^2 \sigma_{sd}^2}{\hat{h}_{sd}^2 \sigma_{sd}^2 + N_0} \right) y_{sd}^2 + \sum_{i=1}^{M} \left(\frac{\hat{h}_{id}^2 \sigma_{id}^2}{\hat{h}_{id}^2 \sigma_{id}^2 + N_0} \right) y_{id}^2 \tag{3.50}$$

According to the test hypotheses, the test statistic is determined as follows:

$$\begin{cases} H_0 : \hat{T}^V(y) = \dfrac{\hat{h}_{sd}^2 \sigma_{sd}^2 N_0}{\hat{h}_{sd}^2 \sigma_{sd}^2 + N_0} \left(\dfrac{y_{sd}}{\eta_{(0)}} \right)^2 + \sum_{i=1}^{M} \dfrac{\hat{h}_{id}^2 \sigma_{id}^2 N_0}{\hat{h}_{id}^2 \sigma_{id}^2 + N_0} \left(\dfrac{y_{id}}{\eta_{id(0)}} \right)^2 \\ H_1 : \hat{T}^V(y) = \dfrac{\hat{h}_{sd}^2 \sigma_{sd}^2 \left(\sigma_{sd}^2 \left(1 - \alpha^{2(k-1)} \right) \delta_{sd}^2 + N_0 \right)}{\hat{h}_{sd}^2 \sigma_{sd}^2 + N_0} \left(\dfrac{y_{sd}}{\eta_{(1)}} \right)^2 + \sum_{i=1}^{M} \dfrac{\hat{h}_{id}^2 \sigma_{id}^2 \left(\sigma_{id}^2 \left(1 - \alpha^{2(k-1)} \right) \delta_{id}^2 + N_0 \right)}{\hat{h}_{id}^2 \sigma_{id}^2 + N_0} \left(\dfrac{y_{id}}{\eta_{id(1)}} \right)^2 \end{cases} \tag{3.51}$$

where $\eta_{(0)}^2 = N_0$, $\eta_{id(0)}^2 = N_0$, $\eta_{(1)}^2 = \sigma_{sd}^2 (1 - \alpha^{2(k-1)}) \delta_{sd}^2 + N_0$ and $\eta_{id(1)}^2 = \sigma_{id}^2 (1 - \alpha^{2(k-1)}) \delta_{id}^2 + N_0$ and (3.51) can be simplified as:

$$\begin{cases} H_0 : \hat{T}^V(y) = \hat{\alpha}_{(0)} \chi_{sd}^2 + \sum_{i=1}^{M} \hat{\beta}_{i(0)} \chi_{id}^2(i) \\ H_1 : \hat{T}^V(y) = \hat{\alpha}_{(1)} \chi_{sd}^2 + \sum_{i=1}^{M} \hat{\beta}_{i(1)} \chi_{id}^2(i) \end{cases} \tag{3.52}$$

where $\hat{\alpha}_{(0)} = \frac{\hat{h}_{sd}^2 \sigma_{sd}^2}{\hat{h}_{sd}^2 \sigma_{sd}^2 + 1}$, $\hat{\beta}_{i(0)} = \frac{\hat{h}_{id}^2 \sigma_{id}^2}{\hat{h}_{id}^2 \sigma_{id}^2 + 1}$, $\hat{\alpha}_{(1)} = \frac{\hat{h}_{sd}^2 \sigma_{sd}^2 \left(\sigma_{sd}^2 \left(1 - \alpha^{2(k-1)}\right) \delta_{sd}^2 + 1 \right)}{\hat{h}_{sd}^2 \sigma_{sd}^2 + 1}$, $\hat{\beta}_{i(1)} = \frac{\hat{h}_{id}^2 \sigma_{id}^2 \left(\sigma_{id}^2 \left(1 - \alpha^{2(k-1)}\right) \delta_{id}^2 + 1 \right)}{\hat{h}_{id}^2 \sigma_{id}^2 + 1}$, $N_0 = 1$, χ_{sd}^2 and χ_{id}^2 are independent and identically distributed Chi-squared random variables with one degree of freedom for the source and destination, and the relay and destination respectively.

The probability density functions of the test statistic $\hat{T}(y)$ is determined as follows [19]:

$$\begin{cases} P(\hat{T}^V; H_0) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \phi_{\hat{T}_{H_0}^V}(\omega) \exp(-j\omega \hat{T}^V) d\omega \\ P(\hat{T}^V; H_1) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \phi_{\hat{T}_{H_1}^V}(\omega) \exp(-j\omega \hat{T}^V) d\omega \end{cases} \tag{3.53}$$

