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Low Complexity Error Correction in Low Density Parity Check (LDPC) Code Decoder and Encoder for Decode and Forward Cooperative Wireless Communication

Jam'aah Binti Suud

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Jam'aah Binti Suud

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DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

……………………………

Signature

Name: Jam'aah Binti Suud

Matric No.: 15010027

Faculty of Engineering

Universiti Malaysia Sarawak

Date :

DEDICATION

To my Parents who Nurtured Me

To my Husband who has Never Doubted Me

To my Teachers who have Inspired and Engaged, who are Passionate and Amazing Human

To All who Continue to Fight

and

To the Readers

"Never give up on anybody, miracles do happen"

“It’s supposed to be hard. If it wasn’t hard, everyone would do it. Hard is what makes it great”.

-Wisdom for the Seeker-

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ABSTRACT

Decoding high complexity is a major issue to design a decode and forward (DF) relay protocol. Thus, the establishment of a low complexity decoding system would be beneficial to assist DF relay protocol. To overcome this problem a DF protocol relay system model using LDPC code is proposed in this thesis. The results show that employing LDPC code for DF protocol relay system can achieve better error rate performance than that of using non-cooperative and other existing relay protocol systems which are AF, DF, and DF protocol relay system using Turbo code. Besides that by using LDPC code the decoding processing time can be reduced. The limitation of the available works on min-sum based LDPC code decoding algorithm specifically for DF protocol relay system motivated this research. The initial investigation on the existing LDPC code decoding algorithms assists to develop a low complexity LDPC code decoding algorithm. By using the optimization min-sum belief propagation approach, a low complexity min-sum (MS) based decoding algorithm called Variable Global Optimization Min-Sum (VGOMS) has been developed. A key aspect of this algorithm is balancing the trade-off between the problem of complexity reduction and error correction performance of the relay node LDPC decoder component. This algorithm only applies the optimization scaling factor at the bit node processing of the variable node operation. The Particle Swarm Optimization (PSO) search method is adopted to search the optimized scaling factor to obtain optimal error rate performance. The source to relay channel is modelled as a cooperative fading that is used extensively in cooperative communication. From the result simulation, the VGOMS algorithm outperforms than well-known existing LDPC code decoding algorithm min-sum, is comparable with Normalized min-sum (NMS), and Offset min-sum (OMS), and closed near to Sum-Product (SP) algorithm at higher SNR in terms of error rate performance.

VGOMS also outperforms NMS, OMS, and SP in terms of check node operation complexity that consumes the most complex decoding operation. VGOMS has shown a better compromise between better error rate performance and low computation operational complexity. One major concerning the LDPC code for the DF protocol relay system is high encoding complexity. Thus, the LDPC code encoder model is developed to identify a low complexity encoding algorithm of LDPC code for the DF protocol relay system. In this model, eight different LU and QR encoding method variants are evaluated in terms of execution time, the number of nonzero, and the pattern of nonzero. The proposed LDPC code encoder model shows that the LUPQ encoding method achieved the lowest execution time and number of nonzero among LU and QR encoding methods. The performance results showed that LUPQ is the most suitable encoding algorithm for the DF protocol relay system using LDPC code as it performs low processing time of the LDPC encoder component.

Keywords: Decode and forward, LDPC code, min-sum, LU algorithm, QR algorithm

Pembetulan Ralat Kerumitan Rendah dalam Kod Ketumpatan Pariti Rendah Semak (LDPC) Penyahkod dan Pengekod untuk Decode and Forward Komunikasi Koperasi Tanpa Wayar

ABSTRAK

Kerumitan tinggi penyahkodan adalah masalah utama untuk merancang protokol relay decode and forward (DF). Oleh itu, pembentukan sistem penyahkodan kerumitan rendah akan bermanfaat untuk membantu protokol relay DF. Untuk mengatasi masalah ini, model relay protokol DF menggunakan kod LDPC yang dicadangkan dalam tesis ini. Hasilnya menunjukkan bahawa menggunakan kod LDPC untuk sistem relay protokol DF dapat mencapai prestasi kadar ralat yang lebih baik daripada menggunakan sistem protokol relay yang tidak koperatif dan sedia ada iaitu sistem relay protokol AF, DF dan DF yang menggunakan kod Turbo. Selain itu dengan menggunakan kod LDPC waktu pemprosesan penyahkodan dapat dikurangkan. Batasan kerja yang tersedia pada algoritma penyahkodan kod LDPC berdasarkan min-sum khusus untuk penyahkod LDPC di nod relay sistem relay protokol DF memotivasi penyelidikan ini. Penyelidikan awal mengenai algoritma penyahkodan kod LDPC sedia ada membantu mengembangkan algoritma penyahkodan kod LDPC dengan kerumitan rendah. Dengan menggunakan pendekatan penyebaran kepercayaan min-sum pengoptimuman, algoritma penyahkodan berasaskan min-sum kerumitan rendah yang disebut Variable Global Optimization Min-Sum (VGOMS) telah dibangunkan. Aspek utama algoritma ini adalah mengimbangi pertukaran antara masalah pengurangan kerumitan dan prestasi pembetulan ralat komponen penyahkod nod relay LDPC. Algoritma ini hanya menggunakan faktor penskalaan pengoptimuman pada pemprosesan nod bit operasi daripada nod berubah. Kaedah carian Particle Swarm Optimization (PSO) digunakan untuk mencari faktor penskalaan yang dioptimumkan untuk mendapatkan prestasi kadar kesalahan yang optimum. Sumber untuk menyalurkan saluran *di modelkan sebagai koperasi memudar yang digunakan secara meluas dalam komunikasi koperasi. Dari hasil simulasi, VGOMS mengatasi min-sum algoritma penyahkodan kod LDPC sedia ada yang terkenal, setanding dengan min-sum Normalized (NMS) dan min-sum Offset (OMS) dan hampir sama dengan algoritma Sum-Product (SP) pada SNR yang lebih tinggi dari segi kadar ralat prestasi. VGOMS juga mengatasi NMS, OMS dan SP dari segi kerumitan operasi nod cek yang menggunakan operasi penyahkodan yang paling kompleks. VGOMS telah menunjukkan kompromi yang lebih baik antara prestasi kadar ralat yang lebih baik dan kerumitan operasi pengiraan yang rendah. Kekuatiran utama kod LDPC untuk sistem relai protokol DF adalah kerumitan pengekodan yang tinggi. Oleh itu, model pengekod kod LDPC dibangunkan untuk mengenal pasti algoritma pengekodan kompleksiti rendah kod LDPC untuk sistem relay protokol DF. Dalam model ini, lapan varian kaedah pengekodan LU dan QR yang berbeza dinilai dari segi masa pelaksanaan, bilangan nombor bukan sifar, dan corak nombor bukan sifar. Model pengekod kod LDPC yang dicadangkan menunjukkan bahawa kaedah pengekodan LUPQ mencapai masa pelaksanaan terendah dan bilangan bukan sifar di antara kaedah pengekodan LU dan QR. Hasil prestasi menunjukkan bahawa LUPQ adalah yang paling sesuai untuk sistem relay protokol DF menggunakan kod LDPC kerana ia melaksanakan masa pemprosesan komponen pengekod LDPC yang rendah.*

Kata kunci: *Decode dan forward, kod LDPC, min-sum, algoritma LU, algoritma QR*

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LIST OF ABBREVIATIONS AND SYMBOLS

AF	Amplify and Forward
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BF	Bit Flipping
BP	Belief Propagation
BPSK	Binary Phase Shift Keying
β	Amplification Factor
CN	Check Node
c_i	Codeword
DF	Decode and Forward
dB	Decibel
d_c	Average Row Weight
d_v	Average Column Weight
ERC	Equal Ratio Combining
E_{ji}	Extrinsic Information From Check Node to Variable Node
FRC	Fixed Ratio Combining
gbest	Global Best
GR	Given Rotation
H	Parity Check Matrix
I	Identity Matrix
LU	Lower Upper
LUP	Lower Upper Permutation
MGS	Modified Gram Schmidt

MIMO	Multi-in Multi-out
MRC	Maximum Ratio Combining
MS	Min-Sum
M_{ij}	Sign and Magnitude Factor
NMS	Normalized Min-Sum
NNZ	Number of Nonzero
N_0	Noise Variance
OMS	Off-set Min-Sum
pbest	Local Best
PSO	Particle Swarm Optimization
P_L	Path Loss
SNR	Signal to Noise Ratio
SP	Sum-Product
SR	Selection Combining
QPSK	Quadrature Phase Shift Keying
QR	Orthogonal Upper Triangular Matrix
VCN	Variable and Check Node
VGOMS	Variable Global Optimization Min-sum
VN	Variable Node
α	Scaling Factor
v	Householder Vector
ρ	Channel Coefficient

CHAPTER 1

INTRODUCTION

This chapter presents the introduction to the cooperative communication concept. The identification of the problem statement and the research objectives are determined. The contributions of this thesis are explained and related publications are provided. Finally, the organization of the thesis is provided giving an overview of the individual chapter's contents.

1.1 Research Background

Recently, with a current worldwide estimated population of 7.8 billion, approximately 4.93 billion people which is 63.2% of the world population uses the internet. From the year 2000 to 2020, the usage of the internet increased by 1,266% [1]. This massive growth in the use of the internet and wireless communication networks industry has led to new technological development. Nowadays in modern life, cell phones, pocket PCs, and laptops are becoming more relevant. About 5.22 billion people use a mobile phone today, equating to 66.6% of the world's total population. Unique mobile users have grown by 1.8% (93 million) since January 2020, while the total number of mobile connections has increased by 72 million (0.9%) to reach a total of 8.02 billion at the start of 2021 [2]. This statistic showed that mobile phone usage keeps increasing over the years and people have become more mobile. Data transfer applications such as download information from the internet or sending a video have emerged on the mobile phone. Services such as wireless broadband internet, mobile television, gaming, and many other applications, however, have tremendous demands on higher data speeds, higher throughput, improved battery life, and more reliable communication connections (less error), yet quality of service (QoS) is guaranteed. The fifth-generation (5G) and advanced generation mobile communication require high technology internet device need such as augmented reality (AR) and virtual reality (VR), cloud-based gaming services, smart grid control, smart retail, and much more as shown in Figure 1.1.

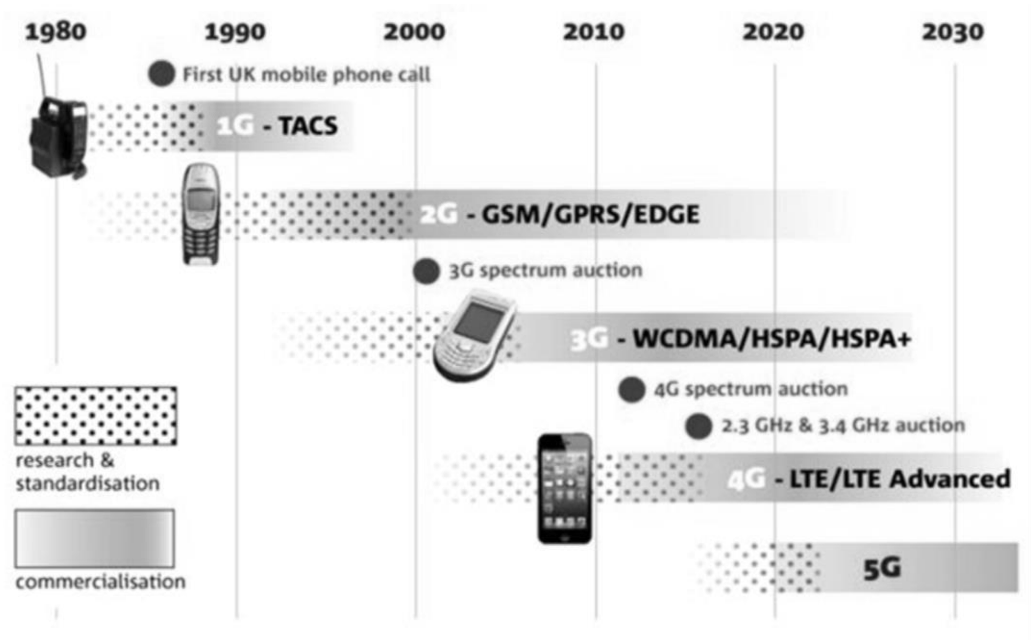


Figure 1.1: Evolution of mobile phone communication [3]

Moreover, because of the wireless system's characteristic and natural effects such as attenuation, reflection, and diffraction, the signals transmitted between transceivers often undergo enormous random fluctuations, making it difficult to build reliable networks [4].

MIMO technology has drawn a great deal of attention to the wireless environment that delivers fruitful results in low power usage and network reliability at a high data rate. It is not easy for MIMO technology to be used in small handheld devices such as mobile phones because of the small size of mobile devices as well as the high cost of MIMO hardware installation that makes the wireless agent may not be able to support multiple transmit antenna [5].

Cooperative communication has recently been suggested to address these limitations of MIMO technology [5-8]. The cooperative communication approach is creating a virtual MIMO system that allows the single wireless device to share its antennas and information with other users during transmission to gain space diversity at the destination terminal [9]. The cooperative prototype's main assumption is to see wireless nodes as a group of distributed antennas. Accordingly, terminal transmission and processing are carried out in a distributed manner, which multiple relay nodes assisting the communication between the source node and destination node terminal. Theoretically, in two different phases, a series of relays is configured to support signal transmission. Firstly, the source signal is transmitted to the destination and relays, and secondly, the signals will be transmitted to the destination after being processed. While the relays are far from the source terminal, the relaying and direct links can be separately considered as fading [10]. In certain cases, a full-rank MIMO channel is used for signals to communicate between the source and destination node's terminal. Furthermore, the signal is received from the source and relays combined at the destination terminal to gain the benefit of spatial diversity. Therefore, cooperative communication is a promising strategy that can enhance communication network efficiency, provide power-saving transmission, and extended coverage areas in shadow zones. The relay nodes assist the signal communication from the cellular user (source node) to the base station (destination node) in the cooperative communication system as shown in Figure 1.2.

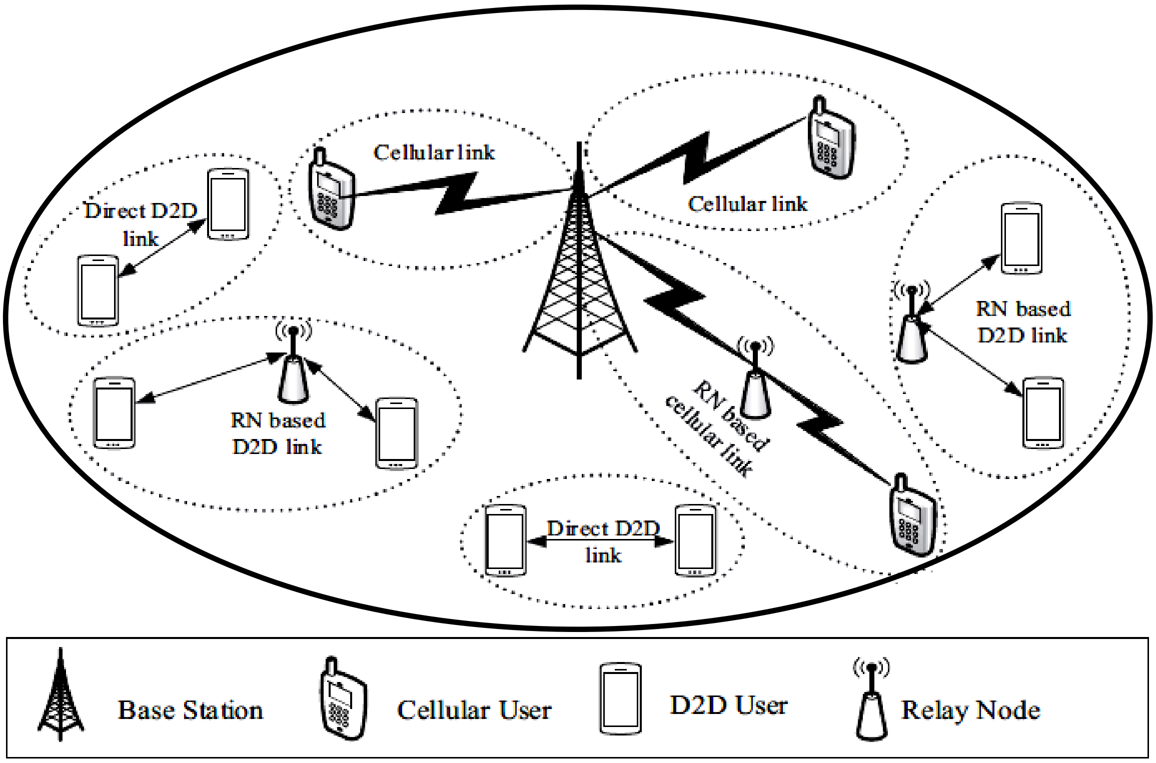


Figure 1.2: Relay assist cellular network [11]

Analysis of the theoretical knowledge attribute of the relay terminal by El Gamal and Cover (1979) in [12] will define the key thought behind the cooperative environment. The research analyzed the source, relay, and destination capacity. In cooperative communication, the data is sent from the source node to both relay and destinations node by cooperative communication and then the data that has been processed at the relay node terminal is sent to the destination. In certain scenarios, the cooperative communication environment is considered to be different from the relay system channel. El Gamal and Cover were exploring the efficiency in the AWGN channel environment. The primary function of the relay in the relay system channel is to assist the main channel, whereas users serve as both the source of information and the relay in cooperation. This thesis focuses on the cooperative relaying protocol aspects of cooperative communication.

1.2 Problem Statement

Decoding high complexity is a major problem in developing a decode and forward (DF) relay protocol in cooperative communication. Setting up a low-complexity decoding technique would, therefore, be useful in assisting DF relay protocol. Some effort is made to devise an ideal relay protocol capable of providing a significantly higher rate with low computational complexity and better error rate performance. It is, therefore, necessary to establish a system model and identify and analyze appropriate techniques for each part of the system component. Recently, LDPC codes have obtained a great deal of attention because of their superior error correction functionality. Due to this, the LDPC code is suitable to be implemented for the DF protocol relay system. Such a DF protocol relay system requires process components including modulator and demodulator, encoder and decoder, channel, and combiner.

DF protocol encounters high decoding operational complexity at the relay node and due to this, it has driven constant research effort aiming at reducing the complexity of decoding techniques at the relay node. The LDPC code decoding algorithm called the min-sum algorithm gives a less complex operation at the expense of error correction performance degradation. Efforts have been made in the min-sum algorithm to get less operational complexity and better error rate performance. Some methods in previous research in [13-16] revealed that keeping the error rate performance near to the SP algorithm with less operational complexity has the potential for practical application. Thus, more effective min-sum based methods in targeting to form the simplified version of the decoding algorithm output performance near to the SP algorithm are needed to deliver satisfying performance with minimum computational complexity. Currently, there is no min-sum based LDPC code decoding algorithm specifically for the DF protocol relay system.

One major concerning the LDPC code for the DF protocol relay system is high encoding complexity. Thus, it is important to identify a low complexity encoding algorithm of LDPC code for the DF protocol relay system. There was very limited research work published to identify a suitable LDPC code encoding algorithm for the DF protocol relay system. LU and QR encoding methods were introduced in [17-20] and [21-26] to avoid the computational complexity of multiplication by dense inverse matrix. But, the research in [17-20] and [21-26] only evaluated the performance of a single encoder method for one encoding process system. To find the lowest complexity encoding algorithm for the DF protocol relay system, it is important to investigate the performance of different encoding algorithms.

1.3 Research Hypothesis

The research hypotheses of this thesis are as follows:

a) Decode and Forward relay protocol is expected to produce a lower probability of error rate to ensure the best QoS in a cooperative communication system.

b) The low complexity LDPC code decoding method is expected to provide a good balance trade-off problem between complexity reduction and error correction performance of the DF protocol relay decoder and the error rate performance tends to be closed to ideal error rate performance at a high SNR value.

c) Identification of the lowest computational complexity of the encoder method for decode and forward protocol relay systems would result in further low computational complexity of the subsequent decoding stage of the DF protocol relay system.

1.4 Research Objectives

The research objectives of this thesis are as follows:

a) To analyze the cooperative communication system and relay protocol.

b) To propose a new model of DF protocol relay system using LDPC code to improve BER.

c) To develop a min-sum based decoding method and encoding model for the DF protocol relay system to improve BER and computational complexity with Matlab simulation.

1.5 Research Contributions

There are four major contributions to this research:

a) *Performance analysis of cooperative communication.* This thesis presents the comparative performance analysis of cooperative communication over non-cooperative communication, the two cooperative communication protocols (AF and DF protocols), and DF protocol with different relay positioning. The main contribution of this research is a better understanding of the error rate performance with AF and DF cooperative protocols. The best error rate performances achieved by either AF or DF protocols determine the choice of the cooperative protocol in this research thesis. From the analysis performance and characteristics of DF protocol, the idea DF protocol with suitable error correction code was identified. The idea is expected to produce better BER with moderate computational complexity. The error rate performance of DF protocol with different relay positions (center, near to source, and near to destination) is also determined.

b) *Model of decode and forward protocol relay system using LDPC code.* This thesis presents the new model of the decode and forward protocol relay system using the LDPC code. Each component of the system required to form the new model is identified. The established component assists to perform gap analysis in this research field. The proposed model of the DF protocol relay system is evaluated by comparing it with other existing relay protocols in terms of BER.

c) *Min-sum based LDPC code decoding algorithms.* The thesis investigates min-sum based LDPC code decoding algorithms to reduce the decoding complexity for decode and forward protocol relay systems. Next, to determine the performance and characteristics of different min-sum LDPC code decoding algorithms, an empirical analysis of the existing min-sum LDPC code decoding algorithms is carried out. Then, a new min-sum LDPC code decoding algorithm called Variable Global Optimization Min-Sum (VGOMS) is developed. The new algorithm proposed adopted a PSO technique to the existing min-sum LDPC code decoding algorithms. The comparison between the new min-sum based decoding algorithm and other existing min-sum based decoding algorithms examines to show its performance is a better compromise between error rate performance and computational complexity compared to other min-sum based existing decoding algorithms. In this thesis, the error rate performance and level of computational complexity used are analyzed. The efficient modulation technique for the decode and forward protocol (DF) based on the proposed algorithm is also identified. Besides that, the effects of the proposed algorithm under a different channel regarding BER performance are also determined.

d) *LDPC code encoder model.* This thesis provides an analysis to determine the lowest complexity encoding algorithm to be used in the LDPC code for decode and forward protocol relay systems. A simulation procedure is devised and an empirical comparison is conducted for the identification of the encoder using the proposed LDPC code encoder model. Identification of the low complexity encoder LDPC code for decode and forward protocol relay systems is extremely important. This will ensure the low complexity encoding algorithm implemented for the LDPC code based on the DF protocol relay system.

1.6 Scope of Research

This thesis covers the research about the Decode and Forward (DF) protocol relay system using LDPC code. This research would enhance the knowledge on the decoding and encoding for the DF protocol relay system where a new decoding method and encoding model will be developed over a cooperative fading channel. The development of decoding method based on low complexity min-sum decoding algorithm while the development of encoding model is based on LU and QR variants encoding algorithms. The developed method and model could minimize the computational complexity operation and improve the error rate performance of the DF protocol relay system using LDPC code. The Matlab software is used for simulating the decoding and encoding of the system.

1.7 Thesis Organization

Chapter 1 outlines the current work that includes the research background, problem statement, research objectives, research contribution, the scope of research, and thesis organization of the research.

Chapter 2 gives an overview of cooperative communication, relay protocols, and wireless channel. Then, an in-depth review of LDPC code for decode and forward protocol relay system and min-sum based LDPC decoder for the DF protocol relay system is carried out. Next, the LDPC encoder for the DF protocol relay system is discussed.

Chapter 3 describes the research methods applied in this research work. It explains the framework of research methods for modeling decode and forward protocol relay system using LDPC code followed by the development of the LDPC decoder approach and development of the LDPC code encoder model for LDPC encoder of DF protocol relay system model using LDPC code.

Chapter 4 elaborated on the results and discussions. They are divided into a few relevant sub-topics that rely on the new scientific findings and observations along with the study. This chapter critically discusses the results of the findings and elaborates on the potential proposed min-sum based LDPC decoder and LDPC encoder model for decode and forward relay systems using LDPC code.

Chapter 5 summarizes the main contribution of this thesis. Besides that, a few recommendations are also outlined for further investigation of LDPC code for decode and forward protocol relay system applications in cooperative communication.

CHAPTER 2

LITERATURE REVIEW

This chapter describes the literature review of the thesis and is divided into two key parts. The first part outlines the general concept of cooperative communication and focuses on cooperative communication protocols namely Amplify and Forward (AF) as well as Decode and Forward (DF) protocols. The fading channel in a wireless environment characteristic is also discussed.

The second part discusses the decoder and encoder components of the DF protocol relay system. The decoder component is an important component of the decode and forward protocol relay system. LDPC code is chosen as an error-correcting code for establishing a decode and forward protocol relay system. Existing work on the LDPC code based decoding approach is presented. The decoder component is the core contribution of this thesis, which a new LDPC code decoding algorithm will be developed. The review of the decoding algorithm concept enables the development of low complexity min-sum based LDPC code decoding algorithm in the next stage. The review contains the comparison of the min-sum based LDPC code decoding algorithm and each of the algorithm components described. A taxonomy of min-sum based LDPC code decoding techniques derived from the review. An overview of particle swarm optimization (PSO) and the performance evaluation measure for cooperative relaying protocol is also provided. Lastly, the review on decreasing the complexity LDPC code encoder component of the DF protocol relay system is discussed.

2.1 Introduction

Malaysian's mobile market has shown remarkable growth over the years as in

2018, there were around 17.2 million smartphone users in Malaysia. This number was projected to grow to almost 21 million in 2023 [27]. The next-generation services have since been rolled out and had started having a major impact on the market. Mobile phone usage keeps increasing over the years and people have become more mobile [28]. According to the World Bank, Malaysia leading Indonesia, Thailand, and the even United States with 140% mobile penetration which means 47% of Malaysians own more than one mobile phone. New data transfer applications such as download information from the internet or sending a video have emerged in mobile phone technology, thus demand higher throughput, high-speed data transfer capability, and less error rate [29]. In mid-2015, the total number of cellular subscriptions according to a major mobile operator in Malaysia with Celcom had the largest mobile market about 12.3 million subscribers (31.3%), followed by Maxis with 31% and then Digi with 30%. By November 2015, the number of internet users in Malaysia has reached 20.6 million [30].

The fifth-generation technologies beyond the current wireless communication networks are required to cater to a tremendous Internet of Things (IoT) era demand. Such demand includes the embedded sensor into a security system, automated door locks, health monitoring, and mobile transportation. The immediate need for IoT devices for 5G technology is expected to double to over 50 billion by the year 2020 [31]. Normally, the performance of the transmitted signal in the overall wireless system is degraded because of the wireless channel fading problem. Due to this, high throughput with a low error rate cannot be achieved. By using a diversity technique called cooperative communication, the wireless channel fading effect can be mitigating effectively. Cooperative communication is accomplished by setting up a virtual antenna system by the interaction among several antenna terminals. Cooperative communication proposed by Van Der Meulen (1971) in

[32-33] based on the relay channel concept was an efficient method for continuous improvement and mitigated all the above factors and at the same time maintaining the reliability of communications particularly for smaller and lighter devices like a mobile phone. Through design architecture, the relay acts as a virtual antenna system between the transmitter and receiver.