The characteristic functions of $\hat{T}^V(y)$ according to the hypotheses H_0 and H_1 in $P(\hat{T}; H_0)$ and $P(\hat{T}; H_1)$ are given by:

$$\begin{cases} \phi_{\hat{T}_{H_0}^V} = \frac{1}{(1 - 2j\omega \hat{\alpha}_{(0)}^V)^{1/2}} + \prod_{i=1}^{M} \frac{1}{(1 - 2j\omega \hat{\beta}_{i(0)}^V)^{1/2}} \\ \phi_{\hat{T}_{H_1}^V} = \frac{1}{(1 - 2j\omega \hat{\alpha}_{(1)}^V)^{1/2}} + \prod_{i=1}^{M} \frac{1}{(1 - 2j\omega \hat{\beta}_{i(1)}^V)^{1/2}} \end{cases} \tag{3.54}$$

where, $\prod_{i=1}^{M} \frac{1}{(1 - 2j\omega \hat{\beta}_{i(0)}^V)^{1/2}} = \sum_{i=1}^{M} \frac{\hat{F}_i}{(1 - 2j\omega \hat{\beta}_{i(0)}^V)^{1/2}}$, with $\hat{F}_i = \prod_{l=1, l \neq i}^{M} \frac{1}{(1 - \hat{\beta}_{l(0)}^V / \hat{\beta}_{i(0)}^V)^{1/2}}$, and $\prod_{i=1}^{M} \frac{1}{(1 - 2j\omega \hat{\beta}_{i(1)}^V)^{1/2}} = \sum_{i=1}^{M} \frac{\hat{D}_i}{(1 - 2j\omega \hat{\beta}_{i(1)}^V)^{1/2}}$, with $\hat{D}_i = \prod_{l=1, l \neq i}^{M} \frac{1}{(1 - \beta_{l(1)}^V / \beta_{i(1)}^V)^{1/2}}$; by introducing (3.54) in (3.53), the PDFs for dual hop (2 segments) relays network are derived as follows:

$$\begin{cases} P(\hat{T}^V; H_0) = \frac{1}{2} \int_{-\infty}^{\infty} \frac{1}{\left(1 - 2j\omega \hat{\alpha}_{(0)}^V\right)^{1/2}} \exp(-j\omega \hat{T}^V) \frac{d\omega}{2\pi} + \frac{1}{2} \sum_{i=1}^{M} \int_{-\infty}^{\infty} \frac{\hat{F}_i}{(1 - 2j\omega \hat{\beta}_{i(0)}^V)^{1/2}} \exp\left(-j\omega \hat{T}^V\right) \frac{d\omega}{2\pi} \\ P(\hat{T}^V; H_1) = \frac{1}{2} \int_{-\infty}^{\infty} \frac{1}{\left(1 - 2j\omega \hat{\alpha}_{(1)}^V\right)^{1/2}} \exp(-j\omega \hat{T}^V) \frac{d\omega}{2\pi} + \frac{1}{2} \sum_{i=1}^{M} \int_{-\infty}^{\infty} \frac{\hat{D}_i}{(1 - 2j\omega \hat{\beta}_{i(1)}^V)^{1/2}} \exp\left(-j\omega \hat{T}^V\right) \frac{d\omega}{2\pi} \end{cases} \tag{3.55}$$

(3.55) represents the inverse fourrier transform and its solution is derived as follows [48].

$$P(\hat{T}^V;H_0)=\frac{1}{2\sqrt{2\pi\hat{T}^V\hat{\alpha}^V_{(0)}}}\exp(-\frac{\hat{T}^V}{2\hat{\alpha}^V_{(0)}})+\sum_{i=1}^{M}\hat{F}_i\frac{1}{2\sqrt{2\pi\hat{T}^V\hat{\beta}^V_{i(0)}}}\exp(-\frac{\hat{T}^V}{2\hat{\beta}^V_{i(0)}}) \quad (3.56)$$

and,

$$P(\hat{T};H_1)=\frac{1}{2\sqrt{2\pi\hat{T}^V\hat{\alpha}^V_{(1)}}}\exp(-\frac{\hat{T}^V}{2\hat{\alpha}^V_{(1)}})+\sum_{i=1}^{M}\hat{D}_i\frac{1}{2\sqrt{2\pi\hat{T}^V\hat{\beta}^V_{i(1)}}}\exp(-\frac{\hat{T}^V}{2\hat{\beta}^V_{i(1)}}) \quad (3.57)$$

Using solutions found in (3.56) and (3.57), the probabilities of false alarm and detection are respectively derived by using [49, Sec.5.3.Eq. 21]:

$$\hat{P}^V_{fa}=\int_{\lambda}^{\infty}P(\hat{T}^V;H_0)d\hat{T}^V=\frac{1}{2\sqrt{\pi}}\Gamma\left(\frac{1}{2},\frac{1}{2\hat{\alpha}^V_{(0)}}\lambda\right)+\sum_{i=1}^{M}\frac{\hat{F}_i}{2\sqrt{\pi}}\Gamma\left(\frac{1}{2},\frac{1}{2\hat{\beta}^V_{i(0)}}\lambda\right) \quad (3.58)$$

and,

$$\hat{P}^V_{d}=\int_{\lambda}^{\infty}P(\hat{T}^V;H_1)d\hat{T}^V=\frac{1}{2\sqrt{\pi}}\Gamma\left(\frac{1}{2},\frac{1}{2\hat{\alpha}^V_{(1)}}\lambda\right)+\sum_{i=1}^{M}\frac{\hat{D}_i}{2\sqrt{\pi}}\Gamma\left(\frac{1}{2},\frac{1}{2\hat{\beta}^V_{i(1)}}\lambda\right) \quad (3.59)$$

where $\Gamma(.,.)$ is the upper incomplete Gamma function.

3.3.4.2 Minimum mean square error (MSE) and bit error probability (BEP) performance analysis

In network model of Figure 3.1, the receiver is equipped with BLM detector, whereby the minimum mean square error (MMSE) estimate of the transmitted signal is given by [19]:

$$\hat{\boldsymbol{s}}^V=\hat{\boldsymbol{H}}\boldsymbol{C}_u\hat{\boldsymbol{H}}^T(\hat{\boldsymbol{H}}\boldsymbol{C}_u\hat{\boldsymbol{H}}^T+N_0\boldsymbol{I})^{-1}\boldsymbol{y} \quad (3.60)$$

Using (3.48), covariance and noise matrix values, (3.60) is derived as follows:

$$\hat{s}^V = \frac{P_s |\hat{h}_{sd}|^2 \sigma_{sd}^2}{P_s |\hat{h}_{sd}|^2 \sigma_{sd}^2 + N_0} y_{sd} + \sum_{i=1}^{M} \frac{P_i |\hat{h}_{id}|^2 \sigma_{id}^2}{P_i |\hat{h}_{id}|^2 \sigma_{id}^2 + N_0} y_{id} \tag{3.61}$$

The mean square error can be derived as follows:

$$MSE_{\hat{s}^V} = E\left\{ \left| (s - \hat{s}^V) \right|^2 \right\} \tag{3.62}$$

The expression (3.62) denotes the Bayesian MSE of the system.

The bit error probability (BEP) for the LMS-BLM receiver can be determined by using the formula given in (2.36) and [38]. Substituting (3.58) and (3.59) into (2.36), we obtain:

$$BEP^V = \frac{1}{2} - \frac{1}{4\sqrt{\pi}} \Gamma\left(\frac{1}{2}, \frac{1}{2\hat{\alpha}_{(1)}^V} \lambda\right) + \frac{1}{4\sqrt{\pi}} \Gamma\left(\frac{1}{2}, \frac{1}{2\hat{\alpha}_{(0)}^V} \lambda\right) - \sum_{i=1}^{M} \left\{ \frac{\hat{D}_i}{4\sqrt{\pi}} \Gamma\left(\frac{1}{2}, \frac{1}{2\hat{\beta}_{i(1)}^V} \lambda\right) - \frac{\hat{F}_i}{4\sqrt{\pi}} \Gamma\left(\frac{1}{2}, \frac{1}{2\hat{\beta}_{i(0)}^V} \lambda\right) \right\} \tag{3.63}$$

3.3.5 Numerical results

In this study, simulation results are presented in order to investigate the performance of the LMS-BLM receiver in multiple relays with time varying channels. During simulations, the theoretical channel h is chosen such that its length corresponds to the order value of the FIR filter with number of steps equal to 10. Two phases are considered during transmission: in the first phase, the signal is generated randomly and transmitted to all relays and destination in the network. In the second phase, the source is silent and each relay amplifies the received signal from the source only and forwards it to the destination. The amplification at the relay is done by only multiplying the received signal with the amplification gain. At the destination, the receiver has to estimate the channel and to recover the original transmitted signal from the source by using the LMS-BLM receiver. The LMS agorithm is functioning such a way that the channel weights are updated only when the BLM detector decides the presence of the signal, otherwise the channel estimates remain unchanged.

In this analysis, four scenarios are considered: in the first scenario, the receiver operating characteristics (ROC) and MSE learning curve are evaluated for different number of relays and same nodes mobility. In the second scenario, the ROC and

MSE learning curve are investigated in multiple relays and various velocities of relays and destination. In the third scenario, the BER is evaluated in multiple relays for different step size (μ), number of relays and nodes' mobility. The fourth scenario investigates the effects of mobility of relay only, destination only or relay and destination on the BER of the system.

In Figure 3.9, the ROC is investigated by considering multiple AF relays (i.e. R=2, R=3 and R=4), relays and destination are moving at the same speed of 108 km/h. In this simulation, we consider a system with carrier frequency of $f_c = 2GHz$, symbol period of $T_s = 0.1ms$, doppler frequency of $f_D = 200Hz$ and the normalized doppler frequency of $f_D T_s = 0.02$. The findings have shown that the probability of detection improves when the number of relays increases and the direct link presents less detection performance compared to other links. In Figure 3.10, the MSE learning curve is investigated with various number of relays in fast fading channels. The findings show that the MSE improves when the number of relays is increased.

In Figure 3.11 and Figure 3.12, the ROC and MSE learning curve are investigated in multiple relays with various velocities of relays and destination (i.e., 0km/h, 27km/h, 54km/h, 108km/h, 216km/h and 324km/h). The results show that the high node speed affects the probability of detection and exhibits the high MSE at the receiver. This can be improved by increasing the number of relays in the network and using appropriate receiver algorithm that can detect the signal efficiently.