Cooperative communications have emerged as a considerable area of research and have become a viable option for next-generation communication systems requirements. Furthermore, various error control code techniques can be adapted to a cooperative communication environment. Sendonaris et al. (2003a), (2003b) in [34-35] was a pioneer in the area of cooperative communication. Hunter et al. (2006) in [36] introduced convolutional codes integrated into cooperative communication called coded cooperation. Further improvement on the existing works led to the development of an embedded Turbo code in the system to increase the coding gain [37]. The number of research in [38-41] was performed using the Turbo code. Then, advanced development in the channel coding technique named LDPC code takes place as an efficient solution by exploiting its superior in transferring data performance over a noisy relay channel. Among all error control codes, the LDPC code has shown great potential error-correcting codes compared to other codes as it approaches Shannon channel capacity [42-44]. LDPC code was first adopted in the relay channel by Khojastepour et al. (2004) in [44].

2.2 Cooperative Communication

The idea of user cooperative communication is usually credited in [45] to Sendonaris, Erkip, and Aazhang, but can also be recalled back to the first discovered relay channel model deployed in [32, 46] and shown in Figure 2.1. The relay system generalizes the notion of a simple point-to-point channel with a one-source terminal (transmitter) and the destination terminal (receiver) to include a relay with the sole purpose of helping to transfer information from source to destination.

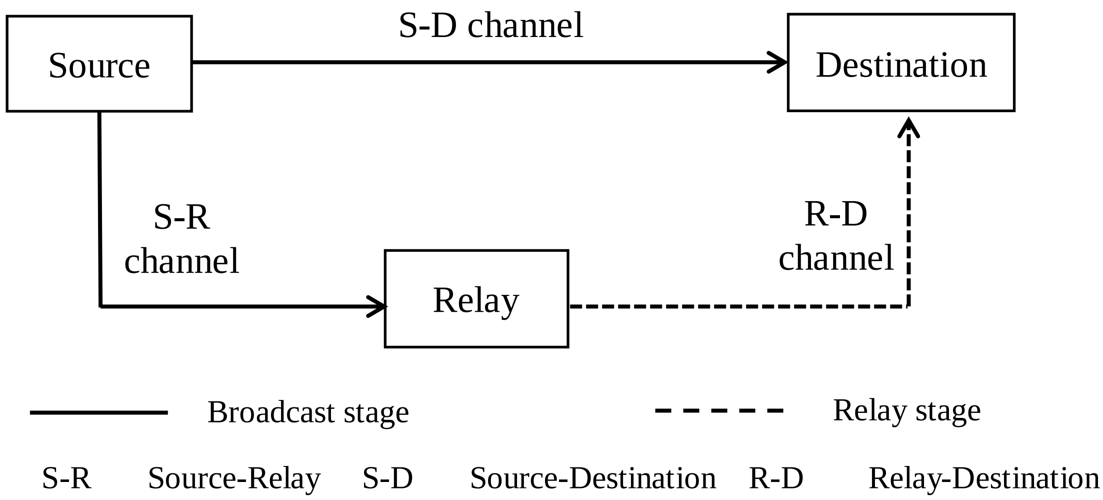


Figure 2.1: Relay channel model [46]

The relay channel was first established by Van der Meulen (1971) in [33, 46]. Cover and El Gamal (1979) in [12, 47] are credited with producing most of the relay channel's theoretical knowledge tests. The relay channel capacity was investigated under the condition of all nodes work in the same band. From this point of view, the network can be divided into the source as a broadcast channel and destination as a multiple access channel Since the presentation of [45] was at the International Symposium on Information Theory in 1998, the concept of diversity in user cooperation first captured the attention of the information theory community. Many of the concepts and findings that appeared shortly after [45] in the literature can be traced back to [12].

While the body of literature on the nature of user cooperation is now far too broad to cover completely, some selected highlights are presented here. Sendonaris, Erkip, and Aazhang (1998) in [45] followed up with a more detailed two-source theoretical information analysis on transmitting cooperation in a mobile uplink scenario in [48-49]. Sendonaris, Erkip, and Aazhang (1998) in [45] explored with a more comprehensive two-source theoretical information analysis on transmitting cooperation in a mobile uplink scenario in [48, 50]. This research was significant because it also highlighted many practical implementation issues in cooperative transmission systems and stimulated communities' interest in communication and signal processing. It is also important to analyze the effectiveness of various operational cooperative communication protocols in the fading environment as stated in [49, 51-53]. Another important series of contributions came in the form of new theoretical findings of information and new insights into the theoretical coding of information in [53]. Several relaying innovations were proposed such as LDPC code relay models, as well as some of the earliest half-duplex relaying models as stated in [54]. Researchers found that the relaying process would replicate multiple antenna systems, even though multiple antennas could not be supported by the interacting entities. Popular literature on the use of space-time relay codes is available in [51, 55-56]. Detailed theoretical characteristics and analysis for the physical layer of multihop wireless communication networks are given in [57-60].

For the most part, the literature on user cooperation diversity has focused on developing the cooperative transmission case with two sources and one destination, whereby each source node acts as a relay to other source nodes. This research line is inspired by the expectation that the fundamental findings generated for the two-source one-destination model will provide insight and propose techniques for analyzing more general network architectures. Extensions to more general network architectures have recently appeared in the literature, but the research community is still actively seeking many of the core findings for the two-source one-destination model.

2.2.1 Cooperative System Model

The advantages of cooperative communication over non-cooperative communication are described in this section. The system is modeled as a DF protocol. The node setup is shown in Figure 2.2. With the DF protocol, the relay node decodes and sends the re-encode version to the destination node. The relay node decodes the input signal from the source node in the DF protocol process and then re-encodes the decoding signal to the destination receiver node.

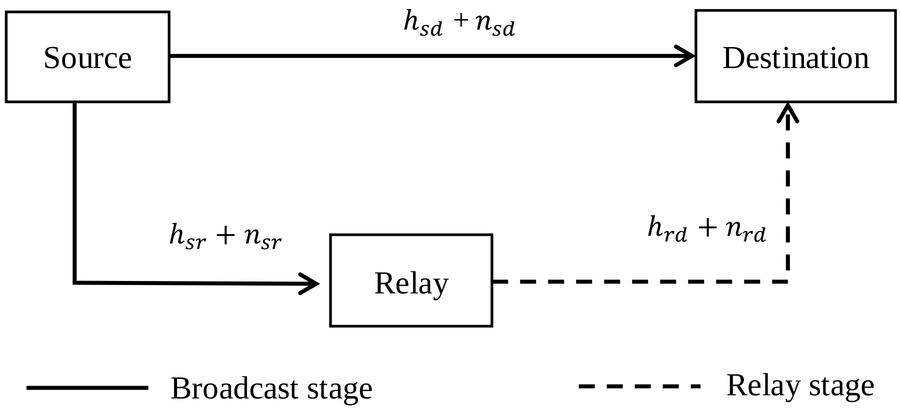


Figure 2.2: Cooperative communication system model

In this model, source to relay distance, d_{sr} and relay to the source, d_{rd} are assumed as half of the source to destination distance with the source to destination distance, $d_{sd} = 1$ and formed the $d_{sr} + d_{rd} = 1$. The data are transmitted in two stages in cooperative communication. These two stages are referred to as broadcasting and relaying stages. The source node modulates signals using BPSK. The source node sent the data to the relay and a destination node in the broadcasting stage while the relay node used the DF protocol to decode the data signal from the source node and then sent the re-encode data bits to the destination node in the relaying stage. At the destination node, a maximum ratio combining (MRC) technique is used, whereas in this technique the data received directly from the source and relay nodes are weighed equally and summed up together. At the broadcasting stage, the signal received at the destination from the source is as follows:

$$y_{sd} = x_s h_{sd} + n_{sd} \tag{2.1}$$

where, x_s is the transmitted signal, n_{sd} is the AWGN noise, h_{sd} is the channel gain assumed as Rayleigh fading and y_{sd} is the signal received at the destination node from the source node. At the relaying stage, it received a signal from the relay as follows:

$$y_{rd} = x_{rd} h_{rd} + n_{rd} \tag{2.2}$$

where x_{rd} is the transmitted signal of the relay node, h_{rd} is the channel gain assumed as Rayleigh fading, n_{rd} is the AWGN noise and y_{rd} is the signal received at the destination node from the relay node. The signal from the source and relay node are combined at the destination node for decoding or decision-making operation. The achievable bit error rate performance for cooperative and non-cooperative communication is analyzed in this simulation.

2.2.2 Comparison of Cooperative and Non-Cooperative Communication

Cooperative communication is a method introduced aimed to mitigate the fading effects. In this method, several fading variants of the signal transmitted from the source node to the destination node. Cooperative communication forms a reliable communication transmission. Generally, among all types of communications, wired communications are considered the most stable with superior speed and strength transmission. However, wired communication might also be interrupted by natural factors such as humans, earthquakes, flooding, and so on. Due to that, wireless communication technologies are designed to reduce restrictions and obstacle effects from the wired cable. Meanwhile, the quality of the signal transmission received at the destination node is different from the actual signal from the source node in wireless communication. Many factors influence this situation. Fading has become one of the factors causing the received signal quality degradation compared with the actual signal from the source node. Due to the MIMO benefits, it has become an important part of wireless communication. Even though a transmission diversity feature of MIMO communication is attractive, it is not feasible for all practical applications. For example, due to the size, hardware limitations, and cost of MIMO wireless communication, it is not able to manage multiple transmissions on a mobile phone [61].

The practical way of cooperative communication set out is to form a practical process of virtual MIMO. To realize virtual version diversity, antennas are shared and function as a relay for data communication transmission among users. On the other hand, the users transmit data directly to a specific destination receiver without the use of any protocol method to obtain original data in non-cooperative communication. The performance of the bit error rate (BER) of the cooperative over non-cooperative will be carried out using

MATLAB software to demonstrate and evaluate their performances.

2.2.3 Cooperative Transmission Protocols

The two main classifications of cooperative relay protocols in cooperative communication are Amplify and Forward (AF) or Decode and Forward (DF). These cooperative relay protocols represent relay terminal activity and indicate what activities are being done at the relay terminal before the information data transmitted to the destination terminal.

2.2.3.1 Amplify and Forward (AF)

AF protocol employed in the situation relay has limited power and time; hence, avoiding delay when the DF protocol operates at the relay terminal. AF protocol is a simple approach to cooperative relay protocol because the received signal from the source at the relay terminal was degraded and has to be amplified before being sent to the destination terminal. At the same time, the signal noise is also amplified which is the limitation of this protocol.

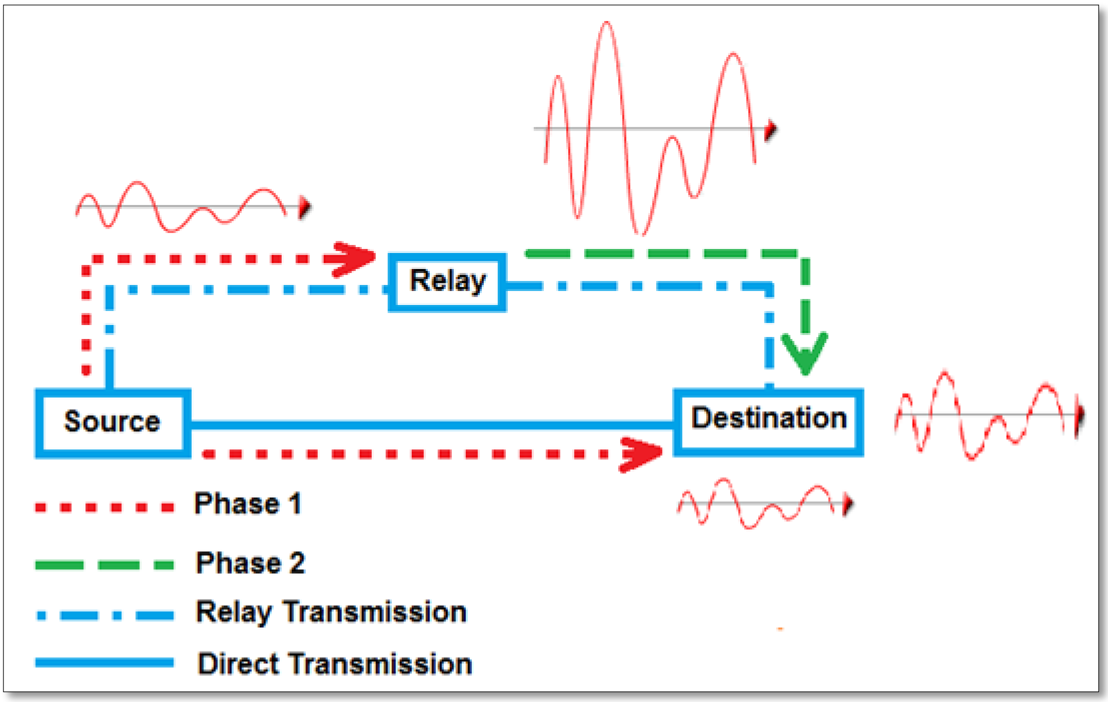


Figure 2.3: Amplify and forward protocol [62]

The cooperative communication process using the AF protocol transmits signals into two phases as illustrated in Figure 2.3. In the first phase, source data information transmits to the relay node and destination node. In the second phase, the distorted signal received from the source by the relay is amplified before it transmits to the destination. The incoming signal amplification process is employed block-wise.

In the first phase, the source transmits its data signal to the relay and destination and source to destination, y_{sd} and source to relay, y_{sr} the received signal are expressed as:

$$y_{sd} = \sqrt{P_1 h_{sd}}.x + n_{sd} \tag{2.3}$$

$$y_{sr} = \sqrt{P_1 h_{sr}}.x + n_{sr} \tag{2.4}$$

where P_1 is the source transmitted power, x is an information symbol transmitted. Source to destination channel gain denote as h_{sd} while source to relay channel gain denotes as h_{sr}. Noise terms, n_{sd}, n_{sr}, and n_{rd} which are considered as n are designed and developed as complex gaussian random variable zero mean.

In the second phase, the relay amplifies the distorted version of the signal transmitted from the source and by using the power P_2, the signal received by the relay transmits to the destination. y_{rd} is the received signal from the relay to the destination. h_{rd} is the relay to the destination channel gain.

$$y_{rd} = \beta h_{rd}.y_{sr} + n_{rd} \tag{2.5}$$

where $\beta = \sqrt{\frac{P_2}{P_1|h_{sr}|^2+N_0}}$

and N_0 is the noise variance and connected to the source to relay the transmission path.

$$y_{rd} = \sqrt{\frac{P_1P_2}{P_1|h_{sr}|^2+N_0}}h_{rd}h_{sr}x + n_{rd} \tag{2.6}$$

AF protocol advantages are the destination terminal received two versions of the fading signal so that it can make a good choice from the detection information signal received. This strategy forms the two diversity orders which are the best result at high SNR chosen. The protocol implementation is very easy and cost-effective, there is no delay in this case and less computing power is used. This protocol's drawback is that noise amplification happens at the relay time. Often, noise is amplified at relay along with signal which is not desirable.

2.2.3.2 Decode and Forward (DF)

The transmission mechanism and the network system model of DF protocol are just like AF protocol. The difference between the DF protocol from the AF protocol is the relay node operation. Relay station simply decodes the received signal and then re-encodes the information which is sent to the destination. The relay node of the DF protocol will decode and re-encode the received signal from the source node and then forward it to the destination node.

For DF protocol, the relay node decodes the distorted version of the signal transmission from the source by using a simple decoding method such as cyclic redundancy check (CRC) to get the y_{DF} and by using the power P_2, the signal received by the relay transmits to the destination. The signal transmitted from relay to destination denotes as y_{rd}. The signal transmitted from relay to destination denotes as y_{rd}. The relay to destination channel gain denotes as h_{rd}.

$$y_{rd} = \sqrt{P_2} h_{rd} . y_{DF} + n_{rd} \tag{2.7}$$

If the relay consumes much computational operation time and power, the DF protocol is desirable. If there are errors in the data signal at the receiving point of the communication system, the errors can be reduced to achieve correct information at the destination by the use of a variety of methods including automatic repeat request, repletion coding methods, and forward error correction. The errors that occurred by the destructive effects of the channel can be decoded and corrected by employing a forward error correction method. An automatic repeat request (ARQ) operates whenever an error is found at the receiver terminal and not correctable, automatically the system requests a new signal. It sends a request to the transmitter to resend that symbol block. In the repletion coding technique, the block codes are sending several times. Then, by comparing the corresponding block bits, the error can be detected and autonomously corrected. This reduces the effective data rate significantly.

For AF protocol, if the received information contains noise, the signal is also amplified and this makes the received signal getting worst, hence, it is discarded at the relay station. Compared with the AF protocol, the DF protocol has no issue regarding the noise amplification problem. DF protocol uses error-correcting techniques to achieve correct information at the destination. However, the relay node decoding operation using the error correction method increases the computational complexity. This is because the whole signal from the source must be decoded and encoded before transmitting to the destination. To form a low computational complexity of DF protocol, a low computational complexity decoding system methods solution is required. Figure 2.4 illustrates the operational structure of the DF relaying protocol used in the cooperative communication system.

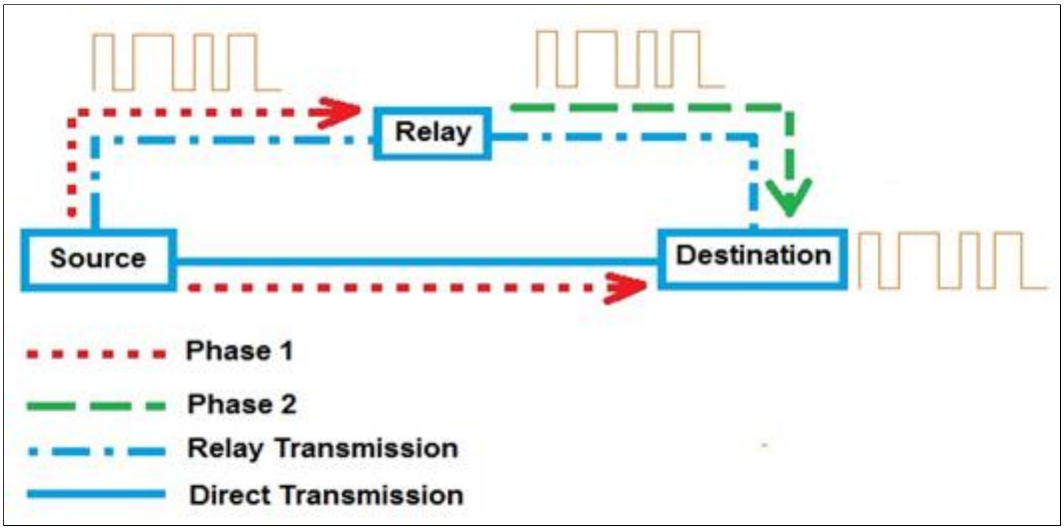


Figure 2.4: Decode and forward protocol [62]

2.3 Fading in Wireless Environment

The antenna transmission spreads electromagnetic wave radiation and the scattering, reflection, absorption, diffraction, and refraction effects occur when it passes by free space. These effects happen because of the surrounding environment, land area, and surrounding objects such as hills, trees, buildings and bridges, and many more. The received signal characteristic feature is determined by all of these physical effects.

In most, wireless mobile networks, the mobile transmitter is lower than the nearby building structure. Because of that, the direct or line of sight connection between transmitter and receiver is impossible propagation occurred in those cases usually because of diffraction, scattering, and reflection effect from the building. Multi-path transmission situations varying in time delays occurred when the signal is transmitted to the destination via several paths.

At the destination, random distributed amplitude and phases of these multi-path signals combine and produce fluctuates in the time and space of the output signal. The short gap location between one destination receiver to another destination receiver is different in signal due to the phase relation difference between the electromagnetic waves. This leads to significant changes in the signal amplitude. At the destination terminal, the effect of the random fluctuations is called fading occurred. The small scale fading named as the short-term amplitude fluctuation by the multipath information signal produced signal which detected about half in wavelength. Under other conditions, the large-scale fading is considered as a long-term fluctuation in the signal frequency average value. In the signal path between the transmitter and receiver destination, large differences happen from the signal going through the long distances. Large scale fading is also described as the shadowing effect due to the mobile unit pass through the shadow of the surrounding objects includes hills, trees, and buildings that generate fluctuation in signal frequency average. In a bad situation, the multipath effect causes the passing signal receiver to encounter several fades in a very short duration of time and causes the moving vehicle to stop at the heavily fading signal point. In that situation, the major concern is to maintain good signal communication.

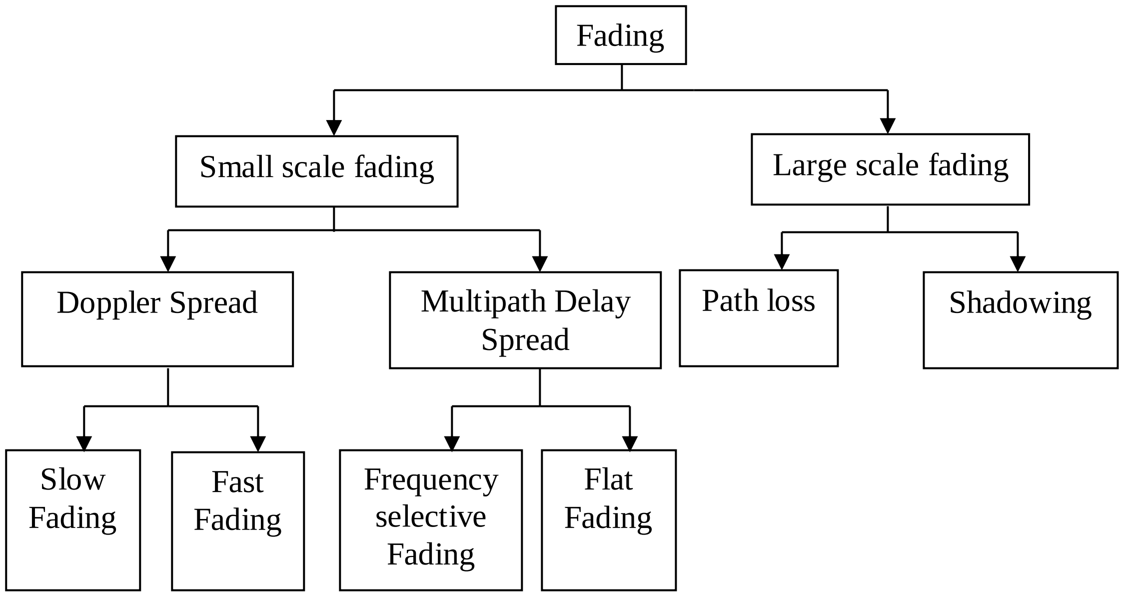


Figure 2.5: Types of fading in wireless communication [63]

Slow or fast fading and selective flat or frequency are considered small-scale fading as shown in Figure 2.5. The flat fading occurred at the destination received signal when the constant gain and the bandwidth linear phase response are larger than the bandwidth signal transmitted in the mobile radio channel system. In this scenario, multipath occurred when the amplitude fluctuation presents in channel gain over time in the transmission signal. Nevertheless, the functional features of the signal transmitted at the destination receiver remain unchanged. The selective frequency fading occurred at the destination received signal when the constant gain and the bandwidth linear phase response is less than the bandwidth signal transmitted in the mobile radio channel system. In this condition, the attenuation, time delay, and various versions of the transmission signal produce the distortion and dispersion at the destination received signal. The time dispersion occurred throughout the signal symbol channel. The inter-symbol interference (ISI) occurred from this variation in time delay.

Doppler spread occurred when a relative motion happens from the transmitter to the receiver in the range of signal transmission and produces the frequency dispersion. In fast fading mode, the signal frequency varied quickly and the doppler's distribution is significant relative to the signal bandwidth transmission. This type of fading usually occurs at very low rates of data. Contrarily, in slow fading mode, the bandwidth of the baseband signal is more than the Doppler distribution channel.

Throughout this thesis, the commonly used model in most of the wireless system communication without any line of sight from transmitter to the destination receiver path called frequency flat Rayleigh fading is employed. An AWGN model with zero mean and variance σ^2 is the channel gain used in this thesis to simulate channel background noise.

2.3.1 Large Scale Fading

Large scale fading indicates the path loss between the transmitter and receiver caused by a large object such as houses, hills, buildings, and so on. This type of fading happens when the mobile transmitter or receiver travels a long distance which contributes to the rapid fluctuations in the range of the received signal. Large-scale fading occurs in urban, outdoor-to-indoor, and indoor areas in mobile communications that include shadowing and path loss effects.

2.3.1.1 Path Loss

An electromagnetic signal transmits to the receiver in the point-to-point network of wireless communication. The signal attenuation occurred when the signal travels through the wireless channel. Once the distance of the transmission signal increases, the signal becomes weaker. The repeater and amplifier are needed to improve the signal periodically when the bad attenuation of the signal occurred over the distance limit. When the distance from the transmitter to the receiver varied, these signal problems become more complicated [64]. The signal strength loss value relative to the signal transmission distance is determined by the ratio of the transmit power P_t, to the receiving power, P_r defined by [65]:

$$P_L = \frac{P_t}{P_r} \tag{2.8}$$

The path loss effect is determined by the ratio Equation (2.8). The path loss also may be influenced by environmental situations such as rural or urban areas, transmission medium whether in moist or dry air, land shape, the antenna position, transmitter to receiver distance, and other related factors. The path loss is commonly expressed in decibels by:

$$P_L(dB) = 10\log_{10}\frac{P_t}{P_r} \tag{2.9}$$

There are few models of path loss such as log-normal, free space, and two ray models. The area from the transmitter to the receiver is assumed to be free from all objects which are capable of reflecting and absorbing the power. It is also assumed that the atmosphere is a non-absorbing medium and the value of refection is so small.

The reference distance value for indoor channels, large cellular radio cells, and microcells are 1 m, 100 m, and 1km respectively. The propagation environment, antenna position, and signal frequency propagation are the factors that influence the path loss exponent, n. If there are obstacles from the transmitter to the receiver, the value of n can be exceeding 2. The path loss in different kinds of environments is illustrated in Table 2.1 [66].

Table 2.1: The path loss exponents in different environments [66]

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

2.3.1.2 Free Space Path Loss

The line of sight path across free space with no surrounding objects causing diffraction and reflection of an electromagnetic wave loss of signal strength and this phenomenon is called the free space path loss. The other factor such as the transmitter and receiver antenna gain and any hardware defect loss is not included.

The free space path loss represents the ratio of the radiated power to the received antenna power in decibels with 10 times the log ratio.

2.3.1.3 Shadowing

Shadowing occurred by the large object blocking the signal transmission direction path. These large objects refer to objects such as large buildings, hills, and mountains. The time taken for a moving receiver to pass these objects is referred to as the “slow fading” condition. The log-normal distribution of mean signal strength is the statistical model used to represent the shadowing effect.