In Figure 3.13, the bit error probability is evaluated in multiple relays by varying the step size (i.e., mu=0.002, 0.004 and 0.008) that controls the convergence of the LMS algorithm, and node speed of 108km/h. The results show that the BER decreases quikly when the value of the step size increases. Similarly, when the number of relays increases, the BER improves as shown in Figure 3.13. The nodes speed also affects the BER performance and this can be compansated by increasing the number of relays as shown the results in Figure 3.14. In Figure 3.15, the effect of nodes speed is investigated for relay speed only, destination speed only, and when the relay and destination have the same speed. The findings showed that the mobility of relays affects the BER performance much more than the mobility of destination and the mobility of both relays and destination affects the BER performance much more than the mobility of relays only or destination only.

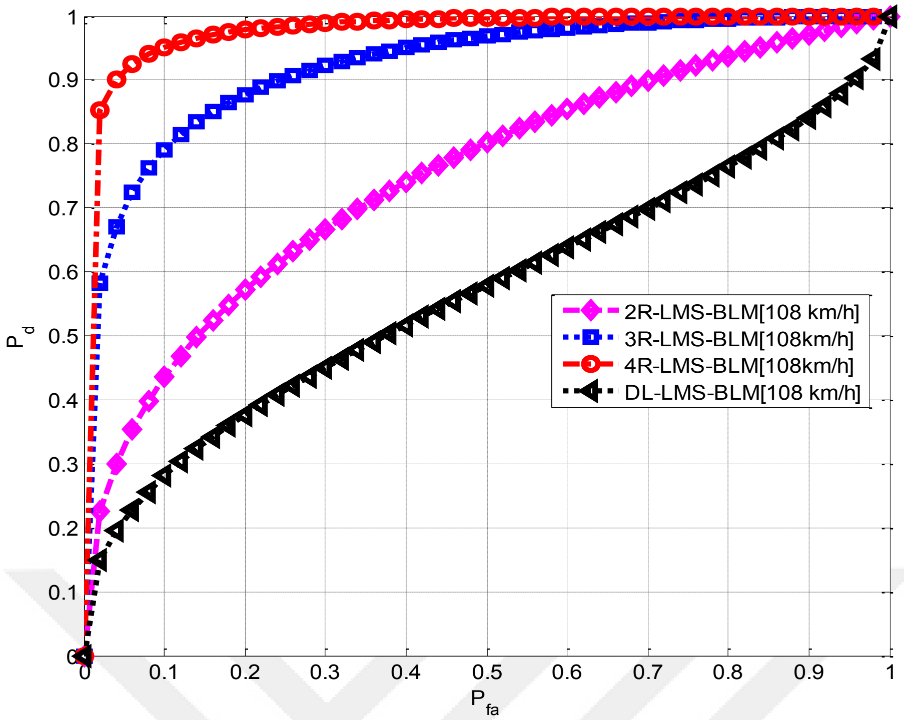

Figure 3.9 : ROC of the receiver with M-relays in fast fading channels.

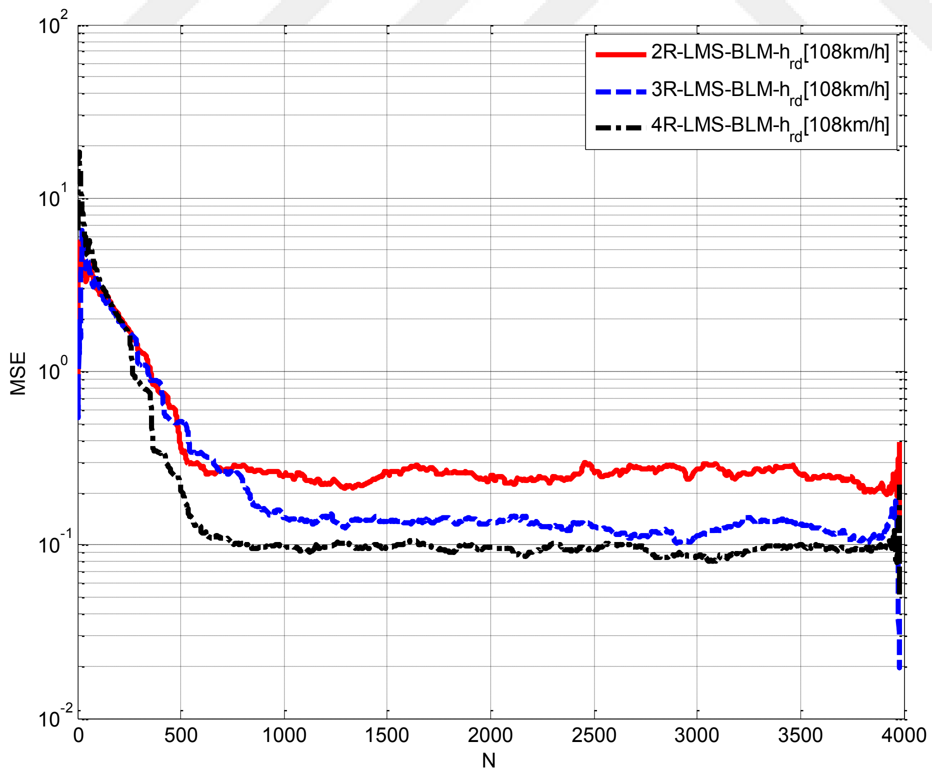

Figure 3.10 : MSE learning curve of the LMS-BLM Receiver with various relays.

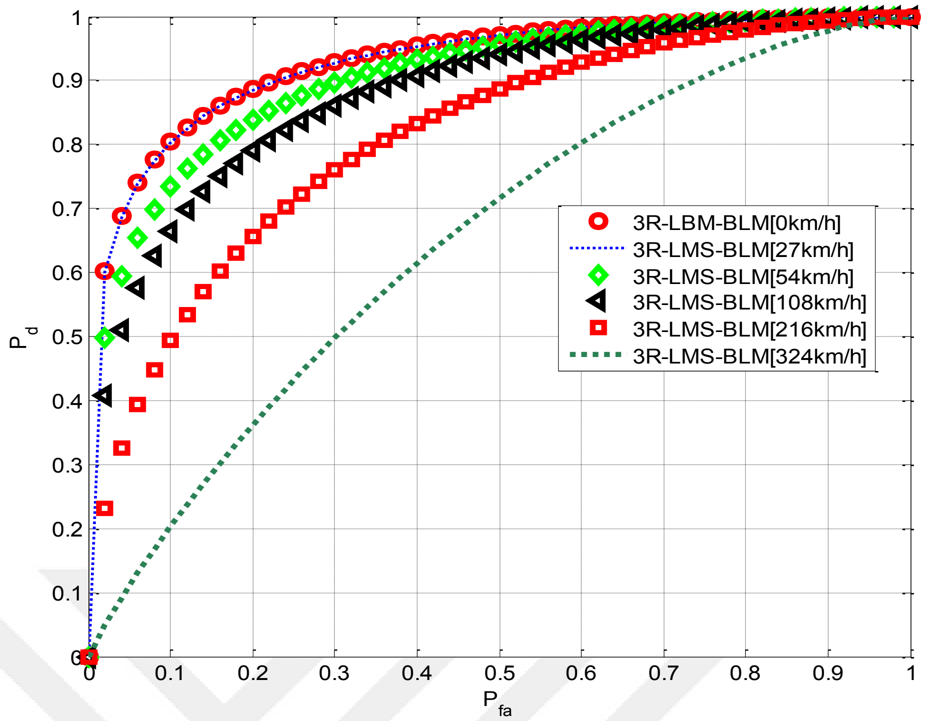

Figure 3.11 : ROC of the LMS-BLM Receiver with various nodes speeds.

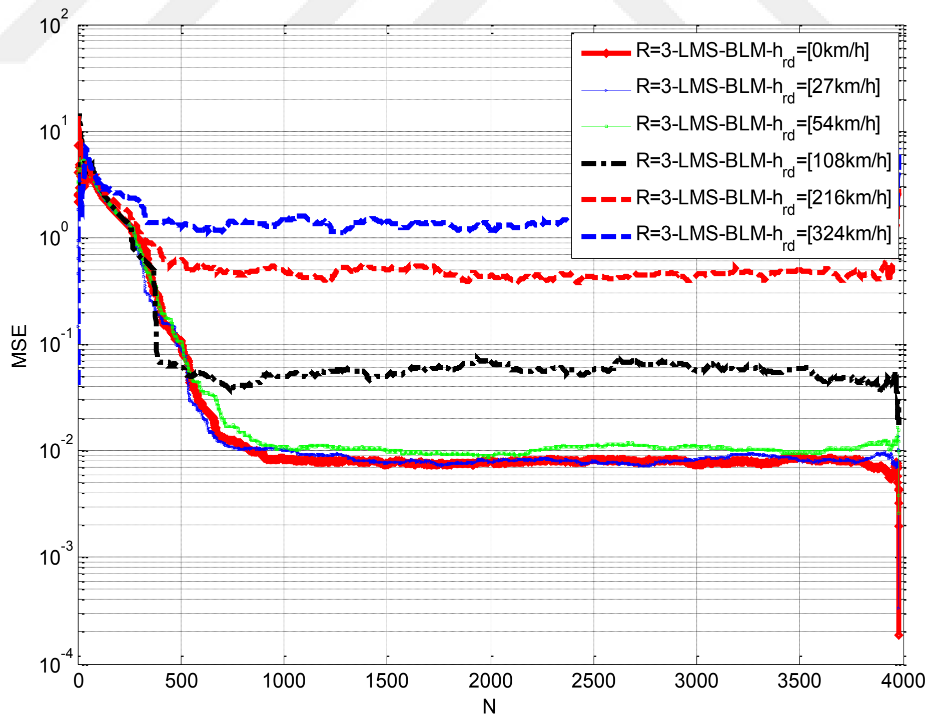

Figure 3.12 : MSE learning curve of the LMS-BLM Receiver with nodes speeds.