2.3.2 Small Scale Fading

In small-scale fading, the signal phase and amplitude rapid fluctuation occurred when the signal travels over a distance in the range of the wavelength. Many models depict the fading phenomenon of small-scale fading and the most commonly used models are AWGN, Ricean, Nakagami, and Rayleigh fading.

2.3.2.1 Rayleigh Fading

Rayleigh fading happens when there is no single dominant path such as a line of sight and multiple indirect paths that exist between transmitters and receivers. This type of fading represents a worst-case scenario and can also be used in difficult environments such as urban areas. The Rayleigh fading is mainly caused by multipath transmission. Rayleigh fading is a statistical model that affects a propagation environment for a radio signal. This type of fading model for the signal transmission at ionospheres and troposphere and also heavily built-up urban affects the radio signal. When there is no line of sight condition from the transmitter to the receiver, the Rayleigh fading is most applicable to be used.

2.3.2.2 Ricean Fading

Ricean fading represents the situation when the line of sight is present and the direct path is usually the main component that enters deeper fade as opposed to the multipath component. This type of fading is applicable in smaller cells, outdoor and indoor environments. The channels can be defined as follows by a parameter K:

$$\mathrm{K} = \frac{\text{dominant path power}}{\text{scattered paths power}} \tag{2.10}$$

If K=0, the channel is in Rayleigh fading condition with the numerator is equals to zero, and if K= ∞, the channel is in AWGN with a denominator equal to zero [64]. The only difference between Ricean fading from the Rayleigh fading model is it has a strong dominant component. This dominant feature is known as the line of sight (LOS) component.

2.3.2.3 Additive White Gaussian Noise (AWGN)

The physical channel thermal noise, electronics device thermal noise is the limitation of the signal transmission in this channel. White noise is a constant spectral density and Gaussian amplitude adds to the transmission signal and this degraded the signal in the AWGN channel. AWGN is used as a standard channel that performs the basic communication channel model. The AWGN is used for the signal to propagate and simulate channel background noise as illustrated in Figure 2.6. The mathematical expression is in the received signal, the received signal's mathematical expression, $r(t)$ is:

$$r(t) = s(t) + n(t) \tag{2.11}$$

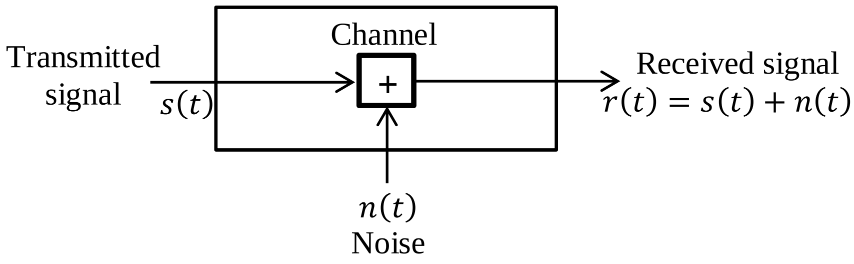


Figure 2.6: The block diagram of the AWGN channel [67]

$s(t)$ is transmitted signal through the AWGN channel and *n(t)* is the background noise. The received signal is obtained by the combination of both the $s(t)$ and *n(t)*.

2.3.2.4 Nakagami Fading

Because the Nakagami fading can model a wider class of fading channel conditions and empirical data well match, this fading is getting much consideration. This type of fading also gained a lot of interest in physical fading radio channel modeling. Nakagami fading can model the fading situation from the worst to the average condition.

2.4 Existing LDPC Code Based Decoding Approach

Md. Noor-A-Rahim et al. (2016) in [68] developed a binary input relay code based on Spatially Coupled Low Density Parity Check (SC-LDPC) under AWGN paths. The newly-devised code reflected an analysis of low complexity density evolution by weighing in the varied nodes that have gone through non-uniform SNRs. Besides, to optimize the new code, a non-intricate optimization step was performed before implementation in the relay for a system that comprised a half-duplex relay.

On the other hand, a decoding structure alteration was carried out by Sreemohan et al. (2017) in [69] for varied and check node architectures based on the implementation of min-sum meant for Field Programmable Gate Array (FPGA). The varied node architecture manipulated the 4-bit quantized node data to minimize overflow errors, whereas the check node enhanced the lost performance for the actual min-sum algorithm. As such, the use of hardware resources was decreased due to the multiplexed storage structure of the node data.

Meanwhile, Lee et al. (2017) in [70] asserted the significance of transferring the initial minimum value within the check node into the memory of a variable node for complete removal in the altered min-sum. This purported notion should occur at the recovery of the check node to that of the variable that requires the initial minimum value, whereby a value deduced from the stored second minimum is applied. If the values of the second minimum exceed the threshold of one that is pre-determined, a minor nonzero positive value is used to refer to the first minimum value, but zero if otherwise. Moreover, the integer is represented by an algorithm developed for first and second minimum values that employed 4-bit quantization, where 1-bit quantization for fractional. This particular algorithm has been applied in the CMOS application.

Next, optimized offset and scaling values for LDPC decoders had been investigated by Seho et al. (2017) in [71] based on 3.0 LDPC codes of Advanced Television Systems Committee (ATSC) via elaborated simulation using a computer. It was reported that although slightly higher intricacy was noted for offset min-sum when compared to normalized in-sum and the actual min-sum, it offered exceptional and stable coding performance.

Meanwhile, the Adaptive Forced Convergence (AFC) algorithm was developed by Jeong Hyeon et al. (2017) in [72] to decrease computational intricacy amidst check nodes by employing a sole value in its adaptive threshold. Besides, this algorithm of AFC applied the function of the altered check node and adjacent variable nodes to disable check nodes. Therefore, by eliminating the threshold value of the check node, the AFC decreased all computational complexity of check nodes and variable nodes. Furthermore, the number of disabled variable nodes appeared to increase rapidly when the threshold value of the variable nodes was lowered by the AFC.

Additionally, Scholl et al. (2016) in [73] developed a novel hybrid technique by amalgamating a conventional min-sum decoder that was enhanced through a scheme of advanced decoding, which is called 'improved saturated min-sum decoding' that served as an 'afterburner' solely to improvise the rate of frame error. The proposed method only functioned upon failure of the decoder, thus greatly decreased its level of intricacy. Parallel and serial architectures for the proposed method have been employed in the Application Specific Integrated Circuit (ASIC), where no impact was noted on the performance of communication, but the architectures did affect area latency and efficiency. Liyuan Song et al. (2016) in [74] proposed the Set Min-Sum (SMS) decoding algorithm to reduce complexity in the decoding of non-binary LDPC codes by setting partition. As for the enhanced check node in the algorithm, partitioned sets of input vectors ensured that the varied components in the virtual matrix have mixed computational stratagems. Thus, exceptional computational efficiency was displayed by the algorithm proposed via strategies devised based on accurate probabilities for the components. The outcomes of the simulation showed a reduction in check node intricacy and a slump in its performance.

A low complex min-sum algorithm, which was developed by Michaelraj et al. (2016) in [75] to decode non-regular LDPC, displayed vital enhancement in correcting errors without complicating its hardware, especially by applying both optimized and adaptive normalization factors for log-likelihood and extrinsic information ratio data bits, respectively. The proposed algorithm employed a non-uniform 6-bit quantization scheme to decrease the effects of the finite length of words on high-precision soft information. The employed quantization scheme led to reduced hardware complexity by minimizing the storage of memory blocks that kept intrinsic data, thus decreasing access of memory for data in bits per iteration.

Besides, Chen et al. (2016) in [76] designed a new partially stopped probabilistic min-sum algorithm (PS-PMSA) to reduce power consumption in check node units. This PS-PMSA managed to eliminate unimportant data in variable nodes to decrease check node computation with insignificant degrading correction of errors and reduced overhead area. The PS-PMSA performs exceptionally with parity check equation (PCE), a viable scheme that discards convergent iterations.

Next, a Multiple Codeword Flooded min-sum decoding method was developed by Sergiu et al. (2016) in [77] to process data from varied codewords via parallel processing unit; check, and variable nodes. The number of variable nodes is equal to the number of columns used in the base matrix. Then, this variable node multiplied with the number of codewords processed whereas the number of check nodes is equivalent to the number of rows with the same condition. Furthermore, the employment of the designed decoding system will increase the Block RAM (BRAM) memory usage and the decoding throughput.

Also, Kang et al. (2016) in [78] proposed the Generalized Mutual Information (GMI) based metric for scaling search in Flooding Structure Variable Min-Sum (FS-VMS) based on two concepts; 1) the scaling factors differ by varied iterations, and 2) the scaling factors differ by varied check nodes with degrees. The scaling factor search for the Horizontal Shuffled Structure Variable Min-Sum (HSS VMS) based on the Quasi Cyclic LDPC (QC-LDPC) structure is used by GMI-based metric in FS VMS scaling search. Upon weighing in the special and simple structure of QC, as well as the HSS features for parallel function, the identically independently distributed (i.i.d) assumption was redefined for every parallel function in HSS VMS. Besides, the improvised GMI was proposed in the HSS VMS parallel degree, which is similar to and larger than the cyclic block stage of QC-LDPC based on scaling search formulas.

Florence (2016) in [79] developed a mutual data-driven rule for the scaling factor between the extrinsic elements to determine the reliability aspect for LLR. The variable scaling factors were modified for both mutual data and check node degrees. The probability of mutual data between the extrinsic elements was applied as an early halting criterion or to send data back to the transmitter through the feedback path. Moreover, this approach can be used for many purposes, for example, to protect transmission. The suggested approach appeared to offer improved yields for BER and significantly decreased the iterations.

Shijie et al. (2018) in [80] developed a Serial Reliability-Based Iterative Min-Sum decoding (RBI-MSD) method for LDPC-coded MLC flash memory systems to obtain the necessary trade-off between complexity and performance. Hence, towards improvising error performance, as well as accelerating serial RBI-MSD algorithm convergence speed, the new LLR distribution based on the non-uniform quantization technique was introduced. This particular non-uniform quantization method greatly utilizes the dispersion features of the Multi-Level Cell (MLC) flash memory path initial LLRs. The outcomes of the simulation showed that the suggested technique displayed exceptional error performance, and it could be applied in other RBI decoding algorithms. Besides, the excellent convergence speed seems attractive for applications of future NAND-flash-memory.

Next, Thien Truong et al. (2018) in [81] developed a technique called non-surjective finite alphabet iterative decoders (NS-FAIDs) to take advantage of an efficient data passing process of LDPC decoder in 2017. This is also to solve the inaccurate calculation of the data exchanged to produce an integrated model for certain published design methods in the literature. NS-FAIDs method has been designed for both irregular and regular LDPC codes and optimized using density evolution. It also provides better error correction decoding performance with moderate hardware complexity. Besides, to escalate throughput, two hardware architectures were applied to increase hardware parallelism and pipelining. The NS-FAID and MS decoding method components have been integrated into two architectures. The results of ASIC synthesis displayed improved efficacy of the NS-FAID method for throughput and area when compared to MS decoder, along with insignificant degradation for performance in decoding.

Ghanaatian et al. (2018) in [82] proposed an unrolled full-parallel architecture for check and variable nodes serial transfer of decoding data, to enable ultra-high throughput for the application of LDPC decoders for huge node degrees codes by minimizing wires for interconnection. The finite alphabet LDPC code decoding algorithm was applied to decrease the required bit width quantization. It is also to increase the throughput of the system which is restricted for the suggested architecture serial data transmission. The implementation of the proposed algorithm was carried out through the use of LUTs, rather than VNs adders, whereas the CNs had been maintained without any changes, in comparison to the decoding of MS. The serial message-transfer decoder that is based on LUT provides more area efficiency and higher throughput, as well as twice the energy efficiency when compared to serial data-transfer architecture with MS decoder. Besides, the proposed algorithm adopted the linear floor plan to be applied for the architecture of unrolled full-parallel, including a pseudo hierarchical flow that is efficient, which permits the application of high-speed physical for the proposed decoder. Through the integration of the above-mentioned methods, the proposed approach offers the most rapid routed and completely placed LDPC decoder within the literature.

2.5 LDPC Solution for Future Decode and Forward Relay Protocol

The choice of appropriate error control code is an important part to overcome the decoding problem at the relay terminal in the DF relay protocol [83]**.** There is no specific coding technique that suits all problems. The factors such as decoding complexity, coding gain, code rate, maximum block length, and BER will influence the best coding technique solution. Turbo code forward error correction (FEC) method works better than the convolution code less or equal to ½ and convolutional block code. However, at high code rates, large information length LDPC codes achieve better performance than Turbo codes. Table 2.2 indicates the comparison of error control code performance throughout the years. In 1963, Robert Gallager developed a linear block error correction code called LDPC code [84]. Nevertheless, LDPC codes have not gained the researcher's attention after 30 years. This is due to the poor execution in the performance in the microelectronics field technology during that range period. However, Mackey and Neal (1996) in [85] rediscovered the LDPC codes since the current demand of modern communications to run very near to the Shannon maximum theoretical limit of the channel capacity [86].

The parallel implementation and lower computational complexity of the LDPC decoding algorithm for long block codes have attracted significant attention from many researchers [87]. This makes it a suitable candidate to be used in most hardware products compared with other error control coding, especially turbo code. The large degree of parallelism of the LDPC code can be exploited in the decoder operation to perform excellent performance. The LDPC code can also be designed at any rate and block length and good for high rates applications. In contrast, turbo codes are typically modified using a puncturing scheme which needs a further design step. Interleaved are not required in the LDPC encoder and decoder operations. A single LDPC code can be universally good for a group of channels. In particular, decoding the LDPC code using the sum-product algorithm of belief propagation consumes a less complex operation than using the BCJR algorithm to decode turbo code. Inherently, in the LDPC decoders test operation, if a codeword satisfying the test equations was found, the decoding is stated as a failure. While in turbo decoders, the additional operation needs to perform to determine the stopping criterion. The operation is not stopped if the decoding result corresponds to a codeword that does not satisfy the test equations.

Table 2.2: Performance comparison of error control coding over the years [88]

Error Control Code	BCH	Turbo	LDPC
Year	1959	1993	1996 and beyond
Code Rate	1/6, 1/4 (Low)	1/3, 1/2 (Medium)	2/3, 3/4 (High)
BER	10^{-3} (Poor)	10^{-6} (Good)	10^{-8} (Very Good)
Decoding Complexity	Average	High	Low

LDPC decoding algorithm which is also well designed, with a belief propagation algorithm can have almost error-free, making it an attractive choice to support most hardware applications. Recently, LDPC codes [88] were adopted in numerous applications include mobile communication, Digital Video Broadcasting, space and satellite communications, Worldwide Interoperability for Microwave Access (WiMAX), optical communication as well as storage systems such as hard disk drives and compact disk.

2.6 Towards Low Complexity of LDPC Code Based Decoding for DF Protocol

Relaying protocol is the fundamental structure of the cooperative communication system. Relay node performs two main kinds of message forwarding strategy which can be grouped as regenerative and non-regenerative that depends on the applied signal processing method. Amplify and Forward (AF) are the most widely used non-regenerative protocol but the signal transmitted by a relay to the destination receiver still has the noise error. Another basic commonly used protocol is the regenerative protocol called Decode and Forward (DF) which in this protocol, the signal transmitted to the relay decode and re-encode, and the output signal of the relay will be transmitted to the destination receiver.

Normally, DF can obtain better performance than AF if designed appropriately at the cost of higher complexity. DF can obtain coding gain and diversity gain in its operation. As DF is the most practical relay approach, DF has obtained much consideration to be used in cooperative communications applications nowadays. Error control code technique can be applied as a decoding method for the DF protocol relay system. The most potential coding technique with good error correction performance for the DF protocol at the relay node was shown by the LDPC code.

There has been little effort to formulate an ideal relay protocol that could be significantly provided a higher rate, low computational complexity, and better error performance. The Hungarian Algorithm was developed by Abrar et al. (2014) in [89] by using the new low-intricate iterative Resource Block (RB)-pairing, as well as a scheme of a provision that leads to low computational intricacy, hence making it adequate to solve issues related to optimization in networks of the relay. Moreover, a genetic algorithm was developed by Nouh et al. (2013) in [90] to decode codes with systematic block, to gain low intricacy for decoding threshold, as well as via polynomial encoding for cyclic codes. There are many work publication which has presented methods for the DF protocol coding approach. Existing work publications in [83, 91-92] use some of the components, only specify the use of LDPC code in decoding operation. A comprehensive system model utilizing the LDPC code for the DF relay protocol is proposed in this thesis. The detailed description of the proposed model will be further explained in the research methodology section. The development of this model is necessary to help understand how each component of the entire process should go together, thus it is crucial to gather the requirement of the system, identify internal factors influencing the system as well as visualize the interaction among the required components.

Given the impact of decoding algorithm in DF protocol relay in reducing error rate performance by using error correction method, obviously that there is a need for a proper analysis for low complexity DF protocol relay model application based on LDPC code decoding algorithm. Research should attempt to explore new low complexity LDPC code decoding at the relay node called the min-sum decoding algorithm. Next, the investigation and discussion on the min-sum low complexity decoding algorithm will be presented.

2.7 Min-Sum Based LDPC Decoder for DF Protocol Relay System Using LDPC Code

Decrease of decoding complexity at relay for Decode and Forward relay channel is particularly important since there are usually stricter hardware and power constraints at the relay. There are still concerns that excessive delay due to decoding high codes at the relay node leads to an increased delay of the destination receiver node operation. This has driven constant research efforts aiming at reducing the complexity of decoding techniques at the relay. The low hardware complexity LDPC code decoding algorithm named as min-sum algorithm operates at the expense of error rate performance deterioration. To reduce error rate performance and also operate with reasonable complexity of the decoding process, improvements have been made in the min-sum algorithm. Various methods are desirable for practical application and try to retain the output performance near to the SP algorithm with less hardware complexity operation as presented in previous research. Therefore, to provide performance fulfilled with minimal computational complexity, more efficient min-sum based methods are purposely needed to put the simplified form of the min-sum based algorithm near the output performance to the SP algorithm.

The developments of the LDPC code based on the decode and forward protocol relay model would provide an objective measure for the decode and forward protocol relay in terms of low computational decoding complexity. The utilization of the min-sum algorithm as the decoding algorithm significantly can reduce the operational complexity of the DF protocol. Although the development of the LDPC code-based decode and forward protocol relay model using the min-sum decoding method is still in its infancy. There is still limited research published about the use of min-sum decoding for decode and forward protocol relay applications. Some of the published work describes the promising technique to represent low complexity decoding performance implementation with an acceptable error correction rate [93]. The major improvement consideration is the technique employed to execute the system model. The result of the min-sum based algorithm revealed its potential to exhibit less computational complexity with acceptable error correction performance. Therefore, replication research is needed to support the existing findings.

In the following subsection, the comparison of the existing min-sum based LDPC decoding system in terms of the Variable and Check Node (VCN) operation, performances, and data used are further described. More evaluations of the low complexity min-sum decoding algorithm at the Variable and Check Node (VCN) operation part are worth to be considered for producing the low complexity and reliable implementation decoding algorithm for DF protocol at the relay node.

2.8 Comparison of Min-Sum Based LDPC Decoding System

The development of a min-sum based decoding system method would contribute to the objective measurement in reducing the decoding complexity with considerable error performance. The comparison review of published works results on min-sum based LDPC code decoding techniques shows the lack and advantages of the employed method revealed feature configuration.

The existing min-sum decoding system performance comparison is presented in Table 2.3. From the information given in published work, the modulation, channel types, the number of iteration, and parity check for the data used group are added. The technique performed in the work publication of the min-sum decoding is added in the variable and check node (VCN) operation methods group. While the measurement was given in the work publication of min-sum decoding, inserted energy consumption, operational complexity, error rate performance, throughput, and coding gain for the performance result group are inserted.

Fabian et al. (2014) in [94] have analyzed the low complexity characteristics in min-sum decoding which saved 32 comparators maintaining the same error performance. The input message data is classified into two categories referred to as odd and even for exhaustive comparison. Yin et al. (2014) in [95] achieved low complexity by a metric called Generalized Mutual Information (GMI), the variable scaling factor is determined according to the degree of the check node and in a single-dimensional iteration. While in Wang et al. (2013) in [96], the variable and symbol combination set performed individually to reduce the search space in the check node (CN) processing and saved around 60% to 70% of computations. A study by Cheng et al. (2014) in [97] reiterated that it requires 51% fewer comparators with a loss of 0.05dB error performance that applied minimum value finder (MVF) which is the three structure decoding by taking out the connection units and a suitable normalization factor to enhance the error performance. Tsatsaragkos et al. (2015) in [98] utilized up to 25% fewer comparators also needed less than 14 iterations for a maximum of 30 iterations by partitioning and minimum identification of approximation process, Meng et al. (2014) in [93] performed a uniform quantization with channel likelihood and information transmission between check nodes and variables nodes, Nguyen et al. (2012) in [16] used early stopping node which reduced the number of iteration and decreased computation processing 5 times using BPSK and 10 times using QPSK compared with a conventional method. Emran et al. (2014) in [99] performed the scaling factor graph measurement at the stair graph with constant horizontal step, S and it only needed 0.08 to 0.24dB greater than SP algorithm along with further low complexity operation. The value of the scaling factor is obtained which is a simple implementation and in exponential function based. Jung et al. (2014) in [100] performed low complexity architecture by combining variable and check node operation with just one multiplier that operated in the early process, used in the next iterative processing part. During initial process, received LLR multiplied by the scaling factor before iterative decoding while during iterative process the extrinsic information multiplied by the scaling factor in each of the iteration.

Although the available research on min-sum for relay channels is still limited, min-sum based decoding is an ideal choice concerning decode error rate performance and computational implementation complexity [93]. The method used to implement the system is the main consideration taken for the improvement. The result of the decoding performance revealed the capability of the min-sum based algorithm to exhibit less computational complexity with acceptable error correction performance. Therefore, similar researches are required to validate the observation results, especially for relay channel application. The proposed taxonomy for the min-sum based LDPC decoding technique is summarized in Figure 2.7. The taxonomy is based on the elements of existing min-sum techniques as presented in Table 2.3. In the taxonomy, the min-sum based LDPC decoding is classified based on their data used, performances, and the variable and check node (VCN) operation. The important part of this review is conducted in this taxonomy, since it demonstrates the important component achieved by scholars, followed by investigating the characteristics and requirements for designing low complexity and error rate performance min-sum decoding for DF protocol relay system. The taxonomy presented in Figure 2.7 depicts the VCN operations methods, which are divided into architecture and optimization-based methods. The optimization-based min-sum method is attractive for hardware and software implementations because it reduces the implementation complexity of the sum-product algorithm without losing much of its performance [101]. As decoding complexity is the major concern in DF protocol operation, this optimization-based min-sum method that could give a better trade-off between "complexity" and "error performance" is required. Thus, optimization VCN operation is considered in this research. The taxonomy details are provided in the next sections.

Table 2.3: Performance comparison of min-sum based LDPC code decoding system

Authors	Year	Method	Parity Check	Iteration	Modulation	Channel	VCN Operation	Results
Fabian et. al. [94]	2014	svwMS	regular	30	BPSK	AWGN	CN: correction factor, comparison- divide into 2 group	BER=10^{-15} (FER=10^{-13}), less 32 comparators, throughput: 12.8 Gbps / area : 3.8 mm^2
Yin et. al [95]	2014	ID-GMI	regular & irregular	50	BPSK, 256 QAM	AWGN	CN: select metric based on density evolution-searching scaling factor	BER= 10^{-7}
Wang et. al [96]	2013	SMSA	regular	20,50,100	BPSK, QAM	AWGN & independent Rayleigh fading	CN: symbol combination set separately-smaller search space	small SNR loss, SMSA-computation saves - 60% to 70% , memory bits- saves 55%.
Cheng et. al. [97]	2014	NPMSA	regular	9	_	_	CN: NPMSA-tree-structure-based MVF & optimal normalization factor, quantization bits, a mix of tree and butterfly types, normalization factor, Early termination method	51%fewer comparators with loss of 0.05 dB, area reduction - 19.8%, energy reduction - 60.6%.
Tsatsaragkos et al. [98]	2015	ExMin-n; rExMin-n	_	10,30	BPSK	AWGN	CN: ExMin-*n* : *n-level* exMin approximation-partitioning and minimum identification, *rExMin-n*, adding a negative factor *r*.	exMin-3 vs MS - coding gain = 0.15–0.2 dB, exMin-3 vs NMS: degrade 0.08 dB at a BER of 10^{-7}, rExMin-3 improve exMin-3performance at BER range below 10^{-6}, rExMin-3 vs exMin-3 : gain of 0.06 dB, exMin : less than 14 iterations, exMin-n :25% less comparators & 65% less multiplexers, exMin - complexity reduction: 6% - 15%. delay reduction: 9% - 23%.
Meng et. al. [93]	2014	Two-stage fixed-point quantization	regular	10	_	_	CN: fixed-point number not float-point number, 1st stage: uniform quantization + channel likehood information, 2nd stage: uniform quantization+ information transmission btw CN & VN	at BER 10^{-6}:4-bit quantization vs float-point calculation: coding gain = 0.025 dB, fixed point vs float point only 0.05 dB loss at BER: 10^{-6}, at BER:10^{-6} two-stage quantization vs single stage : gain = 0.2 dB, 1-stage gain vs 2-stage 0.025 dB:↓complexity + internal information quantization.
Nguyen et. al. [16]	2012	MSA-SN	_	30	BPSK/QPSK	AWGN	CN: Stopping Node	MSA-SN vs MS : 0.1 dB - 0.3 dB BER ↓, Process time: MSA-SN : ↓ 5 x(BPSK) & 10 x (QPSK)
Emran et al. [99]	2014	SVS MS	regular	50	256-QAM	AWGN	approximate scaling factor graph to a stair graph with constant horizontal step	SVSMS vs MS: 0.41 to 0.85 dB, SVSMS vs Scale MS : 0 to 0.43 dB better, SVSMS vs SPA: only 0.08- 0.24 dB more + ↓complexity.
Jung et al. [100]	2014	SANMS	irregular	10,15,30	_	AWGN	VN:SNR received: -ve & +ve effects, log-likelihood ratio received:adaptive scaling factors CN:extrinsic information : adaptive scaling factors, VN + CN architecture (combine)	Max iteration =10, SANMS vs MS: coding gain = 0.4 dB, SANMS + adaptive SFs = 2.6 dB (overestimated) at BER = 9.26×10^{-7}, adaptive SFs = 2.8 (perfect estimated) dB at BER 8.57×10^{-7}
Zhang et al.[102]	2006	2-DNMS	irregular	200	BPSK	AWGN	VN & CN normalization factor based on density evolution & parallel differential optimization.	2-DNMS at SNR=1dB : WER =between 10^{-2} and 10^{-3} 1-DNMS at SNR=1dB : WER=between 10^{-0} and 10^{-1}
Islam et al.[14]	2012	Optimized MS	regular	50	BPSK	AWGN, Rayleigh, Weibul & Log Normal	VN & CN optimization factor is not multiplied in a posteriori information.	BER 10^{-2} : 0.2dB decoding gain over NMS

svwMS simplified variable weight min-sum, *BPSK* binary phase shift keying, *QPSK* Quadrature phase shift keying, *AWGN* additive white gaussian noise, *ID-GMI* iteration and degree dependent generalized mutual information, *QAM* quadrature amplitude modulation, *SMSA* simplified min-sum algorithm, *NPMSA* normalized probabilistic min-sum algorithm, *MVF* minimum value finder, *MSA-SN* min-sum using stopping node, *SVSMS* simplified variable scaled min-sum, *SNR* signal noise ratio, *NMS* normalized min-sum, *SANMS* snr-considered adaptive nms, *Scale MS* scale min-sum, ↓ lower, + with, *btw* between, *CN* check node, *VN* variable node, *BER* bit error rate, *VCN* variable and check node, -ve negative, +ve positive

2.8.1 Parity Check and Iteration

From Table 2.3, six of the studies used regular LDPC code [93-97, 99] while the others [95, 100] utilized the irregular LDPC code. Ahmed. Emran et al. (2014) in [99] stated regular codes give very good performance while irregular is not good enough due to different degrees of the variable node need unequal data scaling factor per iteration to sent unequal message density in irregular codes. From the studies in Table 2.3 above, the iteration is set between 9 and 100 iterations. One iteration is defined as one round of message updates the variable nodes and check nodes. When the number of iteration reached the maximum or hard decision calculation meets the requirement of all the parity check, the iteration will terminate. The number of iterations directly affects the total decoding complexity as shown by Cheng et al. (2014) in [97] proposed the early termination (ET) method reducing the number of decoding iteration and energy dissipation by about 60.6 %. And Nguyen et al. (2012) in [16] employed an early stopping (ES) method to reduce the number of iteration which improves the quality and processing time of the decoding process. This study highlighted the potential use of early termination on the iteration for improving the processing time particularly for min-sum based decoding method relay channel in DF relay protocol.