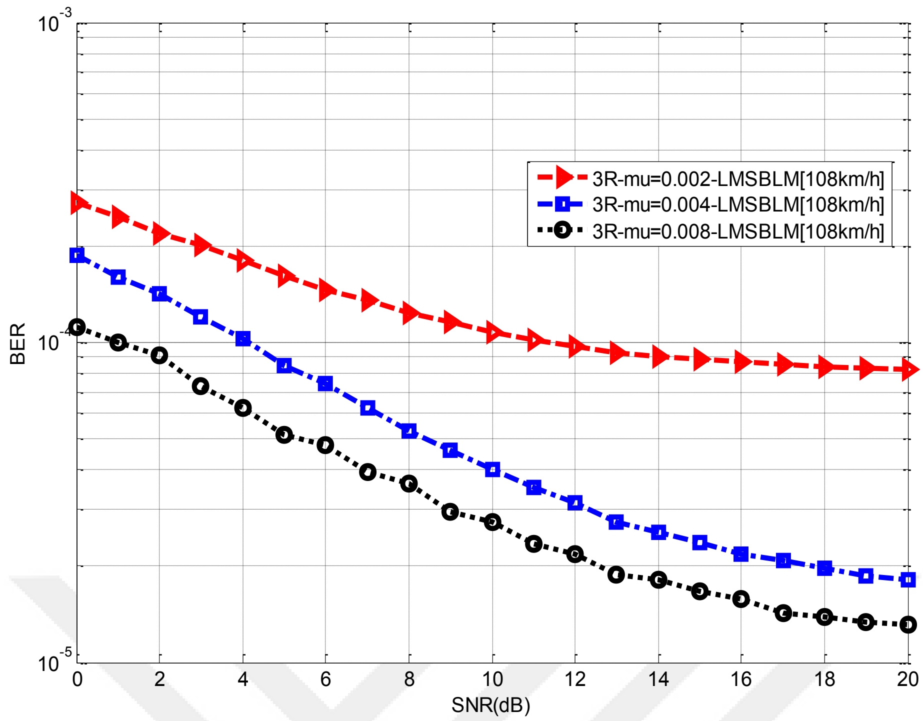

Figure 3.13 : BER of the LMS-BLM Receiver with various step size (μ).

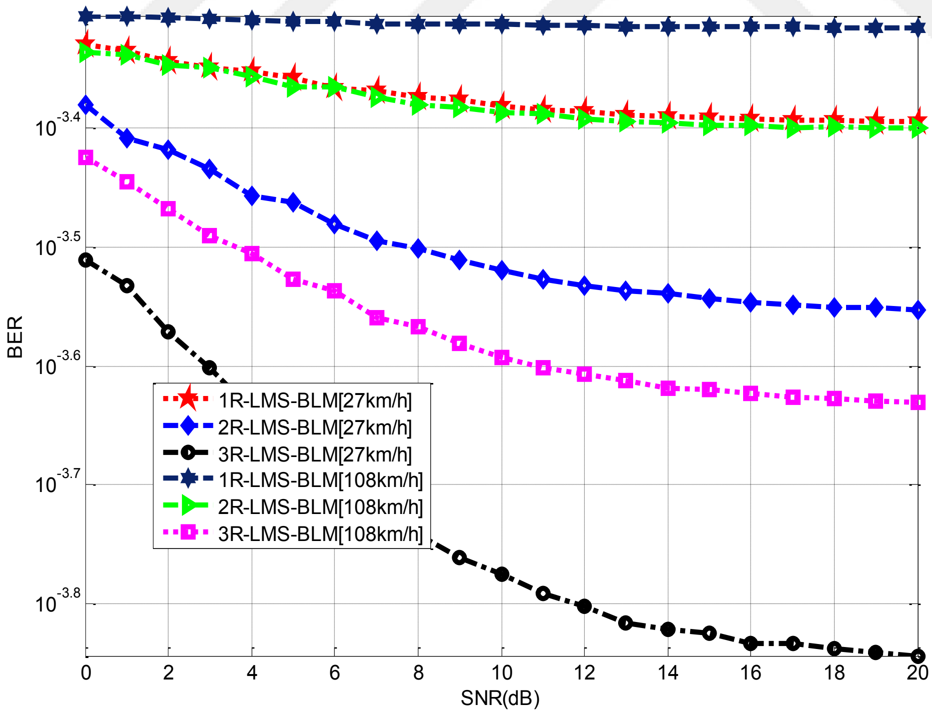

Figure 3.14 : BER for the LMS-BLM Receiver with nodes speeds and M-relays.