2.8.2 Modulation and Channel Scheme

BPSK modulation is the most common modulation technique employed for the min-sum decoding research as shown in Table 2.3. The six published studies implemented BPSK modulation [16, 94-96, 98]. Yin et al. (2014), Wang et al. (2013), and Emran et al. (2014) in [95-96, 99] also utilized the QAM modulation while Nguyen et al. (2012) in [16] also investigated QPSK as a modulator.

As the BPSK modulation is easy to implement and robust among other modulation techniques, it becomes a mostly chosen modulation scheme [103]. Because the QPSK modulate two symbols at one time, it is considered an efficient modulation method compared with BPSK and provides high spectral efficiency. QPSK bandwidth is much better than BPSK and BPSK modulation has a similar characteristic in terms of power efficiency with QPSK. QPSK provides twice spectral efficiency compared with BPSK at the same energy efficiency. Nguyen et al. (2012) in [16] found that by using the BPSK scheme, the processing time decreases five times while the processing time using the QPSK scheme decreases 10 times which is QPSK twice better performance in terms of processing time than BPSK.

Three of the studies in [95-96, 99] used the QAM modulation as a representation of higher-order constellation cases. The effect from higher-order constellation found in QAM provides high efficiency in power and bandwidth that makes QAM have better error correction performance compared to BPSK modulation. Future work should investigate a suitable modulation scheme for min-sum based relay channels in DF relay protocol.

From Table 2.3, all of the published works were simulated with zero mean and variance over the AWGN channel, while Wang et al. (2013) in [96] also simulated over uncorrelated Rayleigh fading channel. Future relay channel research should attempt to consider other channel models like the combination of small and large-scale effects that are commonly employed in a cooperative communication environment.

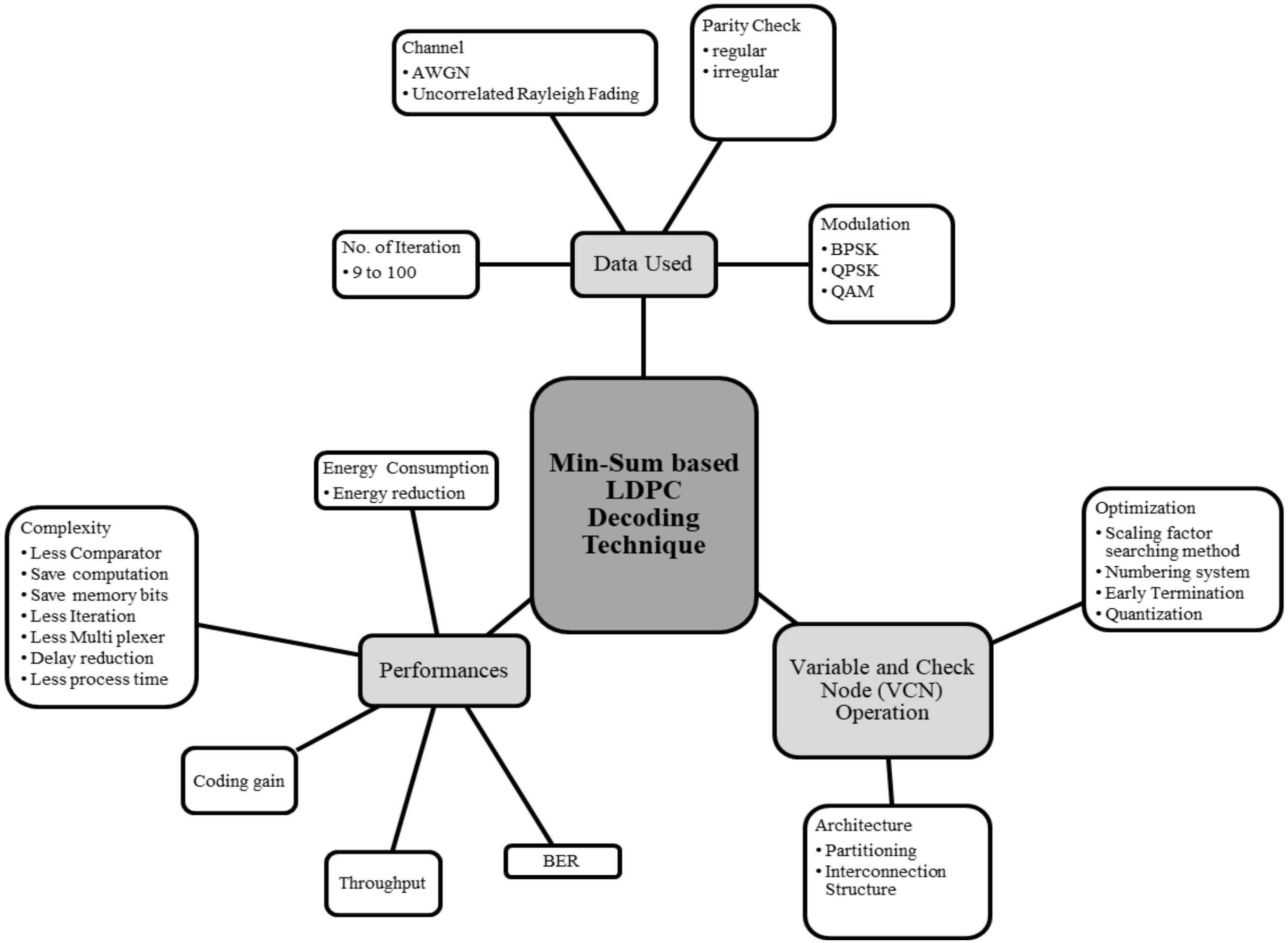


Figure 2.7: Taxonomy of min-sum based LDPC code decoding techniques

2.8.3 Variable and Check Node Operation

The success or failure of the decoding process relies on the VCN operation of the min-sum algorithm. Table 2.3 provides an overview of the research on the VCN operation method employed in the existing published works. Taxonomy in Figure 2.7 shows that the min-sum VCN operation method can be classified into two types of methods which are (1) optimization and (2) architecture.

The optimization approach is the act or process of obtaining the best result of system design under the given circumstances. From Table 2.3, the existing optimization approach has been used in studies including selection searching method for scaling factors [14, 94-100, 102] numbering system [93, 96], early termination [16, 97] and quantization [93, 97-98]. The optimization selection searching method for the scaling factors is important to enhance the BER performance of the fixed scaling factor based on the min-sum algorithm.

In future research, the low complexity searching scaling factors method while maintaining the BER performance must be explored. A suitable numbering system such as fixed-point calculation can be employed in the calculation of the VCN operation function to reduce the calculation complexity. To reduce energy consumption, an early termination-based approach can be exploited in the average number of iterations reduction to avoid unnecessary decoding computation. From the observation, to reduce the operational computation complexity, the proper threshold values-based method has the potential to apply at the early termination method, especially under a high BER scenario. It is also suggested that the proper design quantization method is capable of providing optimization for VCN operation.

Meanwhile, the architecture approach is presented as a modification of the interconnection structure operation of the VCN which can minimize the usage of comparators. The existing architecture approach has been used in studies that including partitioning [98] and interconnection structure [97, 100]. Interconnection structures such as tree and butterfly structures are employed in [97] to execute low complexity operation of the check node by comparing the input value to obtain the minimum value. The above-designed method aims to reduce the area, delay, energy, complexity, BER, processing time, and increase the throughput of the decoding process.

As the VCN operation has a considerable impact on the error correction performance and complexity level of the decoding operation, apparently there is a need to establish a min-sum based VCN modification investigation for relay channel in cooperative communication. Therefore, the min-sum based on VCN operation modification has the potential in future research works and should be looking for the DF relay channel in a cooperative communication environment. Variable and Check Node (VCN) operation modification by optimization approach is highly recommended due to its significant contribution to the low decoding computational complexity analysis process and better error rate performance. This topic will be explored and further explained in the next section.

2.9 Optimized Min-Sum Decoding Algorithm for DF Protocol Relay System

The simplified version of the sum-product algorithm of low-density parity-check (LDPC) code decoding called the min-sum (MS) algorithm has the potential to reduce the complexity of the decoding process and it continues to be an active field of research in optical communications, deep-space communications, and storage systems [94]. No systematic study has yet been carried out for the application of a min-sum based algorithm for a relay node of the DF protocol in the cooperative channel. The min-sum algorithm performs the approximation of complex computations in the check node operation using summation and comparison operations at the expense of some signification degradation in decoding performance. Therefore, min-sum variants have been proposed to enhance performance due to their low complexity, and reliability compared with the Sum-Product (SP) algorithm and are categorized into two distinct groups; normalized min-sum (NMS) and offset min-sum (OMS). Both methods employ a correction factor to resolve the overestimation problem at the check node operation and to improve the performance of the min-sum algorithm. The NMS method proposed by Chen and Fossorier (2002) in [104] normalizes the approximated message using a fixed scaling factor, α where $0 < \alpha \leq 1$ in the check node processing operation. The OMS is set prior to decoding, by subtracting a positive constant β from the magnitude of the min-sum, where $\beta > 0$ in the check node processing rather than taking the output value of each iteration output. Indeed, most of the literature [99, 104-106] has attempted to improve the decoding algorithm.

For example, in the literature [94-95, 99, 104, 106-107], the modification of the NMS approach has been used to search for an optimized scaling factor (SF) to improve the traditional fixed scaling factor algorithm regarding the performance of the bit error rate (BER). The majority of these scaling factors are searched empirically [108] with several [99, 106] indicating a heuristic method to determine the value of the scaling factor. Yin et al. (2014) in [95] applied a metric called Generalised Mutual Information (GMI) which is a heuristic idea of selecting the scaling factor while in another study [99], the Signal-to-

Noise ratio (SNR) is used to consider the adaptive scaling factor value to enhance performance. Accordingly, when the received SNR is low, the scaling factors less than one reduce the adverse effect, while, scaling factors greater than one emphasised the positive impact when the received SNR is high.

In [102], the two-dimension (2-D) normalization approach, two different scaling factors (α and β) are used for the check node and for the variable node operation. Implementing this particular approach requires additional storage to store the scaling factors and complexity in the scaling process in selecting a different scaling factor for each degree. Notably, the optimized min-sum multiplied the same α scaling factor in the check node and in the variable node operation [14] compared with the NMS algorithm which only used the α scaling factor for the check node operation. Moreover, the optimized min-sum [14] algorithm obtained a better compromise between performance and complexity as compared with the original min-sum and normalized min-sum algorithm. Furthermore, by applying the same scaling factor for both the check and variable nodes, the complexity in calculating the two different scaling factors was reduced. Importantly, lower computational complexity is a key objective of the decoding algorithm of the decode-and-forward (DF) protocol for the relay node.

2.10 Particle Swarm Optimization

To further improve the performance of the min-sum decoding algorithm, an optimization algorithm was introduced. In [109], the sum-product algorithm of belief propagation algorithm has been used as a genetic algorithm (GA) as an optimization method for fast search. GA was applied to look for best performance LDPC codes that are easy to implement in hardware [110]. Elkelesh et al. (2019) in [111] used GA for error rate performance optimization and to reduce the decoding latency and complexity of the actual hardware architecture for LDPC decoders. Scandurra et al. (2006) in [112] employed GA to LDPC decoder to estimate the channel information. The decoding performance is improved with much higher computational complexity [112]. All of these above show the optimization algorithm potential to improve LDPC code performances.

Particle Swarm Optimization (PSO) as an evolutionary computational model based on swarm intelligence and population is comparable to GA optimization. PSO was originally developed by Dr. Kennedy and Dr. Eberhart (1995) in [113]. At first, they tried to simulate bird flock migration and aggregation when they were looking for food. Later, they found PSO was an effective optimization method. The PSO has a much better intelligent background compared to GA and could be more easily performed. The high precision and fast convergence characteristics of PSO attract great academic interest that demonstrates its superiority in solving practical problems. Currently, the PSO algorithm is rapidly attracting the researcher's interest and has been commonly used in areas such as pattern recognition, neural network training, function optimization, neural network training, and so on [114]. Additionally, PSO algorithm research has also penetrated electricity and communications. PSO algorithm was used in [115] to design the LDPC codes near the Shannon limit. For irregular LDPC codes, PSO has also been used to optimize degree distribution pairs [116]. Evolutionary computing methods, inspired by nature's evolution, have proved to be an effective method of optimization for complex and discontinuous multidimensional engineering problems, and have already been successfully implemented in many fields. Particle swarm optimization (PSO) algorithms [113, 116] are completely new forms of social intelligence models to be reinterpreted as a form of optimization, learning, and problem-solving. PSO is also able to achieve the same goal as evolutionary computing in a different and faster manner.

The PSO algorithm can be exploited to the construction of a min-sum based decoding optimization method. The PSO algorithm is inspired by a bird flocking or fish schooling social behavior. A group of birds searches for food in an area at random is the scenario in the PSO searching method. Only one piece of food is being searched for in the area. The food location is not known by all the birds. However, they learn how far the food is through their intercommunications in each iteration [113, 116-117]. Therefore, the easiest way to find the food is to track the bird that is closest to the food.

PSO studied this scenario of bird-flocking and used it to solve problems of optimization. Every single solution in the search area is assumed as a “bird” and known as a “particle”. All particles have cost values that are calculated by optimizing the cost function and the velocity that guides the particle flying movement. By following the current optimal particles, the particles travel through the problem region.

PSO is initialized with a group of random particle solutions. Then, each particle updated generations to find the optimal solution. Next, each particle will be updated by two "best" values during iterations. The first “best” value is the vector position of the best solution that this particle has found to that point and the cost value is stored too. This first “best” position is known as “*pbest*”. Another "best" position the particle swarm optimization found is the best position any particle in the population has obtained so far. This best position is the best of the current global position and is known as “*gbest*”. "*gbest*” is the optimal solution to achieve the best performance.

2.11 Performance Evaluation

For a given transmitted signal-to-noise ratio (SNR), the bit error rate (BER) or outage probability is considered to evaluate the performance of the cooperative relaying protocol in wireless network communication.

2.11.1 Bit Error Rate

At the physical layer, the wireless channel's performance is determined by bit error rate, symbol error rate, or block error rate. The system operation performance is expressed by a bit error rate (BER). BER is determined as a ratio amount of bit with an error such as interference, distortion, and noise to the total amount of the bit received during transmission [118].

$$\mathrm{BER} = (\mathrm{Bit\ in\ Error})/(\mathrm{Total\ bits\ received}) \tag{2.12}$$

BER is also defined as the ratio of the bit error number to the total amount of bits transferred for a given period. BER is measured in terms of less error rate performance units. To get low data error, the modulation scheme and Forward Error Correction (FEC) can be an applied rate in data transmission. The BER value is the amount of bit data damages throughout data transmission from the transmitter to the receiver in one period of time. The BER performance is reducing by noise from the environment. The wrong reconstruction of digital waveform called quantization errors has reduced the BER performance. Quantization errors are also caused by modulation process reliability, noise amplitude, and signal filtering. BER may also be expressed in terms of probability of error (POE) as stated in Equation (2.13).

$$\mathrm{POE} = \frac{1}{2}(1 - \mathrm{erf})\sqrt{\mathrm{E_b}/\mathrm{N_0}} \quad (2.13)$$

where N_0 is the noise power spectral density that refers to as noise power in a 1Hz bandwidth, erf is the error function and E_b is the energy in one bit. For different modulation methods, the value of the error function is varied. The POE is proportional to E_b/N_0, which is a form of the signal-to-noise ratio. By averaging carrier pawer with the bit rate, the energy per bit, E_b can be measured. E_b unit is stated as joules as an energy calculation. E_b/N_0 is a numerical ratio without dimensions with N_0 is the noise power in joules per the second unit.

2.11.2 Signal-to-Noise Ratio

Signal-to-Noise Ratio (SNR) is the process of data detection and is calculated at the receiver output. SNR is the evaluation of all the existing performances that are easiest to measure. The overall system performance makes for an excellent measure.

The noise term in the SNR also refers to the thermal noise available in communication because of the fading impairment at the receiver's input. SNR is represented as the signal power ratio or desired data to the unwanted noise signal as stated below:

$$\mathrm{SNR} = \frac{\mathrm{P_{signal}}}{\mathrm{P_{noise}}} \quad (2.14)$$

where P refers to average signal power.

SNR is the physical layer of the Local Area Wireless Network (LAWN) significant parameter. In general, the noise and other unwanted signal interference affect the noise strength level. Since high BER causes a low SNR value, the BER is inversely proportional to SNR. In a high BER situation, the amount of packet loss increases and that consumes more delay and produces less throughputs. In the multichannel environment, the BER and SNR exact relationship among them is not easy to determine. To calculate the communication channel quality, the SNR is usually used and measured in decibels unit and stated as below [119]:

$$\mathrm{SNR_{dB}} = 10\log_{10}\frac{\mathrm{P_{signal}}}{\mathrm{P_{noise}}} \tag{2.15}$$

2.11.3 Energy per Bit to Noise Power Spectral Density Ratio

Another important parameter in digital data transmission is Energy per bit to Noise power spectral density ratio (E_b/N_0). The SNR normalization evaluation measure is also defined as "SNR per bit". Without considering bandwidth, this is particularly helpful in evaluating BER against different modulation methods with no bandwidth consideration taken. E_b/N_0 is expressed as SNR per gross channel spectral efficiency in (bit/s)/Hz unit, where the bits refer to as bits of data transmission including error correction data and other overhead protocols. E_b/N_0 is usually used to refer to the real transmitted power noise which is the energy per bit of the forward error correction (FEC) overhead bits when addressing the FEC [120].

2.12 LDPC Encoder

The encoding of the LDPC code process with an existing Gaussian elimination of the LU algorithm is a relatively simple technique, but the LU factor of the code is generally not sparse and the encoding complexity turns out to relative increase rapidly. Due to high computational encoding complexity operation, many kinds of research are concentrating on reducing the encoding computational complexity operation [121]. However, there is still limited research addressing the encoding algorithm for LDPC code based on the DF protocol relay system application. The most popular encoding method used in the LDPC encoder of the DF protocol relay system is the LU encoding.

Some work considered in investigating the encoding method on decreasing complexity of the LDPC codes encoding processing system are reported next. Neal (1999) in [18] introduced an encoding method, where the LU algorithm is used to avoid the computational complexity of multiplication by dense inverse matrix. The parity check codeword formed by the LU algorithm was formed based on the lower and upper triangular matrices. The LU algorithm demonstrates its potential in reducing the complexity of the encoding process that has a small coefficient and linear in the length of the codeword. Vishnu and Sajith (2015) in [19] applied LU decomposition on the parity check matrix and then perform matrix multiplications to calculate the parity bit for memory requirement reduction in serial and parallel encoder architecture for Quasi Cyclic LDPC codes. Matthew (2014) in [122] investigated permutation used to factorize the LU algorithm to reduce round-off error during computation and reduce numerical instability. LU factorization can be computed with the permutation information either as a matrix or vector.

Meanwhile, Francis (1962) in [21] provided an efficient encoding method, the QR algorithm. QR algorithm is a method for a matrix calculation of eigenvalues and eigenvectors. QR algorithm also formed the parity check codeword. QR generated matrix factorization into orthogonal and triangular components. The orthogonal component is the source of the matrix row space. QR algorithm is good characteristics in error propagation and inevitable results of unit matrices. Due to this factor, it is an effective tool to solve linear equations.

The reported studies that utilized LU variants [122-126] and QR variants [20-26] are variants encoding algorithms. Funderlic and Plemmons (1981) in [123], as well as Cosnard and Grigori (2001) in [124], utilized LU without a pivoting algorithm, while Fu, Jiao, and Yang (1998) in [125] as well as Sun et al. (2015) in [126] employed LU with a partial pivoting algorithm. Matthew (2014) in [122] applied LU full pivoting algorithm in his research. Matsumura and Ohtsuki (2011) in [22] employed the Gram-Schmidt encoding algorithm, while Chen et al. (2010) in [23] used the Modified Gram-Schmidt algorithm, Leung and Cheung (1991) in [25] used the Householder Reflection algorithm, and Merchant et al. (2018) in [26] used the Given Rotation algorithm.

Krishnamoorthy (2014) in [20] presented a QR algorithm with permutation. QR factorization numerical stability for floating-point matrices is improved by the use of permutation. QR function represents data permutation either as a matrix or vector-matrix format. To achieve high capacity in the MIMO broadcast channel, Matsumura and Ohtsuki (2011) in [22] employed three different techniques such as Gram Schmidt, Modified Gram-Schmidt, Householder Reflection, and Given Rotation to compute QR encoding algorithm.

To improve the operational efficiency in the MIMO detection system, the Modified Gram Schmidt algorithm was used by Chen et al. (2010) in [23] to reduce the memory hardware consumption. Heath, Gonzalez, and Rusu (2016) in [24] employed the

Householder Reflection algorithm as the building block of dictionaries due to its low complexity manipulation characteristic. To produce a sparse representation of certain observed data, data learning is used to determine data-dependent transformation. Leung and Cheung (1991) in [25] used the Householder Reflection algorithm for Bidirectional Associative Memory (BAM) and have been shown to have a significant improvement in the storage capacity. Given Rotation was introduced by Wallace Givens in 1950. Merchant et al. (2018) in [26] used the Given Rotation algorithm in generalization for the annihilation of multiple elements of an input matrix simultaneously where the annihilation regime spans over columns and rows. It is intended to expose higher parallelism in Given Rotation through generalization and also reduction in the total number of computations. Such generalization is possible by combining several Givens sequences and performing common computations required for updating trailing matrix beforehand.

The above studies [122-126], and [20-26] evaluated the performance of a single encoder method for the encoding process system. To the best of our knowledge, this is the first study of the performance comparisons of various LU and QR variants encoder algorithms of LDPC code for the DF protocol relay system. This research is directed to search a low complexity LDPC code encoder method for the DF protocol relay system which is further described in the methodology section.

2.13 Combining Technique

Since more than one data signal is sent to the destination node, a combining technique is needed to combine the multiple data signal received into a single improved data signal at the destination [127-128]. Maximum Ratio Combining (MRC) technique has the advantage of its simple and effective combining to combat noise, fading, and to a certain degree of cochannel interference. The receiver does not need to know the actual channel condition for this combining method. To combine the signals, channel quality estimation is important. Less computational operation power requires for this combining technique process.

The combination of the data signal transmits from the source and relay node using the MRC technique at the destination node is presented as follow:

$$y_d = a_1 y_{sd} + a_2 y_{rd} \tag{2.16}$$

where,

y_{sd} and y_{rd} are the data signals from the source and relay to the destination

$a_1 = \frac{\sqrt{P_s} h_{sd}}{N_0}$

$a_2 = \frac{\sqrt{P_r} h_{rd}}{N_0}$

h_{sd} and h_{rd} is a Rayleigh fading channel

N_0 is noise power spectral density

P_s and P_r are the source and relay power

In a multi-hop setting environment, the main drawback of the MRC technique is it only takes the last hop. An error correction code method needs to be employed to solve the wrongly detected data symbols from the relay which can jeopardize the performance.

2.14 Matlab Simulation Sofware

Matlab software offers excellent interactive environments and fast mathematical algorithms. It supports efficient matrix handling, plotting of functions and data, and easy algorithm implementations. In this research, Matlab software is used for simulation experiments due to the following benefits.

a) Matlab software offers a development environment with high-performance numerical computation, development tools, data analysis, and visualization capabilities.

b) In Matlab software, statements are written and calculated instantly so they are tested as you go.

c) Matlab software allows instant access to thousands of written fundamental and specialty functions by experts in addition to the special functions developed by yourself as well as your research colleagues.

d) The in-built GUI builder and graphing tools available in Matlab software allow one to customize one's data and models to be able to easily interpret data for quicker decision-making.

2.15 Summary

This chapter presented a brief explanation of the general concept of cooperative communication focusing on both AF and DF protocols. The min-sum based LDPC code function that is to reduce the high complexity operation of the DF protocol is also explained in this chapter. Additionally, this chapter presented the existing research results comparison using the min-sum based LDPC code algorithm as a method to reduce the DF protocol's decoding computational operation. Recent research shows the ability of the min-sum based LDPC code for DF protocol to reduce the computational complexity of the decoding process.

A review of the LDPC code decoding method for the DF protocol relay system is presented in this chapter. The LDPC code decoding section aimed to discuss each of the LDPC code decoding components, potential, function, variety, and their challenges in a specific manner. This literature review chapter has shown that the LDPC code decoding algorithm is a promising research area that has a significant function to perform better error corrective performance as well as enhance the computational complexity operation performance.

There are also limited research works published regarding the development of the DF protocol relay system using LDPC code and still at an early stage. The component of the DF relay system will be using the LDPC code that will be proposed. Based on a general review of DF protocol in the cooperative communication research area and particularly in the LDPC code decoding method, the model is designed. Further discussion on a major component of the whole system will be addressed in more detail.

CHAPTER 3

RESEARCH METHODOLOGY

This chapter describes the research methods applied in this study. It explains the framework of research methods for modeling decode and forward protocol relay system using LDPC code is followed by the development of the LDPC decoder approach and development of the LDPC code encoder model for LDPC encoder of DF protocol relay system model.

3.1 Research Design and Procedures

The research methodology flow diagram is shown in Figure 3.1. It is divided into three major stages. The first stage involved the study and analysis of the cooperative communication and relay protocol and then modeling of decode and forward protocol relay system using LDPC code is proposed. Next, the model is evaluated in terms of BER.

The second stage performed the development of the LDPC decoder at the relay node. The random bits input signal is generated at the source node followed by encoding the random bit signal using the LU encoder method at the source node. Then, the encoded bits signal modulated using the BPSK modulation scheme at the source node. The modulated signal passes through the channel modeled as cooperative fading with AWGN. The error bits signal demodulated using the BPSK modulation scheme at the relay node. The demodulated signal decode uses the new proposed LDPC code decoding algorithm called VGOMS at the relay node. The decoded bits signal is evaluated in terms of BER and complexity.

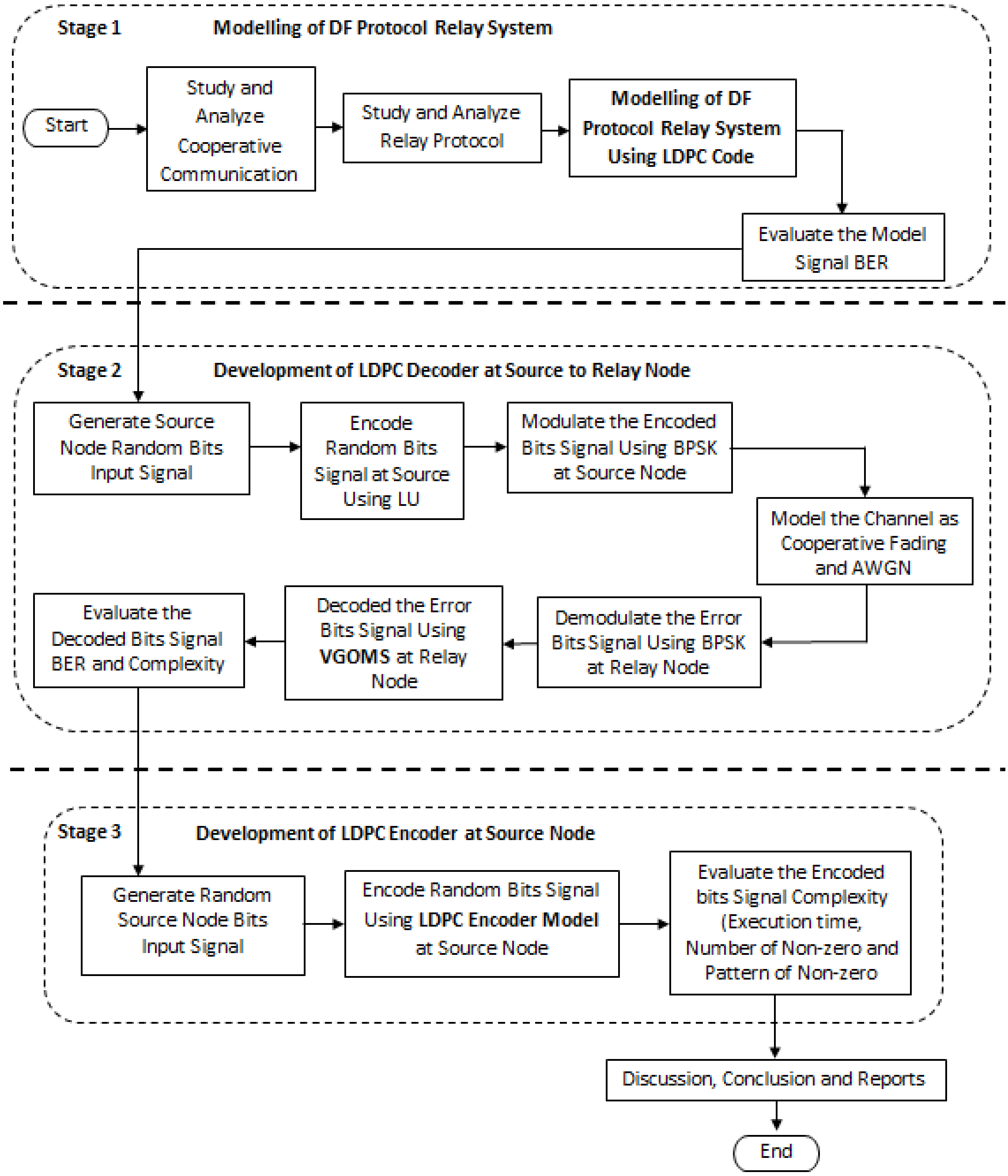


Figure 3.1: Research methodology flow diagram

The third stage involved the development of an LDPC encoder at the source node. The random bits input signal is generated at the source node followed by encoding the random bit signal at the source node using the proposed LDPC Encoder Model. The encoding algorithm complexity is evaluated in terms of execution time, the number of nonzero, and the pattern of nonzero. Finally, the results were discussed, concluded, and reported.

3.2 Modeling of Decode and Forward Protocol Relay System Using LDPC Code

For modeling the decode and forward protocol relay system using LDPC code, the generic structure of decode and forward protocol in cooperative communication is described. Each existing component of the LDPC code decoding methods is mapped into a generic structure of the DF protocol relay system. Next, the decode and forward protocol relay system using LDPC code individual components is explained. Lastly, the model of the DF protocol relay system using LDPC code performance verified using Matlab software simulation and compared against non-cooperative, AF, DF, and DF relay protocol using Turbo code.

3.2.1 The Generic Structure of Decode and Forward Protocol Relay in Cooperative Communication

To present the working operation DF protocol for the relay in cooperative communication, a generic structure of this DF protocol is established in this particular part. The generic structure of this DF protocol comprises three nodes which are the source node, relay node, and destination node as illustrated in Figure 3.2. The source node function is to transmit the input message bit to the relay node and destination node. In the first phase, the source node directly transmits the input message data to the destination node. The working phase is called broadcast phase transmission as the input message from the source node is spreading over the relay node and destination node. Then, the relay node sent the processed message data at the relay node to the destination node in the second working phase. The second phase is also known as the cooperative or relay transmission phase.

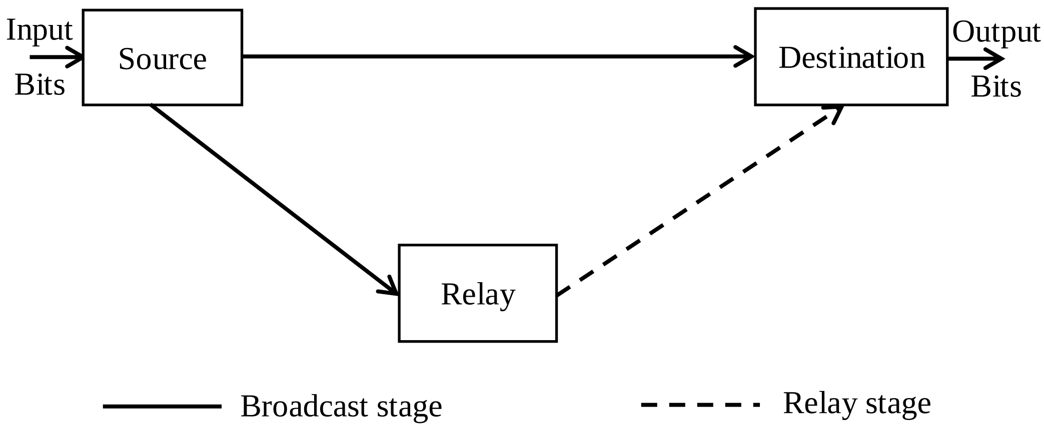


Figure 3.2: Generic structure of the DF protocol relay system in cooperative communication

In the following section, the forward error correction method called LDPC code is designed for the proposed DF protocol relay system. The definition is given for each of the system components. Then, the related existing methods to each of the component is identified and deployed for the DF protocol relay system.

3.2.2 Proposed Model of Decode and Forward Protocol Relay System Using LDPC Code

The model of the proposed DF protocol relay system using the LDPC is code developed based on the generic structure described in the previous section. The proposed model of the DF protocol relay system using the LDPC code is displayed in Figure 3.3. The model comprises three nodes known as the source node, relay node, and destination node. Each node comprises several components, where the input message bit received at the source node is processed by the LDPC encoder and modulator components. A relay node, message received from a source node through source-relay channel going through the demodulator process followed by LDPC decoder, LDPC encoder, and modulator process. Both signals received from the source node and relay node are sent through the source-destination and relay-destination channels respectively. Then, both signals combine at the combiner before they move to the demodulator and LDPC decoder part of the final output of the system at the destination. The proposed model is illustrated in Figure 3.3.

In this proposed DF protocol relay system, the channel is a medium where the signal transmits among the node, referring to the transmission between source to relay node, source to the destination node, and relay to destination. The combination of the large-scale and small-scale fading channel model is employed in this thesis simulation research. The channel model is known as a cooperative channel. It consists of a quasi-static Rayleigh block fading channel and path loss with a value of 3. The channel model is modified and also corrupts the signal going through it. At the receiver, the original information signal is aimed to be recovered and sent to the destination.

To get more efficient signal transmission, the modulator component processes the message signal by shifting the frequency spectrum to a frequency range. Meanwhile, the original form of the signal was obtained by the demodulator process, while the frequency spectrums shift back to the original baseband frequency range. The modulator is also referred to as the process of placing data information on the carrier. At the end of the carrier, a demodulator is employed to recover the original data signal. The demodulator process is also called the detection process which is the reverse process of the modulator.

Before the comparing process for both signals from the source node and relay node has taken place, both signals are combined by using the combiner method at the destination node. The combination process of both signals can reduce the performance degradation from the fading effect. The commonly used combiner techniques include Equal Ratio Combiner (ERC), Fixed Ratio Combiner (FRC), Selection Combiner (SC), and Maximum Ratio Combiner (MRC). In this research, the MRC combiner is used. The signal combiner process is critical to compare both received signals from the source node and relay node. Then, the output signal from the combiner process is going to the demodulator and LDPC decoder process at the destination node. This is the final output of the DF protocol relay system using the LDPC code.

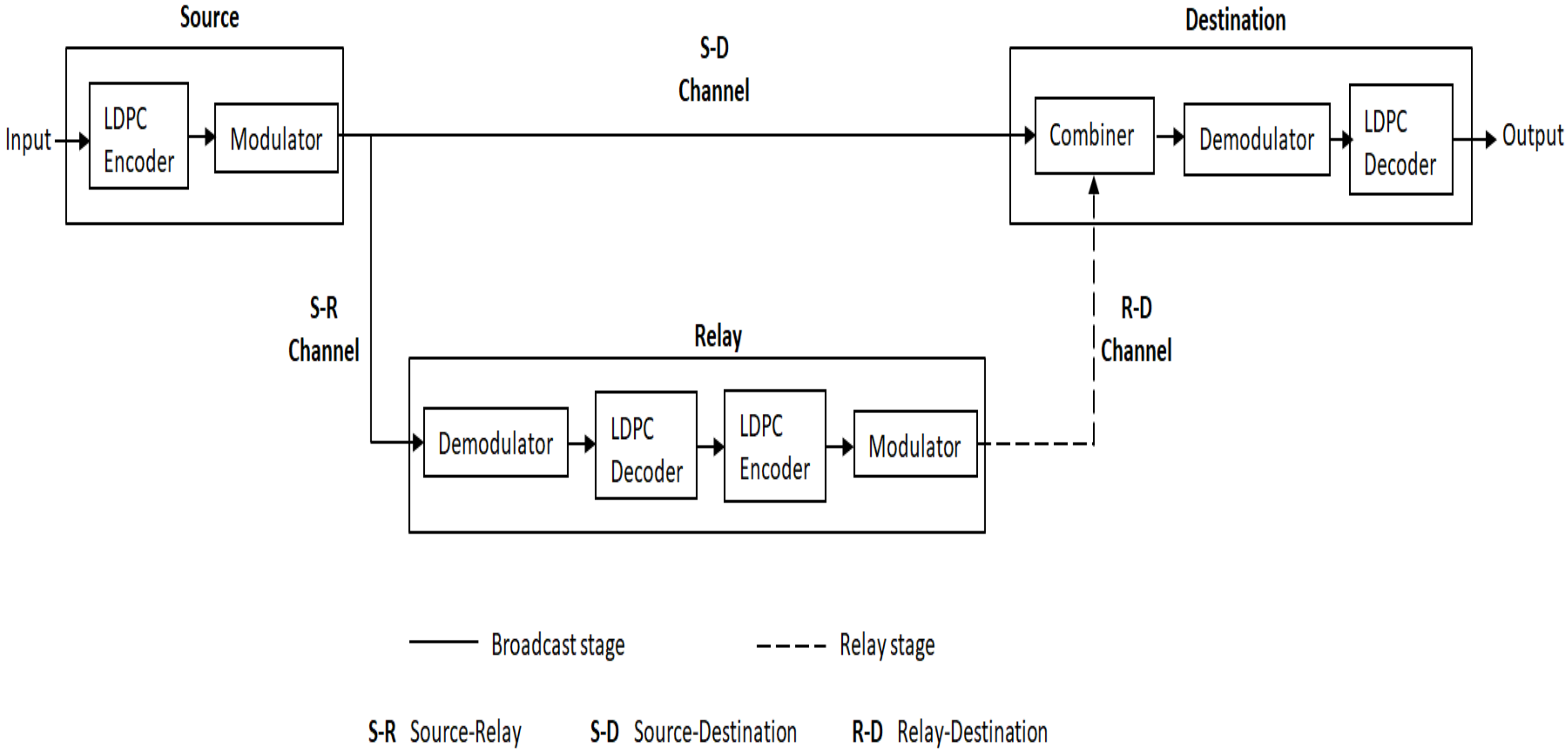


Figure 3.3: Proposed model of decode and forward protocol relay system using LDPC code

3.2.2.1 Channel Model

Normally, the received data signals from the input signal transmission have different phases and amplitudes in the wireless communication environment and this is influenced by many factors. The factor's effects comprised large-scale propagation and small-scale propagation. Path loss or shadowing is the effect of large-scale propagation. Transmission power was reduced when the signal transmission distance increased. This situation leads to low power received at the end of the signal transmission destination. Shadowing is a phenomenon described as the variation of the signal strength measured in separate locations at the receiver caused by a large obstruction effect between transmitter and receiver. The large obstruction is referred to as vegetation, buildings, and intervening terrains. Differently, small-scale propagation is defined as the situation when the small change of the transmitter and receiver location caused the big changes in signal phase and amplitude. At a very high carrier frequency, at about 900 MHz or 1.9 GHz, it refers to as in mobile network, the transmitted signal constructive and destructive interferences are caused by this small scale propagation effect. A lot of models illustrate this small-scale fading effect. The most popular model employed in the various applications is Ricean fading, Rayleigh fading, Nakagami fading and, AWGN. Rayleigh fading is mainly caused by multipath propagation. While in a radio signal environment, the propagation effect is modeled as Rayleigh fading. Rayleigh fading is suitable to represent the signal propagation in the troposphere, ionosphere, and urban environment. In the situation of no line of sight between transmitter and receiver, Rayleigh fading is the most relevant to represent in this situation. The Ricean fading presents a strong dominant component compared with Rayleigh fading. This dominant signal referred to the line of sight (LOS) or fixed signal. AWGN is the basic noise model mobile communication environment and also represents the result of a lot of random processes happening in nature. The specific characteristics of AWGN are additive, white, and gaussian. The additive is added to whatever noise may be inherent to the data signal. White is equivalent to white color that has uniform visible spectrum emission at all frequencies. Gaussian has zero value of an average time domain with a normal distribution. AWGN is a suitable model for many other communication links such as satellite and deep space communication. Generally, AWGN is used to simulate channel background noise. This AWGN channel travels through the channel during data signal transmission to the receiver. At the receiver, the data signal mathematical expression $r(t)$ is:

$$r(t) = s(t) + n(t) \tag{3.1}$$

The received signal at the destination through the AWGN channel is a combination of an original data signal with a noise background. White Gaussian noise is the noise added at the channel where the is a signal going through it. AWGN is used as a standard model for communication networks. Nakagami-m channel can model most of the fading channel conditions and suitable for empirical data. It has gained much attention from researchers caused by these characteristics. It is also modeling the physical fading of radio channels. Nakagami–m fading can be modeled from worse to moderate conditions and it is more flexible.

3.2.2.2 Modulator and Demodulator

The modulator is altering the input data signal to carrier wave and the shape of the carrier wave changed. In the communication system, the modulator purposely generates a modulated signal adapted to the channel transmission features. Then, the demodulator performed the next process to get back the original data signal. For radio communication, the transmission systems require a modulator to convert the input message into a usable high-frequency radio channel. Modulator techniques possess three beneficial properties:

a) Bit error rate (BER): The data signal used this modulator to obtain low BER when it is going through thermal noise, interference, and fading.

b) Spectral Efficiency: The power spectral density of the modulated signals should have a small main lobe and fast sides lobes roll-off. The spectral efficiency is calculated in bit/sec/Hz.

c) Power Efficiency: One of the critical design problems that occurred in mobile and portable applications is power saving. Typically, nonlinear amplifiers are employed to boost power efficiency. Despite that, nonlinearity can reduce BER performance in some modulator methods. To avoid the development of spectral side lobes during the amplification process, a constant envelope modulator method is employed in the system.

Generally, there are two types of modulators which include analog and digital modulators. An Analog or sinusoidal signal is used in an analog modulator as a carrier signal. The Analog modulator modulates the data signal. The amplitude, frequency, and phase, the sinusoidal wave function can be used to obtain analog modulation. The analog modulation types are Amplitude Modulation (AM), Frequency Modulation (FM), and Phase Modulation (PM). The digital modulator method is employed to get efficient and better communication quality. The digital modulator's main advantages over analog modulation are high noise immunity, maximum throughput, and reasonable power. An analog data signal is converted into the digital data signal and modulated by using a carrier wave in digital modulation. The modulated data signal is creating pulses by switching on and off the carrier wave. Digital modulation is determined by the number of carrier wave features such as amplitude, frequency, and phase which is the same as analog modulation. The term keying is used if the data signal is in a digital format. Hence, the terms Amplitude Shift Keying (ASK), Frequency Shift Keying (FSK), and Phase Shift Keying (PSK) are used in digital communications.

A digital modulation technique is opposed to analog modulation whereas the digital signals are converted into a waveform that is aligned with communication channel properties. Phase shift keying and frequency shift keying carry data in a variety of phases or frequencies and used a constant amplitude carrier. Generally, the basic modulation technique can be transformed into more complex modulation techniques. The basic is referred to as amplitude modulation (AM) and frequency modulation (FM) while complex digital modulation is referred to as amplitude shift keying (ASK), quadrature phase-shift keying (QPSK), minimum shift keying (MSK), frequency-shift keying (FSK), and quadrature amplitude modulation (QAM) groups.

BPSK digital modulation technique is the simplest method for phase-shift keying modulation. It uses two phases that are separated by a phase shift of 180° which makes it known as 2-PSK. The signal shifts the phase of the waveform to one of the two states representing either 1 or 0 binary symbols respectively. Coherent BPSK has a one-dimensional signal space with two message points. To generate a BPSK signal, polar form input binary data with symbol 1 and 0 are expressed with a constant amplitude level of $\sqrt{E_b}$ and -$\sqrt{E_b}$. The method for encoding the signal transmission is performed by a

Non-Return Zero level encoder (NRZ). The binary output wave is fed into the product modulator along with the sinusoidal carrier $\emptyset_1(t)$, whose frequency is given by $f_c = \frac{n_c}{T_b}$. The desired BPSK wave will be generated as a modulator output.

The incoming BPSK signal is passed into a correlator to demodulate the original binary series of 1 and 0, which consists of the multiplier and the integrator. The incoming signal is multiplied and the output is fed into the integrator along with the coherent reference signal, $\emptyset_1(t)$. The correlator output x_1 is compared with a 0 threshold and the decision is taken based on the decision rule. If x_1> 0, the device produces an output of 1 but if x_1< 0, the device produces an output of 0.

BPSK is primarily used in satellite communication due to its flexibility and robustness of the implementation. However, it is important to remember that this modulation technique is unreliable in terms of bandwidth since it can only transmit 1 bit/symbol, rendering it unsuitable for applications with a high-speed data rate. For the BPSK signal the mathematical representation can be expressed as:

$$S_c(t) = \sqrt{\frac{2E_b}{T_b}} \cos\ (2\pi f_c t) + \pi(1-n) \tag{3.2}$$

where $n = 0{,}1$

BPSK modulation produces the lowest bit error rate under constant transmitted bit energy, noise level, and other distortions because BPSK modulation has the largest gap between two signal points. The bit error probability of BPSK in AWGN can be obtained using;

$$P_{e,BPSK} = Q\sqrt{\frac{2E_b}{N_0}} \tag{3.3}$$

where E_b is energy per bit and N_0 is the noise power spectral density. Q is the Q function which is used frequently for calculating the area under the tail of the Gaussian pdf denoted by $Q(x)$.

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{-\frac{t^2}{2}}\, dt \tag{3.4}$$

$$\int a^x\, dx = \frac{a^x}{\ln a} + C \tag{3.5}$$

QPSK uses a four-level phase states to transmit 2 bits/symbol simultaneously, by taking one of the four possible equally spaced carrier phase shifts of 0, π/2, π, and 3π/2, where each value of the carrier phase corresponds to a separate pair of message bits of 00, 01, 10, 11. This benefits signal efficiency by using the same bandwidth to carry double information. This means QPSK is more effective in terms of bandwidth than BPSK.

In the demodulator, both in the in-phase and quadrature channels, the received signal is multiplied by a reference signal $\emptyset_1(t)$ and $\emptyset_2(t)$, both in the in-phase and quadrature channels. Through the help of an integrator, the combined output from each channel is incorporated. Each of the outputs x_1 and x_2 integrators are compared with the threshold value of 0 and the decision-maker makes a decision. The condition for the in-phase channel output is; if $x_1 > 0$ is determined, then the production output will be 1 but if $x_1 < 0$ is determined, then it will be 0 while the output for the quadrature channel is if $x_2 > 0$ is determined, then the production output will be 1, but if $x_2 < 0$ is determined, then the production output will be 0. When this is finished, the binary sequences are combined in the multiplexer to produce the demodulated binary data sequence in both the in-phase and quadrature channel outputs.

QPSK is used in satellite transmission applications, such as cellular phone systems, video conferencing, and other wireless RF carrier communication. For the QPSK signal the mathematical representation can be expressed as:

$$S_{qpsk}(t) = \left\{\sqrt{E_s}\ \cos\left[(i-1)\frac{\pi}{2}\right]\emptyset_1(\mathrm{t}) - \sqrt{E_s}\, sin\left[(i-1)\frac{\pi}{2}\right]\emptyset_2(\mathrm{t})\right\} \tag{3.6}$$

where, $i = 1,2,3,4$

$$\emptyset_1(\mathrm{t}) = \sqrt{\frac{2}{T_s}}\cos(2\pi f_c t),$$

$$\emptyset_2(\mathrm{t}) = \sqrt{\frac{2}{T_s}}\cos(2\pi f_c t) \qquad\qquad 0 \le t \le T_s$$

where T_s is the symbol period, E_s is the energy per symbol.

QPSK's probability of bit error is equivalent to BPSK's, but QPSK allows the transmitted information to be sent double in the same bandwidth, without increasing the transmitted bandwidth. Also, QPSK offers double spectra efficiency with the same energy consumption. Similar to BPSK, to enable non-coherent detection, QPSK can be differentially encoded. The bit error probability can, therefore, be calculated as;

$$P_{e,QPSK} = Q\left[\sqrt{\frac{2E_b}{N_0}}\right] \tag{3.7}$$

QPSK has the same probability of bit error as BPSK but is compensated by a 3 dB decrease in its bandwidth because of a 3 dB decrease in the error distance of QPSK.

QAM is a combination of an analog and a digital modulation technique. QAM method is used as a single carrier to transmit two separate data channels. To modulate the amplitude of two carrier waves in QAM, the data signal transmits either using AM analog modulation or ASK digital modulation technique. 64-QAM represents 6 bits for each symbol that equals $2^6 = 64$ probability of signal combination. While 16-QAM represents 4 bits for each symbol that equal to $2^4 = 16$ probability of signal combination. 64-QAM can produce high efficiency, but complex modulation technique operation. The digital frequency modulation technique mainly uses for downstream data transmission across a coaxial cable network. It can achieve peak data transfer speeds up to 28Mbps throughout a single 6 MHz channel and highly efficient. It’s ideal for distorted upstream signal transmissions and sensitive to signal distortion.

3.2.2.3 LDPC Decoder

Excellent error control code is a promising LDPC decoder method that is capable to mitigate error propagation in the relay channel of cooperative communication. However, the complexity problem of the LDPC decoder for the relay channel is an important issue at the relay node as it is normally stricter hardware and power constraints at the relay. Besides that, the throughput at the destination decreases caused by decoder delay at the relay.

Normally, the LDPC code decoder algorithm can be classified into two groups which are soft decisions and hard decisions. Soft decisions are also called belief propagation (BP) algorithms while hard decisions are called bit flippling (BF) algorithms.

The combination of both BP and BF is defined as a hybrid algorithm. BP decoding algorithm achieves high performance but is constrained by its complexity which limited energy resources and computational of nowadays applications. Contrarily with the BF decoding algorithm, it is a simple operation but the performance condition is poor. Due to the high computational complexity of the BP decoding algorithm, some of the research published in [87, 129-130] developed a single hybrid LDPC code decoding algorithm that consisted of BF and BP decoding algorithm. Furthermore, BP modification known as the min-sum algorithm was also developed to reduce the complexity in [14, 93-95, 131-132]. The min-sum algorithm used a simple comparison and summation operation at the check node using the two lowest performance values only [131]. The high computational complexity in the BP algorithm can be reduced by using a min-sum algorithm, but it is less in BER performance. Min-sum can significantly reduce the computational complexity of BP at the cost of a small performance loss. The following subsection will further explain the soft decision decoding and its low complexity modification version known as the min-sum algorithm and its variants.

3.2.2.4 Soft Decision Decoding

The soft decision LDPC code decoding method produces decoding probabilities using a bipartite graph to get the parity check matrix, H tanner graph. Parity check matrix row and column denote as check node (CN) and variable node (VN) respectively. N bit of codeword represented by a variable node and M parity check represented by check node. The parity check matrix can be classified into two groups which are regular and irregular. In regular code, row weight represents the number 1’s in each row, and column weight represents the number 1’s in each column. A regular parity check matrix, H 10 VNs, and 5

CNs with 3 column weights and 6-row weights are presented in Figure 3.4.

$$
\mathbf{H} = \begin{bmatrix}
1 & 1 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 \\
1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 \\
0 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 \\
1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 1 \\
0 & 1 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0
\end{bmatrix}
$$

Figure 3.4: Parity check matrix, H

A nonzero value in the H matrix is represented by the edge connection between the check node and variable node in the graph. Check node, m is connected to a variable node, n when variable n involves in the m parity check constraint with H_{mn} = 1. The word 'low density" refers to a small fraction of nonzero value in H especially for linear block length, *n*. The visual representation of the parity check matrix is illustrated by the tanner graph as visualized in Figure 3.5.