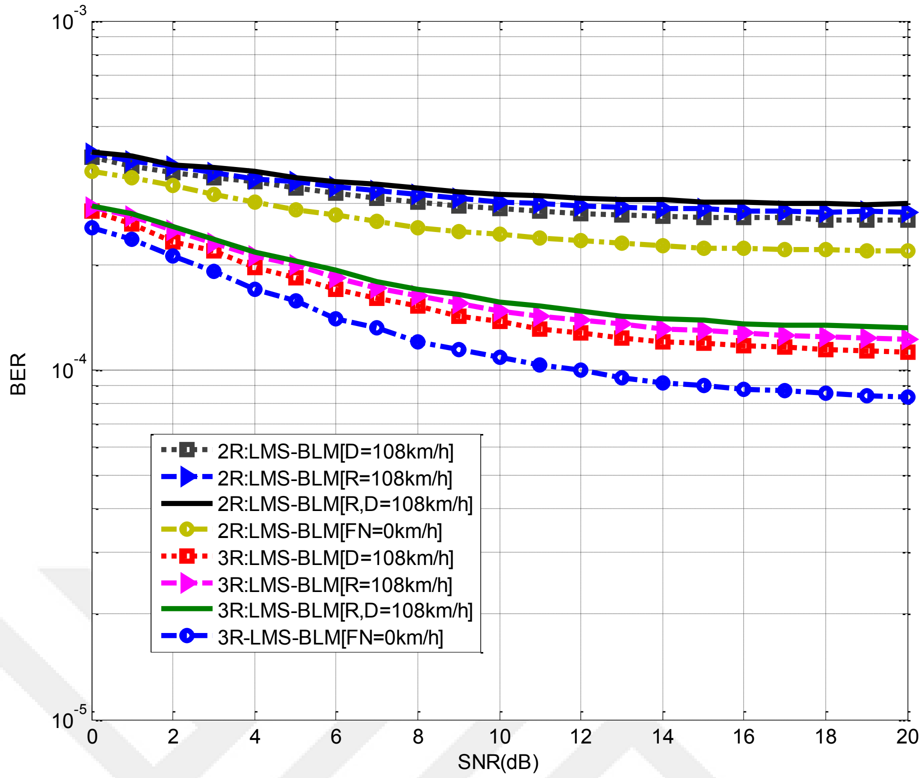

Figure 3.15 : Effect of nodes' mobilities on the LMS-BLM Receiver performance.

3.3.6 Summary

This study investigated the performance of the LMS-BLM receiver in AF relays network with time varying channels. Four scenarios were considered: The first scenario evaluated the ROCs and MSE learning curve (i.e., Figure 3.9 and Figure 3.10) with various number of relays (i.e., R=2, R=3 and R=4) and nodes' speed of 108km/h. The findings showed that the performance of the ROC and MSE learning curve improves when the number of relays increases in the network. The second scenario evaluated the ROCs and MSE learning curve (i.e., Figure 3.11 and Figure 3.12) with various nodes speeds (i.e., 0km/h, 27km/h, 54km/h, 108km/h, 216km/h, and 324km/h). The findings showed that the high speed of nodes affects the system performance particularly when there are few relays in the network. The third scenario evaluated the effect of step size μ, various number of relays, and various number of nodes speeds (i.e., Figure 3.13 and Figure 3.14) on the BER performance. The findings showed that the BER improves when the step size value and number of relays increase at low speeds of nodes. Therefore, the step size μ should be well choosen in the specified range in order to ensure the stability and good convergence of the algorithm.

In the fourth scenario, the effects of mobility of relays only or mobility of destination only were evaluated (i.e., Figure 3.15). The findings showed that the mobility of relays affects the BER performance more than the mobility of destination. Therefore, the mobility of relays must be put into account when designing a wireless network.

In this study, different scenarios and simulation parameters have proven that the proposed receiver can be applied in the current and future wireless networks where carrier frequencies are in the range of 2GHz and networks that can allow the use of multiple relays.

4. CONCLUSIONS

In this thesis, theoretical and numerical findings on proposed models of channel estimation and data detection for cooperative wireless communications were presented. The effects of channel impairments (i.e., time varying multipath fading, shadowing, noise, etc.) on wireless communication networks were discussed. Consequently, relaying networks based cooperative wireless communications were assessed due to their role in providing diversity gain in wireless networks that can mitigate directly the effects caused by multipath fadings. Numerous advantages of relaying cooperations in wireless networks were pointed out such as the coverage extension, throughput enhancement, reduction of power consumption at the transmitter as well as the receiver, low implementation complexity and costs. Relaying cooperations also found various applications in wireless systems such as 3GPPLTE, WiMAX, WLANs, vehicle to vehicle communications and wireless sensor networks. Signal processing protocols for relaying cooperations were also considered by focusing on common protocols in literature such as amplify and forward (AF) protocol, and decode and forward (DF) protocol.

Even though, relaying cooperation can address the problem of channel impairments, it was revealed that the receiver would still be challenged by the unknown channel state information (CSI) and unknown transmitted signal. Therefore, practical models related to adaptive channel estimation and data detection in cooperative wireless communications were investigated. Two main schemes based on Bayesian linear model (BLM) detector and least mean square (LMS) algorithm were proposed and implemented in multiple relays in order to address the problem of signal recovery at the reicever. The proposed algorithms presented some advantages including linear computations, low implementation complexity and feasibility.

Specifically, the main contributions were mainly examined into two chapters (i.e., Chapter 2 and Chapter 3); in chapter 2, a network model operating in stationary environment was proposed and divided in two main parts as follows:

In the first part, a wireless network with AF multiple relays was considered and it was assumed that the channel state information (CSI) was available at the destination. Therefore, the BLM detector was proposed for signal recovery at the destination. The results of receiver operating characteristics (ROC) of the BLM detector were compared with the energy detector combined with the maximum ratio combining (MRC) and found that the proposed method provides higher detection performance in all scenarios considered (i.e., Figure 2.3). The effects of the number of ralays on receiver performance were also evaluated and found that the performance improved proportionally with the number of relays in the network (i.e., Figure 2.5 and Figure 2.7). In addition, the effect of relay position from the source and destination was investigated and it was found that the system performance improved when the relay was closer to the source (i.e., Figure 2.4 and Figure 2.6). Therefore, wireless network designers should consider the relays' positions for enhancing the system performance.

In the second part, a wireless network with AF multiple relays was considered and it was assumed that the CSI was not available at the destination. In this case, the joint LMS-BLM algorithm was proposed in order to estimate the channel and recover the original signal from noisy signals. Different performance metrics were evaluated including receiver operating characteristics (ROCs), complementary ROCs, probability of error and MSE learning curve. The results of the ROCs and C-ROCs showed that the performance improved as the number of relays increased in the network (i.e., Figure 2.9, Figure 2.10 and Figure 2.11). The minimum MSE could also be achieved by choosing the appropriate step size μ that controls the convergence and stability of the algorithm (i.e., Figure 2.12). The results of the error probability also showed that it improved proportionally with the number of relays (i.e., Figure 2.13).

The third chapter considered a wireless network model in non stationary environments. In this chapter, a typical wireless network that comprised of fixed base station (BS), multiple mobile stations (MSs) acted as relays and single mobile destination that could move at any direction was considered. In this chapter, two main parts were also considered as follows:

The first part of chapter 3 assumed that the CSI was available at the destination and the performance of the BLM detector in multiple AF and DaF relays with time varying channels was evaluated. In this part, the generated signal at the source was encoded differentially and transmitted to the relays and destination. At the receiver, differential decoder with BLM detector was utilised in order to recover efficiently the transmitted signal. The probability of detection and BER performance metrics were evaluated in multiple relays with different node speeds and different number of relays. The obtained results were compared with differential MRC detector and showed that the proposed BLM detector was effective and could detect efficiently the transmitted signal in multiple relays with time varying channels (i.e., Figure 3.4). In addition, the effects of nodes speeds were evaluated and found that the high speed of relays affected the system performance much more than the speed of destination (i.e., Figure 3.5). The high speed of nodes could also increase the cascading order of Rayleigh channel model, which could decrease the detection performance (i.e., Figure 3.3). Furthermore, the AF protocol and DaF protocol were compared and found that the DaF outperformed the AF for higher number of relays and AF was better for low number of relays (i.e., Figure 3.6). The effects of number of relays with same speeds were also evaluated and found that the higher number of relays could compansate the loss of signals due to high speeds (i.e., Figure 3.7).

The second part of chapter 3 assumed that the CSI was not available at the destination and the performance of the LMS-BLM receiver in multiple AF relays with time varying channels was evaluated. In this part, the LMS algorithm estimated the unknown dynamic channel while the BLM detector recovered the transmitted signal from noisy signals. The joint algorithm was working in a way that the tap weights of the channels were only updated when the BLM detector decided the presence of the signal, otherwise, the channel remained invariable until the next step. The performance analysis considered different nodes speeds, different number of relays and different steep sizes μ of the LMS algorithm in order to evaluate the effectiveness of the proposed algorithm. Different performance metrics were considered in order to evaluate the performance of the proposed algorithm such as ROCs, MSE learning curve, and bit error probability performance. The findings showed that the proposed algorithm was effective, with the ability to estimate the channel and recover the transmitted signal in time varying channels (i.e., Figure 3.9, Figure 3.10). The effects of nodes speeds were also evaluated and found that the speeds affected the system performance in various scenarios considered (i.e.,Figure 3.11, Figure 3.12, Figure 3.14, and Figure 3.15). Furthermore, the network performance could be improved by increasing the number of relays in the networks and choosing the appropriate step size μ within the appropriate range for the LMS algorithm (i.e., Figure 3.13). Various numerical parameters utilized in this thesis have proven that the proposed methods can be applied in the current and future wireless networks that can support carrier frequencies classified in the range of 2GHz and can employ multiple relays.

In summary, this thesis proposed and derived new models based on Bayesian linear model (BLM) detector and least mean square (LMS) algorithm and implemented them in cooperative wireless communications. The performance of the proposed methods was evaluated in both stationary and non stationary environments. It is recommended that network designer should assess the position of relays in stationary environment and the speed of relays in non stationary environment so as to obtain the desired signal at the receiver. Even though different performance parameters and assumptions were considered and investigated in this thesis, some other important metrics can be considered in future works as follows:

- Investigating the performance of the LMS-BLM receiver in relays networks with the application of test bed or emulation models.
- Assessing the performance of the LMS-BLM receiver in relays networks by using other relaying protocols such as detect and forward protocol or compress and forward protocol.
- Exploring and deriving other performance metrics such as ergodic capacity, bit error rate (BER), outage probability and power allocation in relays networks with the LMS-BLM receiver.
- Examining the detection performance of the BLM detector or the LMS-BLM receiver over various channel fading distribution such as Rician, Nakagami-m, etc.
- Comparing the LMS-BLM receiver with other existing schemes such as zero-forcing equalization, maximum likelihood sequential estimation, etc.
- Mobility and link states prediction models for cooperative wireless networks with multiple relays.

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PUBLICATIONS, PRESENTATIONS AND PATENTS ON THE THESIS:

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