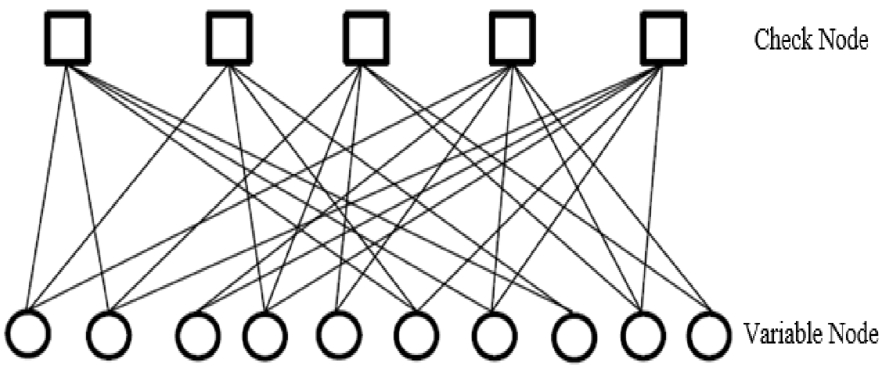


Figure 3.5: Tanner graph of Parity Check Matrix, H

Regular code, C presents a parity check matrix with N length and K dimension. The number of column weight and row weight denoted as M = N – K rows and N columns respectively. The value of *m* row and *n* column in H is represented by H_{mn}. The number of bits involved in the variable node is denoted by $N_m = \{n: H_{mn} = 1\}$. The number of bits involved in the check node is denoted by $M_n = \{m: H_{mn} = 1\}$.

Assume codeword, $c = [c_1, c_{2,} c_3 \dots \dots \dots, c_N]^T$ [14]

To obtain the vector, *t* the input signal modulates whereas it is mapped to the constellation. Before transmission, it is mapped to a signal constellation (modulation) to obtain the vector,

$t = [t_1, t_{2,} t_3 \dots \dots \dots, t_N]^T$ where;

$$t_n = 2 * c_n - 1 \tag{3.8}$$

The obtained vector is transmitted via the AWGN channel with variance, σ^2

$$\sigma^2 = N_0/2 \tag{3.9}$$

$$r = [r_1, r_{2,} r_3 \dots \dots \dots, r_N]^T$$

where received message, r_n

$$r_n = t_n + v_n \tag{3.10}$$

The AWGN channel with zero mean is denoted as v_n. The hard decision vector is

$z = [z_1, z_{2,} z_3 \ldots \ldots \ldots, z_N]^T$ be

$$z_n = sgn\ (r_n) \tag{3.11}$$

where $sgn(r_n) = \begin{cases} 1, & r_n > 0 \\ 0, & otherwise \end{cases}$

Notation:

Ln: A bit node priori information data, *n*

$\overline{Ln}$: A bit node posteriori information data, *n*

Em, n: The *m* check to *n* bit data signal

Fn, m: The *n* bit to *m* check data signal

a) Sum-Product (SP) Algorithm

The flow process of the SP Algorithm can be divided into four steps: [14]

Step 1: Initialization

A priori information data, $Ln = -r_n$

Initialization of bit to check node data signal, $Fn, m = Ln$

Step 2: Horizontal Procedure

Check node operation:

$$Em,n = log\frac{1+\prod_{n\prime\in N(m)\backslash n}\tanh(\frac{Fn',m}{2})}{1-\prod_{n\prime\in N(m)\backslash n}\tanh(\frac{Fn',m}{2})} \qquad (3.12)$$

Step 3: Vertical Procedure

A posteriori information data:

$$\overline{Ln} = Ln + \sum_{m\in M(n)} Em,n \qquad (3.13)$$

Bit node operation:

$$Fn,m = \overline{Ln} + \sum_{m\prime\in M(n)\backslash m} Em,n \qquad (3.14)$$

Step 4: Decoding Decision

$\overline{Ln} > 0, \overline{Cn} = 0, else\ \overline{Cn} = 1$

The algorithm terminates and $\overline{\mathrm{Cn}}$ is assumed as valid decoding results

if H$\overline{Cn}$ = 0.

If not, it will go to the next iteration before the iteration number reaches its maximum limit.

b) Min-Sum Algorithm

To reduce the complexity of decoding operation, the min-sum algorithm which simplified version of the sum-product algorithm is preferable.

The simplification is involved at horizontal step check node operation of the SP algorithm as stated in Equation (3.15): [14]

$$Em, n = log \frac{1 + \prod_{n\prime \in N(m)\backslash n} \tanh(\frac{Fn',m}{2})}{1 - \prod_{n\prime \in N(m)\backslash n} \tanh(\frac{Fn',m}{2})} \tag{3.15}$$

using the relationship:

$$2tanh^{-1}p = log \frac{1+p}{1-p} \tag{3.16}$$

Equation (3.15) can be rewritten as,

$$Em, n = 2tanh^{-1} \prod_{n\prime \in N(m)\backslash n} \tanh(\frac{Fn',m}{2}) \tag{3.17}$$

The modification of Equation (3.17) stated as Equation (3.18),

$$Em, n = 2tanh^{-1} \prod_{n\prime \in N(m)\backslash n} \mathrm{sgn}\ (\mathrm{Fn}', \mathrm{m}) \prod_{n\prime \in N(m)\backslash n} \tanh(\frac{|Fn',m|}{2})$$

$$Em, n = \prod_{n\prime \in N(m)\backslash n} \mathrm{sgn}\ (\mathrm{Fn}', \mathrm{m})\ \ 2tanh^{-1} \prod_{n\prime \in N(m)\backslash n} \tanh(\frac{|Fn',m|}{2}) \tag{3.18}$$

Numerous scaling factor methods were introduced in the literature to reduce the error correction performance degradation in the min-sum algorithm. Then, Chen and Fossorier (2002) in [104] proposed the min-sum based decoding algorithm called Normalized min-sum (NMS) and Offset min-sum (OMS). To improve the decoding error correction performance, both of these algorithms applied to the scaling factor at the check node operation. The scaling factor value can be either a fixed value or varied. The common scaling factor value for the fixed NMS algorithm is 0.8. Meanwhile, the varied scaling factor value is α where $0 < \alpha \leq 1$ in check node operation by using a searching method such as an exhaustive searching algorithm. In the OMS algorithm, the magnitude of the min-sum algorithm is substracted to an offset factor which is a positive constant value, β. Each iteration output does not consider as the offset factor is determined before the decoding process starts. This leads to the optimization of decoding result performance in the OMS algorithm.

i) Normalized Min-Sum

NMS min-sum algorithm operation is the multiplication of the scaling factor, α where $0 < \alpha \leq 1$ at the check node operation. The scaling factor is employed to get a better error correction performance near to SP algorithm. The NMS algorithm calculation is stated in Equation (3.19).

$$E_{mn} = \alpha \,.\, \prod_{n' \in (m)\backslash n} sgn\left(F_{n',m}\right) \quad \min_{n' \in N(m)\backslash n} |F_{n',m}| \tag{3.19}$$

ii) Offset Min-Sum

In the OMS algorithm, the magnitude of the min-sum algorithm is substracted to an offset factor which is a positive constant value, β where $\beta > 0$ at check node processing. The decoding error correction performance improved and the bit error rate calculation is near to the SP algorithm. The OMS algorithm calculation is stated in Equation (3.20).

$$E_{mn} = \prod_{n' \in (m)\backslash n} sgn\left(F_{n',m}\right) . max \left\{ \min_{n' \in N(m)\backslash n} |F_{n',m}| - \beta, 0 \right\} \tag{3.20}$$

3.2.2.5 LDPC Encoder

The objective of the LDPC encoder is to solve parity calculation given by a parity check matrix H:

$$HC^T = 0,$$

where, C is the systematic codeword consisting of parity code vector, P, and the information data bit vector, S.

LDPC code is not regularly being used in any application system since it has been developed for many years. The weakness of the LDPC coding technology is very complex. If the encoding is performed by generating a matrix, there will be a large and sparse matrix being stored. However, the LDPC code will show its advantages in the case of long code length. Once the length of the code gets longer, the problem is to store the matrix even though the matrix for LDPC code checking is sparse. From the coding point of view, the LDPC code is still facing a series of problems. For example, storage space is an important reason for restricting the application of LDPC codes. The code length needs more storage space. Therefore, the LDPC code communication system must have a simpler encoding and decoding process. At the same time, the LDPC code is not only considered communication speed, but it also has to take the code operational complexity for performance improvement. The research of the LDPC coding algorithm is based on this idea. Generally, the parity check matrix can be encoded by an iterative method as long as it has a lower triangular structure. The operational complexity of the encoding process can be reduced by this iterative method. The LU encoding algorithm is built on this concept. The parity check matrix is a matrix of full rank in a row. The parity check matrix, H can be simplified, if the row is not ranked. The matrix H can be check to approximate diagonal elements all in the form of L. The problem of the LU encoding algorithm is that the complexity of preprocessing is very high, and more importantly, after the pretreatment, the new check matrix is likely to be a sparse matrix, so the calculation of the coding is very large.

LU encoding of a matrix, H in the form H=LU, where L is unit lower triangular and U is upper triangular, is called an LU factor of H. LU factor of H exists if all of its leading principal minors are nonsingular. A classical elimination scheme, called Gaussian elimination, is used to obtain an LU factor of H. Gaussian elimination without pivoting is, in general, an unstable process. Gaussian elimination with partial pivoting is considered to be a stable process in practice.

QR encoding of a matrix, H in the form H=QR, where Q is orthogonal and R is an upper triangular matrix, is called a QR factor of H. The QR factor of H can be obtained using Classical Gram Schmidt, Modified Gram Schmidt, Householder Reflection, and Given Rotation method. The Gram Schmidt processes do not have favorable numerical properties. Both Householder Reflection and Given Rotation methods are numerically stable procedures for QR encoding. The householder Reflection method is slightly more efficient than the Given Rotation method.

3.3 Relay Positioning

For this thesis, linear placement will be considered in the simulation. In this simulation, the source, relay, and destination are positioned linearly on the same axis. The three different position settings will be considered in this simulation namely relay centered, relay near to source, and relay near to the destination.

3.3.1 Relay Centered

Each source to relay and relay to destination distance is equal to half of the source to destination which the relay positioned in the middle between source and destination node as illustrated in Figure 3.6.

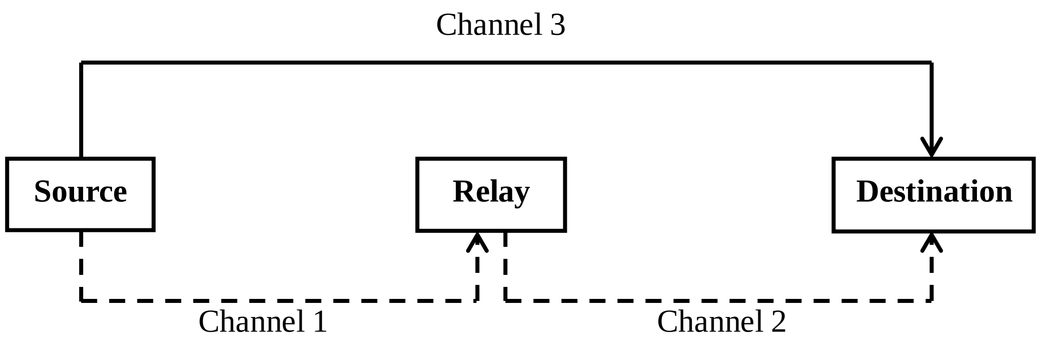


Figure 3.6: Relay Centred

3.3.2 Relay Near to Source

The relay node is positioned near to the source node and the distance of the source to the relay node is less than the relay to the destination node as illustrated in Figure 3.7.

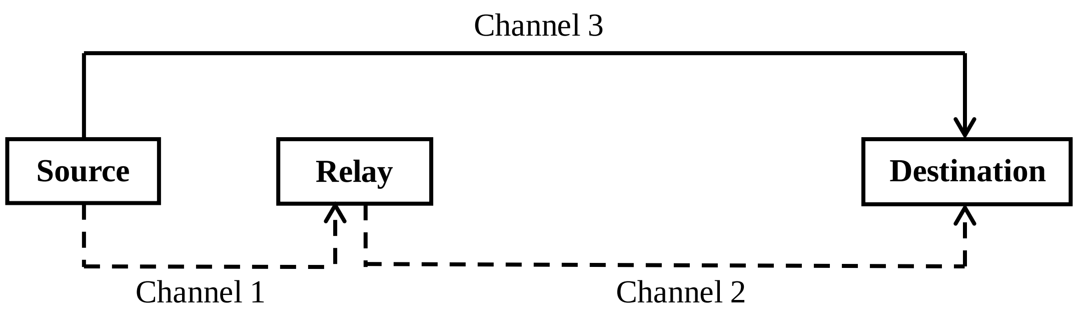


Figure 3.7: Relay near to the source

3.3.3 Relay Near to Destination

The relay node is positioned near the destination node and the distance of the relay to the destination node is less than the source to the relay node as illustrated in Figure 3.8.

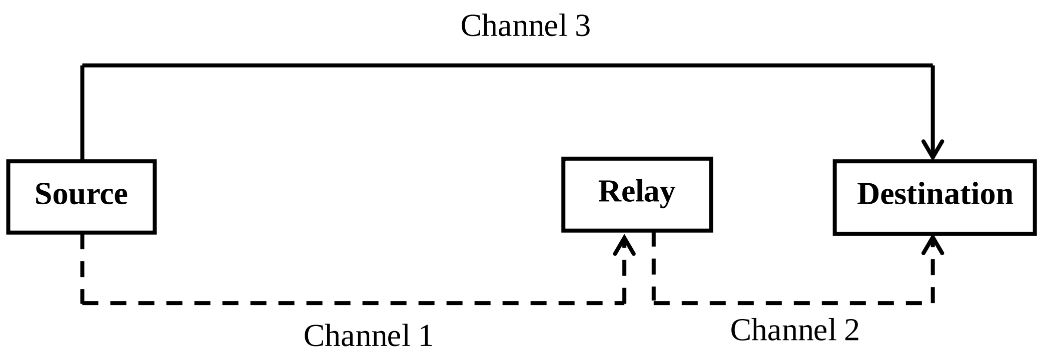


Figure 3.8: Relay near to the destination

3.4 Simulation Setup for DF Protocol Relay System Model Using LDPC Code

To verify the DF protocol relay system using LDPC code, a simulation was designed and carried out using Matlab software. The Sum-Product algorithm was employed as the LDPC code decoder method. In this simulation, the performance of the proposed DF protocol relay system using LDPC code was compared against non-cooperative, AF, DF, and DF relay protocol using the Turbo code. The decoding algorithms in terms of BER performance are compared. All the comparative methods used the same input random bits data. The rate for both Turbo codes and LDPC codes is ½. BPSK modulation scheme is considered. The channel was modeled as Rayleigh fading with AWGN. The signal was received from the source node to the relay node combined using the MRC method. The message from the broadcasting message transmitted over the channel was modeled as Rayleigh fading with AWGN. The signal received from the source node to the relay node combine using the MRC method. The maximum number of iteration is set to 10. The simulation parameters are presented in Table 3.1.

Table 3.1: Simulation parameters

Parameter	Value
Code rate	1/2
Iterations	10
Modulation	BPSK
Channel Model	Rayleigh fading + AWGN
Combiner	MRC

All the comparative methods are briefly introduced as the following:

a) Non-cooperative: No relay is considered. The source transmits during the broadcasting stage. Then it interleaves, re-encodes, and transmits during the relaying stage. Both transmissions experience the same channel.

b) AF: Relay first amplifies the received information signal by using the amplification factor and then forward it to the destination to combine with the source signal.

c) DF: Relay performs fixed decode and forward transmission. The message signal will only be received at the destination if the combined received signal from the source and relay is successfully decoded. If the relay’s transmission contains errors, it is impossible for the destination recovered the message from the combined signal.

d) Turbo code: Turbo code decoding algorithms employ the BCJR algorithm. The Turbo code defined in [40] was used for obtaining the error performance curve. The

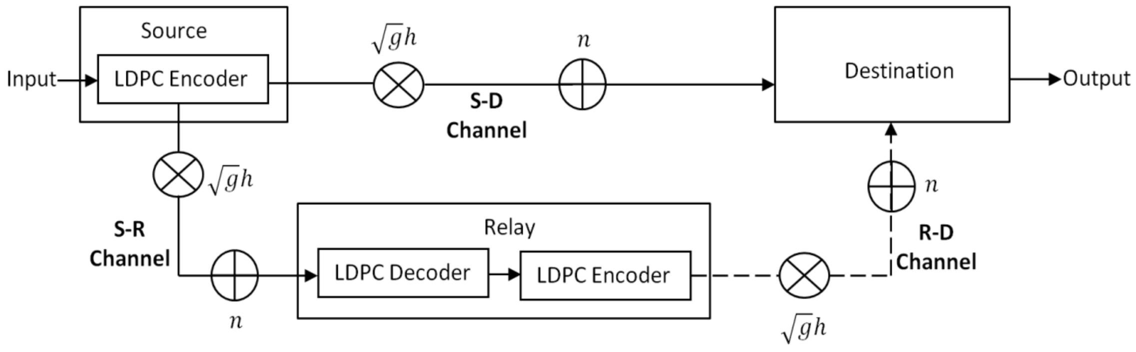
BCJR algorithm is a symbol-based decoder and delivers probabilities of the correctness of the symbol decoding together with each decoded bit. The turbo code decoder consists of two Soft-Input Soft-Output (SISO) decoders. These decoders are similar to the convolutional decoder, except for some modifications. The systematic stream and the first parity stream are fed to the first decoder while an interleaved version of the systematic stream and the second parity stream are fed to the second one. The first decoder starts, and instead of generating a final LLR, it generates a cleared-up version, called extrinsic information. This is interleaved and sent to the second decoder. It performs decoding, which is more reliable compared to the case where it does not have the additional information from the first decoder. Similarly, it generates extrinsic information for the first decoder, and instead of interleaving, it performs deinterleaving, and at this point, iteration is completed. On the next iteration, the first decoder starts the same as before, but now it has extrinsic information from the second decoder, and therefore a more reliable output is calculated. The decoding continues until a stopping criterion is satisfied, or the maximum number of iterations has been reached. After any iteration, the total LLR is calculated. If the interleaver is designed appropriately, then it would appear as if the original and interleaved streams are uncorrelated.

3.5 Min-Sum Based LDPC Decoder

LDPC decoder is the component of the DF protocol relay system using the LDPC code model at the relay node. In this research work, a new LDPC Decoder method is proposed based on a min-sum based decoding algorithm. The proposed min-sum based decoding algorithm is called the Variable Global Optimization min-sum (VGOMS) algorithm. The concept embedded in this algorithm is described in the author's published research work in [133]. The main objective of the algorithm is on dealing with the problem of high complexity. The optimization min-sum based decoding approaches achieved very good error-correcting performance and at the same time retaining the main characteristics of the min-sum based decoding which is low computational complexity operation and independent concerning noise variance estimation errors in [14, 93, 134]. The VGOMS algorithm operates based on min-sum modification by employing an optimized scaling factor at the bit node processing of the variable node operation. Moreover, the proposed VGOMS algorithm also utilized Particle Swarm Optimization (PSO) technique to determine the optimized scaling factor. The proposed VGOMS algorithm will be further described.

3.5.1 The Operation Set Up for DF Protocol Relay System Using VGOMS at Relay Node

The operation set up for the DF protocol relay system using the LDPC code is illustrated in Figure 3.9. In this model, it is assumed that nodes S (Source), R (Relay), and D (Destination) are aligned as such, $d_{SR} + d_{RD} = d_{SD}$. The link distance among the source to destination (SD), source to relay (SR), and relay to the destination (RD) are normalized. This is representing SR and RD distances which are normalized against SD distance. In this case, the SD link is assumed as the longest distance among the three links. Consequently, $d_{SR} + d_{RD} = 1$ which means d_{SR} and d_{RD} distances are smaller than 1.



——— Broadcast stage ------ Relaying

S-R Souce-Relay S-D Source-Destination R-D Relay-Destination

Figure 3.9: Model of DF protocol relay system using LDPC code

Data transmission is organized in a bit by bit fashion. The transmission of each bit is divided into two stages, namely broadcasting and relaying. The channels connecting all three nodes are modeled as a combination of large-scale and small-scale fading effects, a quasi-static Rayleigh block fading channel with path loss of 3 named as a cooperative channel. A quasi-static Rayleigh block fading channels are constant over the combined broadcast and relay stages for each bit and change independently between adjacent bit transmissions. The channel coefficient is modeled as given in Equation (3.21):

$$\rho = \sqrt{g}h, \tag{3.21}$$

where h $(h_{sr}h_{sd}h_{rd})$ is the circularly symmetric complex random variable with zero mean and average unit power, and g is the channel gain related to distance, d, as given in Equation (3.22):

$$g = \frac{1}{d^{v}} \tag{3.22}$$

where v is the path-loss exponent. Equation (3.21) indicates that the channel model combines large-scale and small-scale effects. This model is also found in the literature [134-135]. In this model, the common path loss exponent for an urban cellular radio channel at the same time is a number between 3 and 5 in [66]. The path loss component of 3 is considered in this research work.

During the broadcasting stage, the source encodes the information bits using the LU encoding method and broadcast it to the destination and relay. The destination delays decoding operation until the end of the relay stage. The relay decodes the broadcast message using VGOMS. During the relaying stage, the relay node sends the encoded bits to the destination node and at the same time, the source node remains silent. The equation of the signal received at the relay and destination node is given by:

$$Y_{sr} = \sqrt{g_{sr}}h_{sr}t_s \ + n_{sr} \tag{3.23}$$

$$Y_{sd} = \sqrt{g_{sd}}h_{sd}t_s \ + n_{sd} \tag{3.24}$$

$$Y_{rd} = \sqrt{g_{rd}}h_{rd}t_r \ + n_{rd} \tag{3.25}$$

where Y_{ab} $(Y_{sr,}Y_{sd,}Y_{rd})$ is the received signal vector at the node a sent b by the source node, while t_a $(t_{s,}t_{s,}t_r)$ is the encoded bit at node a, and n_{ab} $(n_{sr}, n_{sd,}n_{rd})$ is the AWGN vector with a variance of $N_0/2$ per dimension at node b. The DF protocol pseudo-code is presented in Figure 3.10. The received signals at the relay are processed and the VGOMS algorithm is applied to decode the transmitted bit.

Algorithm 1: DF Protocol

Initialization: Set $t, d, v\ g, h, n, SNR$;

Start;

for each iteration **do**

----------------First phase--

Source transmits t encoded bits.

Compute Y_{sr} based on (3.23).

Compute Y_{sd} based on (3.24).

Relay obtains the detected bit based on VGOMS

----------------Second phase--

Relay that successfully detected the bits forward them to destination.

Compute Y_{rd} from each forwarding relay based on Equation (3.25).

Destination uses obtained Y_{sd} and Y_{rd} to detect the bits.

end

Figure 3.10: Pseudo-code of the DF protocol algorithm using VGOMS at the relay

3.5.2 Simulation Development of Min-Sum Based LDPC Decoder at Relay Node

To evaluate the error corrective and computation operational complexity performance of the proposed decoding algorithm and its other competing algorithm, the systematic simulation setup was designed and developed. The proposed min-sum based decoding algorithm performance was compared with the other existing min-sum based decoding algorithms in terms of error corrective and computation operational complexity.

The proposed min-sum based decoding algorithm for the LDPC decoder of the DF protocol relay system using LDPC code is illustrated in Figure 3.11. The channel is modeled as cooperative fading and AWGN. Cooperative fading is a combination of large-scale and small-scale fading effects which extensively model as used in a cooperative communications environment. The small-scale fading effect is referred to as a quasi-static Rayleigh block fading channel and the large-scale effect is referred to as path loss of 3.

The proposed min-sum based LDPC decoder algorithm is named as Variable Global Optimization Min-Sum (VGOMS) algorithm. The main feature of this algorithm is low computation processing complexity and better BER for the LDPC decoder of the DF protocol relay system model. The values of the scaling factor obtained from the PSO technique used at the bit node processing of variable node operation are important to produce the minimum BER. The multiplication of the scaling factor at the bit node processing of variable node operation will only further reduce the decoding complexity processing.

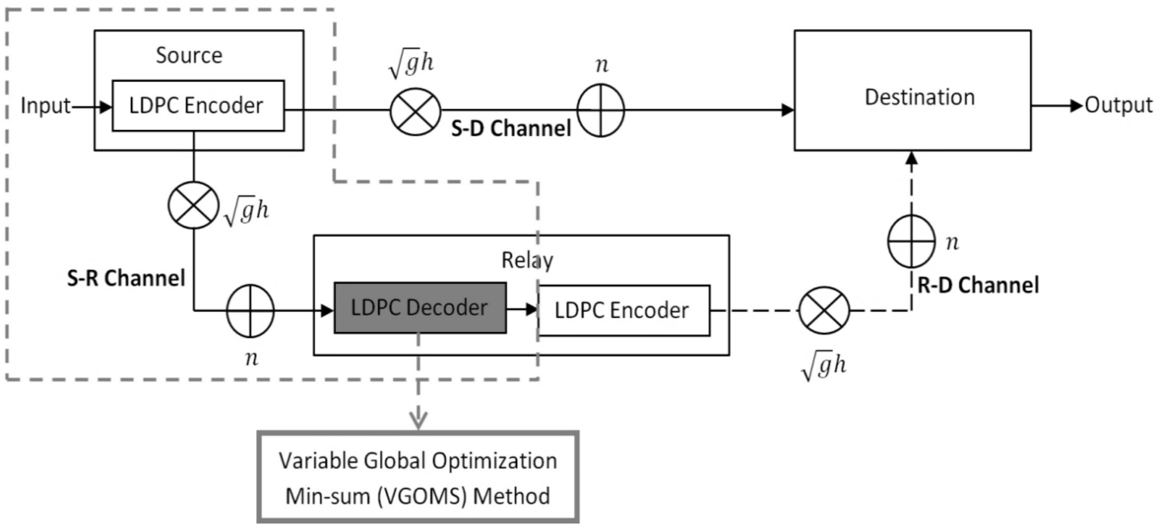


Figure 3.11: Min-sum based decoding algorithm for LDPC decoder of the DF protocol relay system using LDPC code

3.5.3 Variable Global Optimization Min-Sum Algorithm

The flowchart of the proposed VGOMS algorithm is depicted in Figure 3.12 and the pseudo-code of the proposed VGOMS algorithm is presented in Figure 3.13. The proposed VGOMS algorithm aims to minimize the error rate with low complexity implementation. In this work, the VGOMS algorithm was found to improve performance by adopting different approaches. For example, in the normalized min-sum algorithm, the scaling factor is multiplied in the check node operation, whereas, in the VGOMS algorithm, the scaling factor is multiplied in the variable node operation which is performing at lower complexity. Notwithstanding, the PSO method is used to determine the optimal scaling factor value which is known as the best fitness value in deciding the optimized error rate performance of the proposed algorithm. Figure 3.12 illustrates the process of the proposed VGOMS algorithm.

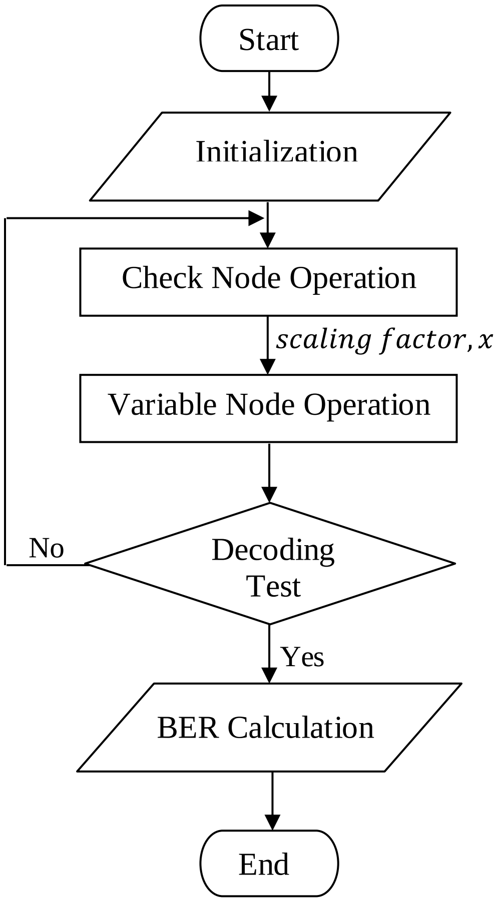


Figure 3.12: The flowchart of the proposed VGOMS algorithm

In this work, random (128, 64) regular LDPC codes with code rate ½, column weight 3, and row weight 6 are used to test our VGOMS algorithm. The codes are transmitted on a cooperative channel as given in Equation (3.23) with BPSK modulation. The maximum number of iterations is set to be 10.

a) Initialization

The random bits input signal was generated at the source node. Then, the random bits input signal encoded using the LU encoder method at the source node. The encoded bits signal is modulated using the BPSK modulation scheme at the source node. The S-R channel was modeled as cooperative fading and AWGN. Next, the error bits signal demodulated using BPSK at the relay node. These error bits signals were used as the first iteration's input message signal to the check node update operation of VGOMS at the relay node. The check node and variable node processing steps in the VGOMS algorithm were carried out as follows:

b) Check Node Operation:

i) Message received, $M_{ij} = Y_{sr}$

ii) Sign and magnitude factor, M_{ij},

Sign (M_{ij}) = α_{ij} ,

Magnitude (M_{ij}) = β_{ij},

iii) Check node output message, E_{ji}

$$E_{ji} = \prod \alpha_{ij} \cdot \min \beta_{ij} \tag{3.26}$$

where E_{ji} is the extrinsic information from check node j to variable node i, and is expressed as a Log-likelihood Ratio (LLR).

The process then proceeds to the variable node operation.

c) Variable Node Operation

Total Log-likelihood Ratio (LLR) of the i[th] bit, L_i^{total}

$$L_i^{total} = L_i + \sum E_{ji} \tag{3.27}$$

where,

L_i = input LLR,

M_{ji} = bit node processing output.

$$M_{ji} = L_i + \sum E_{ji} - xE_{ji} \tag{3.28}$$

To reduce the complexity, only multiplying the scaling factor, *x* at the bit node processing of the variable node operation update is considered instead of at the check node or both check node and variable node. Given the check node operation is a complicated process, this can reduce the complexity of the algorithm.

d) Decoding Test Procedure

If $L_i > 0, c_i = 0$, else , $c_i = 1$

If $Hc_i^T = 0$, then the algorithm stops and c_i is considered as a valid decoding result.

Else, it will go to the next iteration before the number of iteration reaches its maximum limit.

where,

H = parity check matrix

c_i = codeword

e) Bit Error Rate (BER) Calculation

$$f(x) = \frac{c_r}{c_t} \quad (3.29)$$

where,

$f(x)$ = Bit error rate (BER)

c_r = No of corrupted bits codeword received

c_t = Total number of bits codeword transmitted

Algorithm 2: VGOMS algorithm

---

procedure DECODE(Y_{sr})

I = 0 //Initialization

for i = 1 : n **do**

  for j = 1 : m **do**

    $M_{ij} = Y_{sr}$

    $\alpha_{ij} = sign\ (M_{ij})$

    $\beta_{ij} = |M_{ij}|$

  end for

end for

repeat

// Check Node Operation

for j = 1 : m **do**

$$E_{ji} = \prod \alpha_{ij} \cdot \min \beta_{ij}$$

end for

for i = 1 : n **do** // Decoding test

$$L_i^{total} = L_i + \sum E_{ji}$$

$$c_i = \begin{cases} 1 & if\ L_i^{total} < 0 \\ 0 & else \end{cases}$$

end for

if $I = I_{max}$ or $Hc^T = 0$ **then**

Finished

else

// Variable Node Operation

for i = 1 : n **do**

$$M_{ji} = L_i + \sum E_{ji} - xE_{ji}$$

end for

$I = I + 1$

end if

until Finished

Count the number of erroneously detected bits, and store it.

Compute BER as the ratio of the total erroneous bits to the total transmitted bits.

end procedure

Figure 3.13: Pseudo-code of the proposed VGOMS algorithm

3.5.4 Selection Scaling Factor Using PSO

The main feature of the proposed VGOMS is the use of a variable scaling factor at the bit node processing of variable node operation. The multiplication of the scaling factor, only at the bit node processing of the variable node can be defined as the difference between the VGOMS algorithm with both normalized min-sum and 2-D min-sum algorithms in [102]. In the normalized min-sum algorithm, the fixed scaling factor was applied at the check node operation and therefore, the computational complexity of the proposed VGOMS algorithm will reduce as the variable node complexity process is less complex, as compared with the check node operation. Furthermore, the values of the scaling factor, x determined from the PSO technique for different Signal to Noise Ratio (SNR). Then, the selected scaling factor, the x value is applied to the bit node processing to produce the minimum BER.

The pseudo-code of the scaling factor, *x* selection procedure using the PSO method is shown in Figure 3.14. Particle Swarm Optimization (PSO) is a useful optimization method initially introduced by Kennedy and Eberhart in 1995 and is a population-based search algorithm inspired by the social behavior of animals. The population in the context of PSO is called a ‘swarm’, and the individuals are called ‘particles’. PSO starts with a set of possible solutions or particles as a swarm, which is created randomly. The population size in this simulation is at 20 particles to keep the computational requirement low. The range in which the algorithm computes the optimal control variables is called search space. The algorithm will search for the optimal solution in the search space between 0 and 1. When any of the optimal control values of any particle exceed the searching space, the value will be reinitialized. In this simulation, the lower and upper boundaries are set to 0 and 1. A new swarm position is generated by updating the particle's velocity and position iteratively and then comparing it with their old position. This is inspired by the fact, that newer positions of the particles in the swarm will be better than older ones. PSO-based optimization operates with an objective function that obtains a search based on the population. Particles in this algorithm are used as solutions. Such particles are initialized randomly. Next, they are ready to move freely and fly around the multidimensional search space. When the particles are moving freely in the search space, the particles update their velocity. Then, the particles adjust their location according to the best experiences of both particles and the population. The velocity calculation of all particles in each iteration is updated using the following equation:

$$v_i{}^t = wv_i{}^{t-1} + c_1 r_1 (pbest - p_i^t) + c_2 r_2 (gbest - p_i^t) \tag{3.30}$$

where p_i^t and $v_i{}^t$are the position and velocity of the particle i, respectively. The random velocity of all particles is distributed in a range [-1000, 1000]. While *pbest* and *gbest* is the 'best' position (position with the 'best' fitness value) discovered particle i and the entire population respectively. Here w is inertia weight parameter is equal to 0.1 which is controlling the flying dynamics. r_1 and r_2 are two random variables between 0 and 1. The factors which are controlling the weight of corresponding terms are c_1 and $c_2$which their values are bounded between 0 and 2 [136]. $v_i{}^t$ should be checked after updating, so that it lies within the predefined range. This step is necessary to avoid violent random walking. The positions of every particle between successive iterations are updated according to the following equation:

$$p_i^t = p_i^t + v_i{}^t \tag{3.31}$$

This updating of velocity and position drives the particle towards the region with a better objective function value (BER value) as given in Equation (3.29). In each iteration, local best and global best value both are updated according to the following conditions:

$$pbest = p_i^t \qquad \text{if } f(p_i^t) < f(pbest)$$

$$gbest = g_i^t \qquad \text{if } f(g_i^t) < f(gbest)$$

Where, $f(x)$ is the objective function subject to minimization. After 100 iterations, the algorithm stops. After termination of the process, all particles come together at the point having the lowest objective function value. Hence, the values of $gbest$ and $f(gbest)$ indicate the problem's solution. As a result, the decoding performance will be at the optimized value, and the best BER performance of the VGOMS is obtained.

PSO is reasonably straightforward to implement compared with other optimization methods, as it can quickly determine many high-quality solutions, with notable stable convergence characteristics. Moreover, the PSO computational method is flexible and is a reliable mechanism for improving and adjusting to widespread searching capabilities.

Algorithm 3: Selection Scaling Factor Using PSO

Function PSO for Scaling Factor, x selection

Input: scaling factor, x from VGOMS

Output: Optimal scaling factor, x_{best}(Best *gbest*)

Begin

Objective Function: $f(x)$ = BER

Find *gbest* from min $f(x)$

while termination criteria not true **do**

Initialize parameter c_1, c_2, w and population size

for each particle in the swarm

Initialize its position and velocity randomly

end for

do

for each particle in the swarm

Update the particle velocity according to the equation:

$v_i{}^t = wv_i{}^{t-1} + c_1r_1(pbest - p_i^t) + c_2r_2(gbest - p_i^t)$

Update the particle position according to the equation:

$p_i^t = p_i^t + v_i{}^t$

end for

for each particle in the swarm

Evaluate the fitness function

Update local best, *pbest*

if the objective fitness value is better than the personal best objective fitness value (*pbest*) in history **then**

current fitness value set as the new personal best (*pbest*)

end if

end for

Update global best, *gbest*

Sort all the particles or neighborhood, choose the particles with best fitness value as the *gbest*

end while termination criteria are true

end Begin

return Best *gbest* of all particles as the solution in VGOMS

Figure 3.14: Pseudo-code of the scaling factor selection using PSO

3.5.5 Baseline Algorithm

In this work, four different popular LDPC code decoding algorithms are selected as baseline algorithms to develop the VGOMS algorithm. All of these algorithms have different error corrective performance and computational complexity measurements. The algorithms are SP, MS, NMS, and OMS. In previously published research work results proved that the SP algorithm achieved is considered as the most efficient decoding technique and produces a good result performance. However, the SP algorithm is computational instability, depends on estimation errors of thermal noise and high computational complexity [137]. MS operates in low computation complexity and independence about estimation errors of the noise variance. However, MS operates by overestimation at the check node operation. This results in a loss of performance compared with SP decoding [14]. NMS and OMS mitigate error rate performance reduction. Similarly, with the MS decoding algorithm, both NMS and OMS decoding algorithms operate estimation at the check node operation message. In the NMS decoding algorithm, a constant scaling factor with a value of less than 1 multiplies at the check node operation message. While in the OMS decoding algorithm, a constant offset parameter is subtracted from the check node operation message to minimize the overestimation [138]. Both NMS and OMS decoding methods put more emphasis on optimization at check node operation only to recover performance loss due to overestimation of check node operation of MS. These four algorithms (SP, MS, OMS, and NMS) were chosen because they have a potential to provide a good characteristic to balance the trade-off problem between complexity reduction and error correction performance of the DF protocol relay decoder [102].The pseudo-code of the SP, MS, NMS and OMS is detailed in Figure 3.15 until Figure 3.18.

3.5.5.1 SP Algorithm

SP algorithm performs a good decoding result performance. The check node computation operation of the SP algorithm required many logarithmic and multiplicative operations. The SP algorithm check node operation consumes high computational operation complexity which leads to higher execution time implementation. The pseudo-code of the SP algorithm is presented in Figure 3.15.

Algorithm 4: SP algorithm

procedure DECODE(Y_{sr})

I = 0 //Initialization

for i = 1 : n **do**

  for j = 1 : m **do**

    $M_{ij} = Y_{sr}$

    $M_{ij} = \alpha_{ij}\, \beta_{ij}$

    $\alpha_{ij} = sign\,(M_{ij})$

    $\beta_{ij} = |M_{ij}|$

  end for

end for

repeat

// Check Node Operation

  for j = 1 : m **do**

    for input = x **do**

      $\emptyset(x) = -\log[\tanh(x/2)] = \log\left(\frac{e^x+1}{e^x-1}\right)$

    end

$E_{ji} = \prod \alpha_{ij} \cdot \emptyset\left(\sum \emptyset\left(\beta_{ij}\right)\right)$

end for

for i = 1 : n **do** // Decoding test

$L_i^{total} = L_i + \sum E_{ji}$

$c_i = \begin{cases} 1 & if\ L_i^{total} < 0 \\ 0 & else \end{cases}$

end for

if $I = I_{max}$ or $Hc^T = 0$ **then**

Finished

else

// Variable Node Operation

for i = 1 : n **do**

$M_{ji} = L_i + \sum E_{ji} - E_{ji}$

end for

$I = I + 1$

end if

until Finished

Count the number of erroneously detected bits, and store it.

Compute BER as the ratio of the total erroneous bits to the total transmitted bits.

end procedure

Figure 3.15: Pseudo-code of the SP algorithm

3.5.5.2 MS Algorithm

MS algorithm performs less complex check node operation with simple comparison and summation operations and independent estimating errors of the thermal noise. MS operates by overestimation at the check node operation. This results in a loss of performance compared with SP decoding. The pseudo-code of MS is presented in Figure 3.16.

Algorithm 5: MS algorithm

procedure DECODE(Y_{sr})

I = 0 //Initialization

for i = 1 : n **do**

  for j = 1 : m **do**

    $M_{ij} = Y_{sr}$

    $\alpha_{ij} = sign\ (M_{ij})$

    $\beta_{ij} = |M_{ij}|$

  end for

end for

repeat

// Check Node Operation

  for j = 1 : m **do**

    $E_{ji} = \prod \alpha_{ij} \cdot \min \beta_{ij}$

  end for

  for i = 1 : n **do** // Decoding test

    $L_i^{total} = L_i + \sum E_{ji}$

    $c_i = \begin{cases} 1 & if\ L_i^{total} < 0 \\ 0 & else \end{cases}$

  end for

  if $I = I_{max}$ or $Hc^T = 0$ **then**

    Finished

  else

// Variable Node Operation

    for i = 1 : n **do**

      $M_{ji} = L_i + \sum E_{ji} - E_{ji}$

end for

$I = I + 1$

end if

until Finished

Count the number of erroneously detected bits, and store them.

Compute BER as the ratio of the total erroneous bits to the total transmitted bits.

end procedure

Figure 3.16: Pseudo-code of the MS algorithm

3.5.5.3 NMS Algorithm

NMS performs the overestimate at check node processing message and L_i^{total} can be corrected by a fixed scaling factor. The pseudo-code of NMS is presented in Figure 3.17.

Algorithm 6: NMS algorithm

procedure DECODE(Y_{sr})

$I = 0$ //Initialization

for i = 1 : n **do**

for j = 1 : m **do**

$M_{ij} = Y_{sr}$

$\alpha_{ij} = sign\,(M_{ij})$

$\beta_{ij} = |M_{ij}|$

end for

end for

repeat

// Check Node Operation

for j = 1 : m **do**

$$E_{ji} = 0.8 \prod \alpha_{ij} \cdot \min \beta_{ij}$$

end for

for i = 1 : n **do** // Decoding test

$$L_i^{total} = L_i + \sum E_{ji}$$

$$c_i = \begin{cases} 1 & if\ L_i^{total} < 0 \\ 0 & else \end{cases}$$

end for

if $I = I_{max}$ or $Hc^T = 0$ **then**

Finished

else

// Variable Node Operation

for i = 1 : n **do**

$$M_{ji} = L_i + \sum E_{ji} - E_{ji}$$

end for

$I = I + 1$

end if

until Finished

Count the number of erroneously detected bits, and store it.

Compute BER as the ratio of the total erroneous bits to the total transmitted bits.

end procedure

Figure 3.17: Pseudo-code of the NMS algorithm

3.5.5.4 OMS Algorithm

OMS performs overestimate at check node processing message and L_i^{total} can be corrected by subtracting a fixed positive constant from the magnitude of L_i^{total}. The pseudo-code of OMS is presented in Figure 3.18.

Algorithm 7: OMS algorithm

procedure DECODE(Y_{sr})

I = 0 //Initialization

for i = 1 : n **do**

  for j = 1 : m **do**

    $M_{ij} = Y_{sr}$

    $\alpha_{ij} = sign\ (M_{ij})$

    $\beta_{ij} = |M_{ij}|$

  end for

end for

repeat

// Check Node Operation

  for j = 1 : m **do**

    if ($\min \beta_{ij} > 0.2$)

      $E_{ji} = \prod \alpha_{ij} \cdot (\min \beta_{ij} - 0.2)$

    else

      $E_{ji} = 0$

    end

  end for

for i = 1 : n **do** // Decoding test

$$L_i^{total} = L_i + \sum E_{ji}$$

$$c_i = \begin{cases} 1 & if\ L_i^{total} < 0 \\ 0 & else \end{cases}$$

end for

if $I = I_{max}$ or $Hc^T = 0$ **then**

Finished

else

// Variable Node Operation

for i = 1 : n **do**

$$M_{ji} = L_i + \sum E_{ji} - E_{ji}$$

end for

$I = I + 1$

end if

until Finished

Count the number of erroneously detected bits, and store them.

Compute BER as the ratio of the total erroneous bits to the total transmitted bits.

end procedure

Figure 3.18: Pseudo-code of the OMS algorithm

3.5.6 Simulation Set up of VGOMS

Four simulations were designed and carried out. Simulation is performed on Mathworks Matlab. These are as follows:

a) *Simulation 1: Scaling Factor, x*

In this simulation, transmission over a combination of large-scale and small-scale fading effects, a quasi-static Rayleigh block fading channel with path loss of 3 named as a cooperative channel is considered. The BPSK modulation scheme and LDPC code rate of ½ are used over the transmission. The maximum number of iteration is set to 10. Next, in the VGOMS decoding stage, broadcast messages received at the relay node are updated in the check node operation and variable node operation. In this work, multiplied the scaling factor, x at the bit node processing of the variable node operation is considered. The best scaling factor, x for different Signal to Noise Ratio (SNR) performed in this simulation. To find the best solution (the best scaling factor), x and the fitness value are used at the bit node processing in the variable node operation as given in Equation (3.28). Finally, the best scaling factor, x for each SNR is used to produce the optimal minimum Bit Error Rate (BER) as stated in Equation (3.29).

b) *Simulation 2: Performance comparison between the VGOMS algorithm against four existing decoding algorithms: MS, OMS, NMS, and SP*

In this simulation, the performance of the proposed VGOMS algorithm was compared against that of four existing decoding algorithms: MS, OMS, NMS, and SP. The decoding algorithms are compared in terms of BER performance and computational complexity. The message from the broadcasting message transmitted over cooperative channel used in simulation 1 with code rate ½ after the BPSK modulation scheme. The maximum number of iteration is set to 10. The optimal BER performance is achieved by Equation (3.29) using the best scaling factor (*gbest*) from the PSO method. The scaling factor searching flow process of the VGOMS algorithm using the PSO method is illustrated in Figure 3.19.

For the computational complexity of the check node equation performance evaluation, the computational complexity of the check node operation equation in the original min-sum algorithm was determined by comparison and through additional operations, as shown in Equation (3.26). Moreover, the check-node degree is assumed as d_c and $d_c + [\log d_c] - 2$ as additional operation.

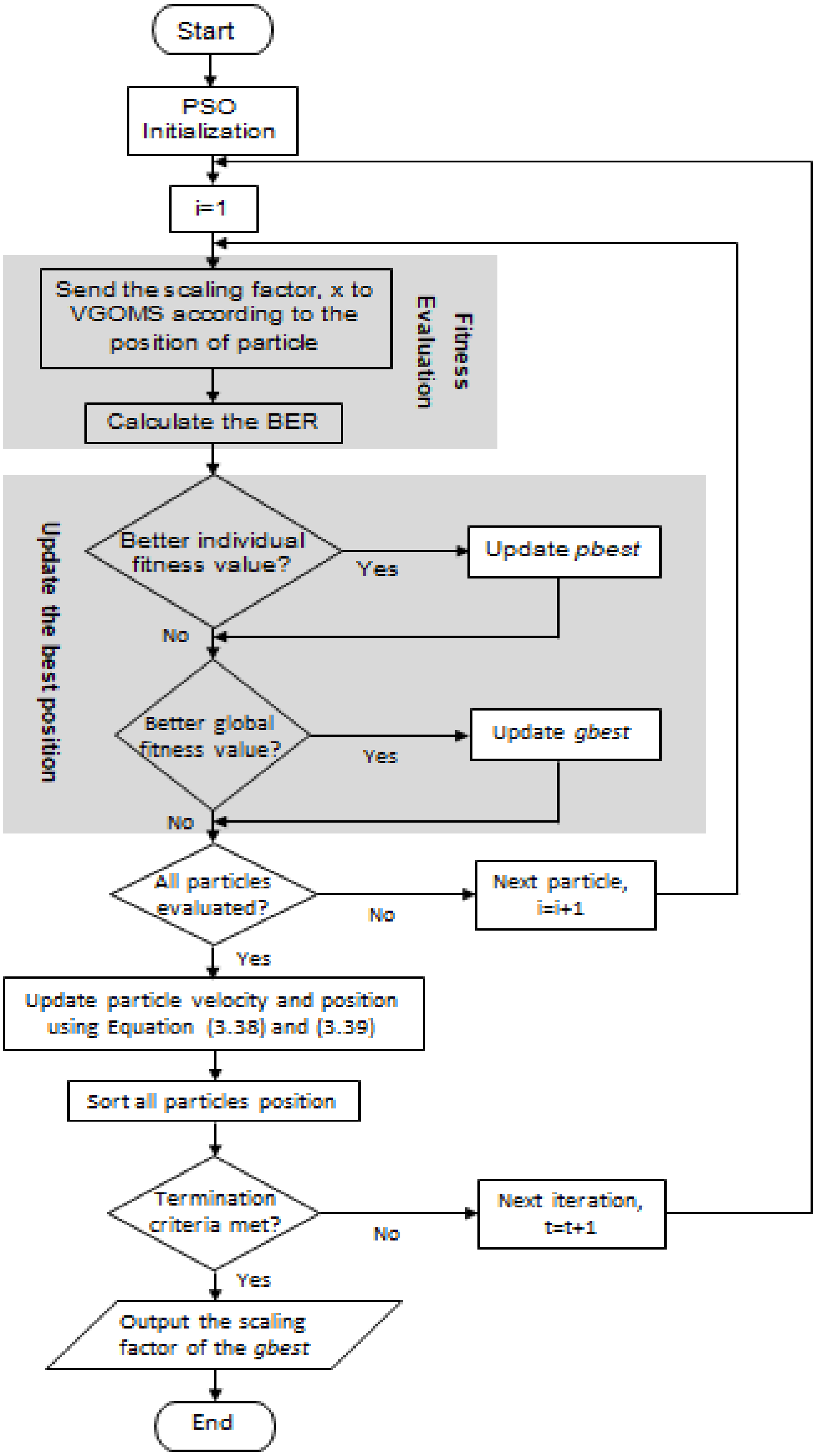


Figure 3.19: The scaling factor searching flow process of the VGOMS algorithm using the PSO method

c) *Simulation 3: BER Performance with BPSK and QPSK*

In this simulation, the BER performance of the proposed VGOMS algorithm analyzed for Binary Phase Shift Keying (BPSK) and Quadrature Phase Shift Keying (QPSK) modulation schemes are compared. The channel is modeled as a cooperative channel which is a combination of large-scale and small-scale fading effects, a quasi-static Rayleigh block fading channel with path loss of 3. The number of iteration was set to 10 iterations and an LDPC code rate of ½ was used in the decoding process.

d) *Simulation 4: BER performance under AWGN, Rayleigh fading, and Cooperative channel*

In this simulation, the BER performance evaluation of the proposed VGOMS algorithm under three different channel models; AWGN, Rayleigh fading, and Cooperative channel were compared. BER calculation against different Signal-to-Noise ratios (SNR) was adopted to evaluate the performance. The code rate of ½ and BPSK modulation were employed. The maximum number of iteration was set to 10.

3.6 Simulation Development of LDPC Encoder at Source Node

LDPC encoder is the process of converting input data messages in the format version needed for the data processing needs. LDPC encoder is the pre-processing stage of the LDPC decoder stage in the DF protocol relay system using the LDPC code. The proposed LDPC encoder model for the LDPC encoder of the DF protocol relay system using LDPC code is illustrated in Figure 3.20.

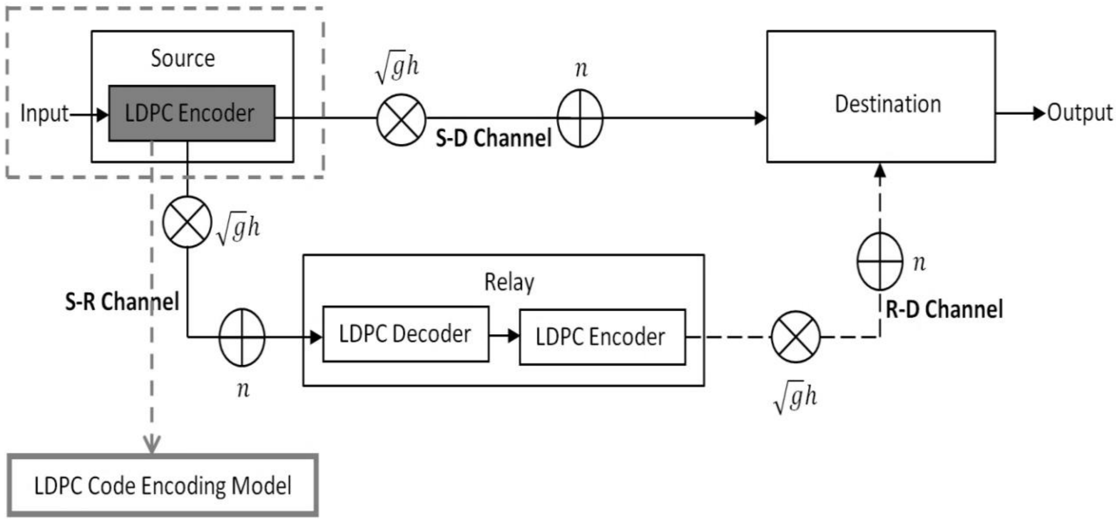


Figure 3.20: LDPC encoder model for LDPC encoder of the DF protocol relay system using LDPC code

One major concern of the LDPC code for the DF protocol relay system is high encoding complexity. In this section, the research is directed to search for a low complexity LDPC code encoding method for the DF protocol relay system. To identify the suitable encoding algorithm, an empirical comparison simulation process is established. This is significant to make sure of the low computational complexity processing operation of the system. Eight different encoding algorithms are selected and evaluated, which are LU, LU Permutation (LUP), LU Permutation Vector (LUpvector), LU Permutation Row Column (LUPQ), original Gram Schmidt, Modified Gram Schmidt, Householder Reflection, and Given Rotation, respectively. The simulations were conducted using MATLAB software.

3.6.1 LDPC Encoder Model Implementation

This section aims to evaluate the best low complexity encoding methods of LDPC code for DF protocol. The LDPC encoder model implementation is illustrated in Figure

3.25. The encoding method selection processing steps are presented in this encoder model. Matlab simulation software is used to evaluate all the encoding methods involved. The simulation process is composed of three components: pre-processing, encoding, and code generation as illustrated in Figure 3.21. Firstly, the pre-processing step is to construct a parity check matrix, H required by the encoding step. Then, the L and U factors of LU variants, as well as Q and R factors of QR variants, are generated by using LU and QR variants encoding method at the encoding step. Lastly, the codes reorder and form the encoded codeword at the code generation step. A brief description of each component is given as follows.

3.6.1.1 Pre-processing

The pre-processing step involves three parts which are constructing a regular parity check matrix, row checking, and removing girth 4. In this work, the (64, 128) regular LDPC codes parity check matrix, H with a column weight of 3 and a row weight of 6 is constructed to test the encoder model. In constructing a regular parity check matrix step, two methods that were used to construct a regular parity check matrix are presented. The first method is called evencol whereas, for each column, 1s are uniformly placed randomly. The second method is called evenboth whereas, for each column and row, 1s are uniformly placed randomly. Next, the row checking part is presented for the row that has 1 or only has one 1. If the row has no 1, two 1s are added and if the row has only one 1, one 1 is added. Then, any girth 4 is removed. The constructing parity check matrix, H is used for the next encoding step.

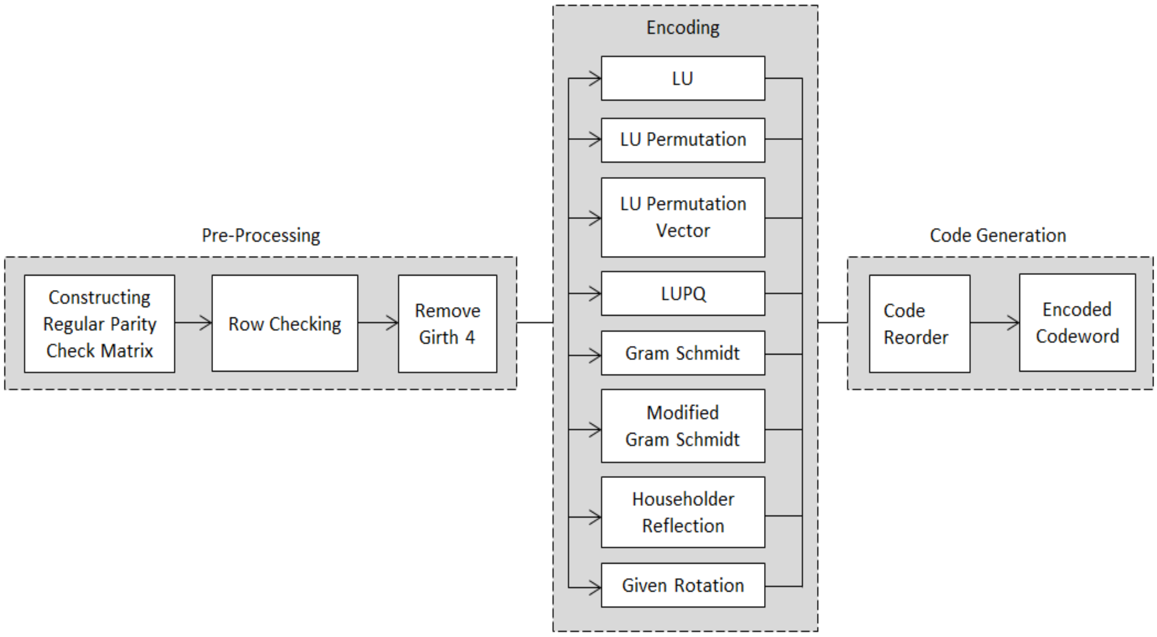


Figure 3.21: LDPC encoder model for DF protocol

3.6.1.2 Encoding

The encoding component is used to generate L and U factors of LU variants as well as Q and R factors of QR variants by using LU and QR variants encoding methods. Eight different encoding methods implemented in this research work consisted of LU and QR variants are LU, LUP, LUpvector, LUPQ, Gram Schmidt, Modified Gram Schmidt, Householder Reflection, and Given Rotation. These eight QR and LU variants algorithms were chosen because they have a great potential in providing low computational complexity, high CPU efficient operation, and better encoding operation performance of the DF protocol relay encoder process [139]. The performance comparison of the encoding algorithms carried out at the encoding step is illustrated in Figure 3.21. The evaluation matrices used to compare the performance of the eight encoding algorithms are encoding execution time, the number of the nonzero, and the pattern of nonzero. These allow a more direct comparison of the encoders. An encoding execution time evaluation measure was used for calculating the complexity for each encoding method. The lowest encoding execution time was selected. The lowest and higher execution time for each LU and QR variants encoding method is also highlighted. The lowest execution time overall results of all encoding methods are determined. Besides that, the encoding algorithms number and pattern of nonzero were also analyzed to determine the computational complexity.

Pseudo codes of these algorithms are given in Figure 3.22 to Figure 3.29 and have been converted into MATLAB codes to find the result of required operations.

a) LU

LU algorithm or regular LU algorithm is used to factorize parity check matrix, H into H=LU, where L is lower triangular and U is upper triangular. This algorithm used Gaussian elimination without permutation. The pseudo-code of the LU algorithm is shown in Figure 3.22. Initially, the parity check matrix, H is set. Then, H is factorized without permutation is set as H=LU. The matrix equation is set as a hx=b form to solve x. Next, the matrix equation rewrites as LUx = b. The equation Ly=b is solved for y using forward distribution. The equation Ux=y is solved for x using backward substitution. Lastly, the solution matrices L and U factor returns.

Algorithm 1 LU

Input : m x n Parity Check Matrix, H

Output : L = lower triangular matrix part of H

U = upper triangular matrix part of H

Algorithm:

Set H = m x n; // Initialize Parity Check Matrix, H

Set H = LU; // LU factorization without permutation

Set Hx=b; // Set matrix equation in this form to solve x

Rewrite LUx=b; // Rewritten in this form

// Solve the equation for y using forward substitution method

Set $L_{ii}y_i = b_i$

do for i = 2 to n

$$y_i = \frac{b_i - \sum_{j=1}^{i-1} l_{ij} y_i}{l_{ii}}$$

end do

// Solve the equation for x using the backward-substitution method

Set $U_{ii}x_i = y_i$

do for i = n-1 to 1

$$x_i = \frac{y_i - \sum_{j=i+1}^{n} u_{ij} y x_i}{u_{ii}}$$

end do

return L and U Factor

Figure 3.22: LU algorithm

b) LUP

LUP is used to factorize the parity check matrix, H into PH = LU, where L is lower triangular and U is upper triangular, and P is the permutation matrix. This LUP is also known as LU factorization with partial pivoting and often refers to LU factorization with row permutations. The pseudo-code of the LUP algorithm is shown in Figure 3.23. Initially, the parity check matrix, H is set. Then, H is factorized with permutation is set as PH=LU. The matrix equation is set in the Hx=b form to solve x. Next, the matrix equation rewrites as LUx = Pb. The equation Ly=Pb is solved for y using forward distribution. The equation Ux=y is solved for x using backward substitution. Lastly, the solution matrices L and U factor returns.

Algorithm 2 LUP

Input : m x n Parity Check Matrix, H

Output : L = lower triangular matrix part of H

U = upper triangular matrix part of H

Algorithm:

Set H = m x n; // Initialize Parity Check Matrix, H

Set PH = LU; // LU factorization with permutation

Set Hx=b; // Set matrix equation in this form to solve x

Rewrite LUx=Pb; // Rewritten in this form

// Solve the equation for y using a forward substitution method

Set $L_{ii}y_i = Pb_i$

do for i = 2 to n

$$y_i = \frac{Pb_i - \sum_{j=1}^{i-1} l_{ij}y_i}{l_{ii}}$$

end do

// Solve the equation for x using a backward-substitution method

Set $U_{ii}x_i = y_i$

do for i = n-1 to 1

$$x_i = \frac{y_i - \sum_{j=i+1}^{n} u_{ij}yx_i}{u_{ii}}$$

end do

return L and U Factor

Figure 3.23: LUP algorithm

c) LUpvector

LUpvector is used to factorize parity check matrix, H into H(p,:) = LU, where L is lower triangular and U is upper triangular, and (p, :) is permutation vector. This algorithm used gaussian elimination with permutation information stored as a vector, p. The pseudo-code of the LU algorithm is shown in Figure 3.24. Initially, the parity check matrix, H is set. Then, H is factorized with permutation is set as H(p,:) = LU. The matrix equation is set as Hx=b form to solve x. Next, the matrix equation rewrites as LUx = pb. The equation Ly=pb is solved for y using forward distribution. The equation Ux=y is solved for x using backward substitution. Lastly, the solution matrices L and U factor returns.

Algorithm 3 LUpvector

Input : m x n Parity Check Matrix, H

Output : L = lower triangular matrix part of H

U = upper triangular matrix part of H

Algorithm:

Set H = m x n; // Initialize Parity Check Matrix, H

Set H(p,:) = LU; // LU factorization with permutation

Set Hx=b; // Set matrix equation in this form to solve x

Rewrite LUx=pb; // Rewritten in this form

// Solve the equation for y using a forward substitution method

Set $L_{ii}y_i = pb_i$

do for i = 2 to n

$$y_i = \frac{pb_i - \sum_{j=1}^{i-1} l_{ij} y_i}{l_{ii}}$$

end do

// Solve the equation for x using a backward-substitution method

Set $U_{ii}x_i = y_i$

do for i = n-1 to 1

$$x_i = \frac{y_i - \sum_{j=i+1}^{n} u_{ij} y x_i}{u_{ii}}$$

end do

return L and U Factor

Figure 3.24: LUpvector algorithm

d) LUPQ

LUPQ is used to factorize parity check matrix, H into HPQ = LU, where L is lower triangular and U is upper triangular, P is a row permutation matrix and, Q is a column permutation matrix. This LUPQ is also known as LU factorization with full pivoting that involves both rows and columns. The pseudo-code of the LUPQ algorithm is shown in Figure 3.25. Initially, the parity check matrix, H is set. Then, H is factorized with permutation is set as HPQ=LU. The matrix equation is set in the Hx=b form to solve x. Next, the matrix equation rewrites as LUx = PQb. The equation Ly=PQb is solved for y using forward distribution. The equation Ux=y is solved for x using backward substitution. Lastly, the solution matrices L and U factor returns.

Algorithm 4 LUPQ

Input : m x n Parity Check Matrix, H

Output : L = lower triangular matrix part of H

U = upper triangular matrix part of H

Algorithm:

Set H = m x n; // Initialize Parity Check Matrix, H

Set PQH = LU; // LU factorization with row and column permutation

Set Hx=b; // Set matrix equation in this form to solve x

Rewrite LUx=PQb; // Rewritten in this form

// Solve the equation for y using a forward substitution method

Set $L_{ii}y_i = PQb_i$

do for i = 2 to n

$$y_i = \frac{PQb_i - \sum_{j=1}^{i-1} l_{ij}y_i}{l_{ii}}$$

end do

// Solve the equation for x using a backward-substitution method

Set $U_{ii}x_i = y_i$

do for i = n-1 to 1

$$x_i = \frac{y_i - \sum_{j=i+1}^{n} u_{ij}yx_i}{u_{ii}}$$

end do

return L and U Factor

Figure 3.25: LUPQ algorithm

e) Gram Schmidt

Gram schmidt algorithm also is known as classical gram schmidt is used to factorize parity check matrix, H into H = QR where Q is an orthogonal matrix and R is an upper triangular matrix. The pseudo-code of the modified gram schmidt algorithm is shown in Figure 3.26. Initially, the parity check matrix, H is set. Then, in the orthogonal matrix, Q is set as zero matrices and R is set as zero matrices. Then, matrix-vector, v_j is set as a parity check matrix, H_j. Next, the projection is subtracted from v which causes v to become perpendicular to all columns of Q. In this gram schmidt, each vector takes one at a time and makes it orthogonal to all previous vectors. The Q factor solved by $Q_j = v_j / \|v_j\|_2$ and the R factor solved by $R_{jj} = \|v_j\|_2$. Lastly, the solution matrices Q and R factor returns. Gram schmidt has no row-wise version of gram schmidt.

Algorithm 5 Gram Schmidt

Input : m x n Parity Check Matrix, H

Output : Q = orthogonal matrix part of H

R = upper triangular matrix part of H

Algorithm :

Set H = m x n; // Set Parity Check Matrix, H

Set Q = zeros (m, n); //Set Q as zero matrices

Set R = zeros (n, n); //Set R as zero matrices

for j = 1 to n **do**

$v_j = H_j$; // Initialize vector, v

for k = 1 to j-1

$v_j = v_j - \left(Q_k^T * H_j\right) * Q_k$ //Subtract the projection from v which

//causes v to// become perpendicular to

//all columns of Q

end

$Q_{j} = v_j / \|v_j\|_2$ //Solve Q

$R_{jj} = \|v_j\|_2$ //Solve R

end

return Q and R Factor

Figure 3.26: Gram Schmidt algorithm

f) Modified Gram Schmidt

A modified gram schmidt algorithm is used to factorize parity check matrix, H into H = QR where Q is an orthogonal matrix and R is an upper triangular matrix. The pseudo-code of the modified gram schmidt algorithm is shown in Fig. 7. Initially, the parity check matrix, H is set. Then, in the orthogonal matrix, Q is set as zero matrices and R is set as zero matrices. Then, matrix-vector, v_j is set as a parity check matrix, H_j. Then, Q_j computes as $v_j / \|v_j\|_2$. Next, the projection is subtracted from v which causes v to become perpendicular to all rows of Q. In this modified gram schmidt (MGS), each vector takes and modifies all forthcoming vectors to be orthogonal to it. The Q factor solved by $Q_{j} = v_j / \|v_j\|_2$ and the R factor solved by $R_{jj} = \|v_j\|_2$. Lastly, the solution matrices Q and R factor returns. The difference between solution by rows and solution by columns is a matter of reversing the order of subscripts. MGS algorithm has been used for its improved numerical stability. The MGS algorithm is to orthogonalize against the emerging set of vectors instead of against the original set. There are two variants, a column-oriented one and a row-oriented one. They produce the same results, in a different order. Figure 3.27 is the row version. Row wise MGS has the advantage that column pivoting strategy can be used, giving an upper triangular matrix, R with non-increasing diagonal elements.

Algorithm 6 Modified Gram Schmidt

Input : m x n Parity Check Matrix, H

Output : Q = orthogonal matrix part of H

R = upper triangular matrix part of H

Algorithm :

Set H = m x n; // Set Parity Check Matrix, H

Set Q = zeros (m, n); //Set Q as zero matrix

Set R = zeros (n, n); //Set R as zero matrix

for j = 1 to n **do**

$v_j = H_j$; // Initialize vector, v

for j = 1 to n **do**

$Q_j = v_j / \|v_j\|_2$;

for k = j + 1 to n

$v_k = v_k - (Q_j^T v_k) Q_j$ //Subtract the projection from v which causes //v to become perpendicular to all rows of Q

end

end

$Q_j = v_j / \|v_j\|_2$

$R_{jj} = \|v_j\|_2$

end

return Q and R Factor

Figure 3.27: Modified Gram Schmidt algorithm

g) Householder Reflection

Householder Reflection algorithm is used to factorize parity check matrix, H into H = QR where Q is an orthogonal matrix and R is an upper triangular matrix. The pseudo-code of the Householder Reflection algorithm is shown in Figure 3.28. Initially, the parity check matrix, H is set. The reflection hyperplane is computed that defines by a column unit vector, v. Then, householder reflection matrix, P is computed as:

$$P = I - 2vv^{T} \tag{3.32}$$

where P = Householder reflection matrix

I = Identity matrix

v = Householder vector

The Q factor solved by $Q = \ Q\,P$ and R factor solved by $R = \ P\,R$ is transformed into an upper triangular form R. Q is obtained by taking the dot product of each successfully formed householder matrix. Lastly, the solution matrices Q and R factor returns.

Algorithm 7 Householder Reflection

Input : m x n Parity Check Matrix, H

Output : Q = orthogonal matrix part of H

R = upper triangular matrix part of H

Algorithm :

Set H = m x n; // Set Parity Check Matrix, H

for i = 1 to n **do**

Compute Householder vectors, v

Compute Householder reflection, P matrix where $P = I - 2vv^T$

end

$Q = Q\,P$ //Solve Q

$R = P\,R$ //Solve R

return Q and R Factor

Figure 3.28: Householder reflection algorithm

h) Given Rotation

Given rotation algorithm is used to factorize parity check matrix, H into H = QR where Q is an orthogonal matrix, and R is an upper triangular matrix. The pseudo-code of the given rotation algorithm is shown in Figure 3.29. Initially, the parity check matrix, H is set. Then, orthogonal matrix, Q is set as identity matrix and R is set as parity check matrix, H. Given rotation matrix, G is set as an identity matrix. The algorithm computes c and s for each entry below the diagonal using this equation:

$$c^2 + s^2 = 1 \tag{3.33}$$

The c is the cosine angle and s is the sine angle of the rotation from each entry below the diagonal. Given rotation matrix, G is obtained by applying a cosine angle, c, and sine angle, s of the rotation. Next, the Q factor solved by $Q = Q\,G$, and the R factor solved by $R = G^T R$. Lastly, the solution matrices Q and R factor returns.

Algorithm 8 Given Rotation

Input : m x n Parity Check Matrix, H

Output : Q = orthogonal matrix part of H

R = upper triangular matrix part of H

Algorithm :

```
Set H = m x n;                                  // Set Parity Check Matrix, H
Set Q = I;                                      // Set Q as identity marix
Set R = H;                                      // Set R as Parity Check Matrix, H
for j = 1 to n do
    for i = m: -1 : j + 1 do
        Set G = I;                              // Set G as identity marix
        [c, s] = givensrotation ( R(i-1,j),R(i,j) );  // Compute angle of cosine, c and sine, s
        G ([i-1, i],[i-1, i]) = [c -s; s c];    //Compute Given Rotation matrix, G
    end
    Q = Q G                                     //Solve Q
    R = G^T R                                   //Solve R
end
return Q and R Factor
```

Figure 3.29: Given Rotation algorithm

3.6.1.3 Code Generation

In this code generation step, the code reordered by bits mapping vector namely information bit vector, s, and parity code vector, p are reordered. By solving the sparse LU and QR matrices from encoding parts specifically $p = L^{-1}U*s$ for LU variants and $p = Q^{-1}R*s$ for QR variants, the parity check vector, p is found. Finally, the systematic form of encoded code forms the output encoded codeword, c = [p s]. The output encoded codeword will be used as input in the decoding part [140].

3.6.2 Performance Evaluation

The performance evaluation that has been used to evaluate the methods for the encoder model of LDPC code for DF protocol relay includes execution time, number of nonzero, and pattern of nonzero. The three elements are described as follows:

3.6.2.1 Execution Time

The starting and end of the execution of a specified program are called execution or CPU time. This execution time calculation for the specified program is referred to as the routine of the operating system operated on behalf of the program. This does not involve the waiting time of I/O and other program's running time. The true measure of processor or memory performance is called CPU time.

3.6.2.2 Number of Nonzero

The number of nonzero elements in the sparse matrix is called a number of nonzero (NNZ). The maximum number of nonzeros determines the maximum number of elements that can be accommodated within the workspace. The maximum number of nonzero always is no less than the number of nonzero, such that the workspace has additional space available for inserting more elements into the sparse matrix. If the number of nonzero is greater than the maximum number of nonzero, the internal workspace will automatically enlarge. If the sparse matrix allows a large number of elements, specify a large value for the maximum number of nonzero to get better performance when inserting elements.

Density is a measure of nonzero elements in a sparse matrix. Density is equivalent to the ratio of the number of nonzero to the number of rows multiplied by the number of columns. The number of nonzero in H, nnz(H) is an important parameter for a description of a sparse matrix, H. The level of computer storage needed and computational operations complexity are proportional to nnz. The number of nonzero elements of H is denoted as nnz(H). It is executed by scanning complete matrices and by accessing the sparse matrix's internal data structure.

3.6.2.3 Pattern of Nonzero

A matrix is primarily populated by zero elements known as a sparse matrix. Conversely, a matrix is primarily populated by nonzero elements known as a dense matrix. The pattern of nonzero is the distribution of nonzero elements in a sparse matrix. Pattern, or sparsity pattern, considers the coordinates, the row, and column indices of nonzero elements more than the actual values.

3.7 Summary

This chapter presented the research method involved in this research. The research methods framework is subdivided into three major stages. In the first stage, the modeling of decode and forward relay system. This modeling is conducted to construct a low complexity decoding algorithm for the DF relay protocol. LDPC code decoding method employed in the DF protocol relay system to achieve the low complexity decoding operation. The model of the DF protocol relay system using LDPC code performance was evaluated using Matlab software simulation and compared against non-cooperative, AF, DF, and DF relay protocol using Turbo code.

In the second stage, the LDPC decoder at the source to relay node is developed. A new LDPC decoder method based on a min-sum algorithm called Variable Global Optimization min-sum (VGOMS) is proposed. The VGOMS algorithm operates based on min-sum modification by employing an optimized scaling factor at the bit node processing of the variable node operation. The Particle Swarm Optimization (PSO) technique was adopted in the VGOMS algorithm to determine the optimized scaling factor. Four simulations were designed and carried out which are the scaling factor searching using PSO method, VGOMS BER, and complexity computational operation comparison against four existing LDPC decoding algorithms: MS. OMS, NMS and SP, VGOMS BER comparison using BPSK and QPSK modulation, and VGOMS BER comparison under AWGN, Rayleigh fading, and Cooperative channel.

In the third stage, the LDPC encoder model at the source node is developed. An empirical comparison simulation process is established to identify the low complexity LDPC code encoding method for the DF protocol relay system. Eight different encoding algorithms are selected and evaluated, which are LU, LU Permutation (LUP), LU Permutation Vector (LUpvector), LU Permutation Row Column (LUPQ), original Gram Schmidt, Modified Gram Schmidt, Householder Reflection, and Given Rotation. The evaluation matrices used to compare the performance of the eight encoding algorithms are encoding execution time, the number of the nonzero, and the pattern of nonzero. An encoding execution time evaluation measure was used for calculating the complexity for each encoding method. The lowest and higher execution time for each LU and QR variants encoding method was highlighted. The lowest execution time overall results of all encoding methods are determined. Besides that, the encoding algorithms number and pattern of nonzero were also analyzed to determine the computational complexity operation.

CHAPTER 4

RESULTS AND DISCUSSION

This chapter describes the result and discussion for Modelling of DF protocol relay system using LDPC code, min-sum based LDPC decoder at the relay node, and LDPC encoder model at source for DF protocol relay system using LDPC code.

4.1 BER Comparison of Cooperative and Non-Cooperative Communication

This section analyzes the BER comparison for cooperative over non-cooperative communication. Figure 4.1 illustrates the BER comparison for signal transmission using cooperative and non-cooperative communication. A better BER can be achieved in cooperative communication compared with non-cooperative communication as shown in Figure 4.1. This is because the relay protocol in cooperative communication helps in combating the unreliable channel noise effect during signal transmission between transceivers. This indicates a promising future for cooperation in assisting cellular networks to increase network coverage.

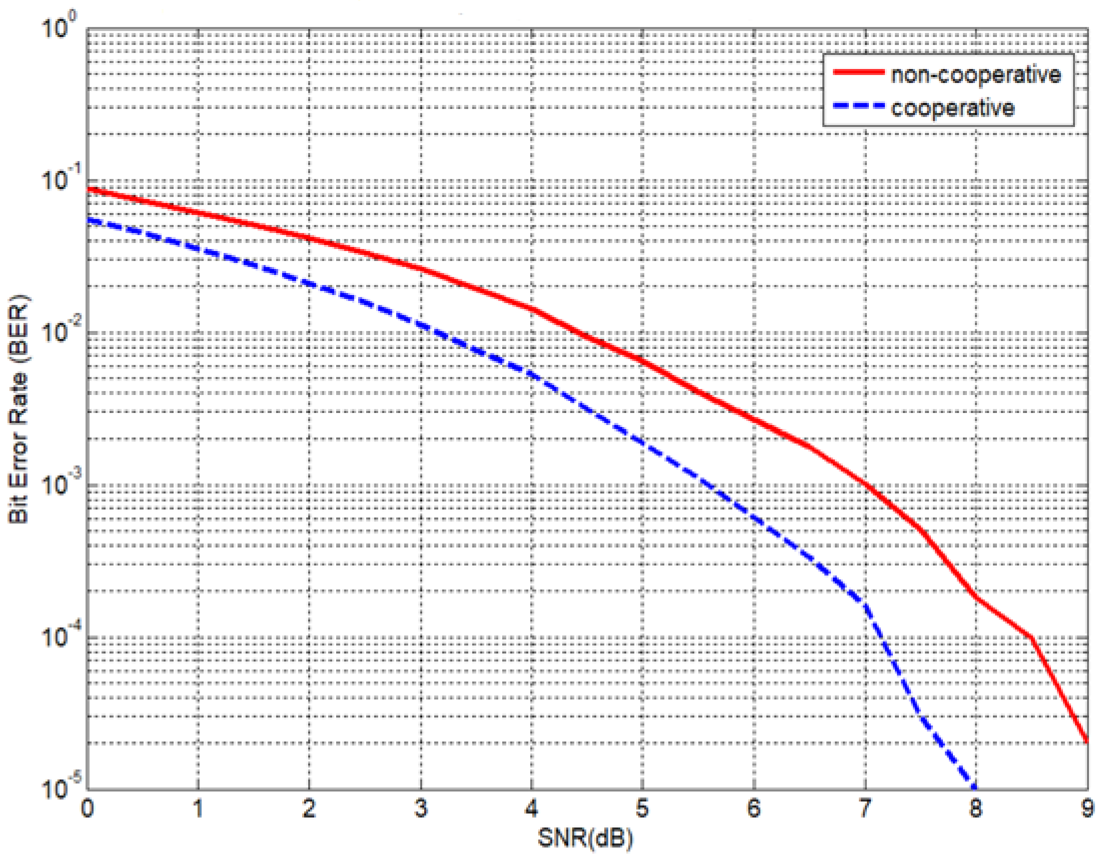


Figure 4.1: BER comparison of cooperative and non-cooperative communication

4.2 BER Comparison of Direct Transmission, Amplify Forward and Decode Forward Protocol

This section presents the BER comparison between direct transmission, AF, and DF protocol. The direct transmission performs higher BER compare with transmission employing the AF and DF relaying protocols as shown in Figure 4.2. This is because, without the help from the relay protocol, the unreliable channel noise effect during signal transmission between transceivers cannot be mitigated. This indicates that relaying protocol is beneficial as compared to a direct-link-based system. The advantage of each of the cooperative relaying protocols that achieved the lowest BER is highlighted. The Rayleigh fading channel is employed in this simulation channel transmission.

In this simulation, the result in Figure 4.2 shows that AF protocol produces higher BER than DF protocol due to the noise amplification effect that exists in the transmitted signal. AF protocol working operation is based on data signal amplification at relay before it is sent to the destination node. This noise effect caused a bad impact on the received signal quality at the destination node. However, the signal processing amplification operation in AF protocol is low computing power and bandwidth at the relay node without additional signal processing.

Contrarily, the DF protocol achieved better BER than the AF protocol. This is because of the employment of the decoding method at DF protocol whereas there is no noise amplification involved as in AF protocol. However, a high amount of computing operation power is needed in the DF protocol. Because of that, a low complexity decoding method is required for the DF protocol's working operation.

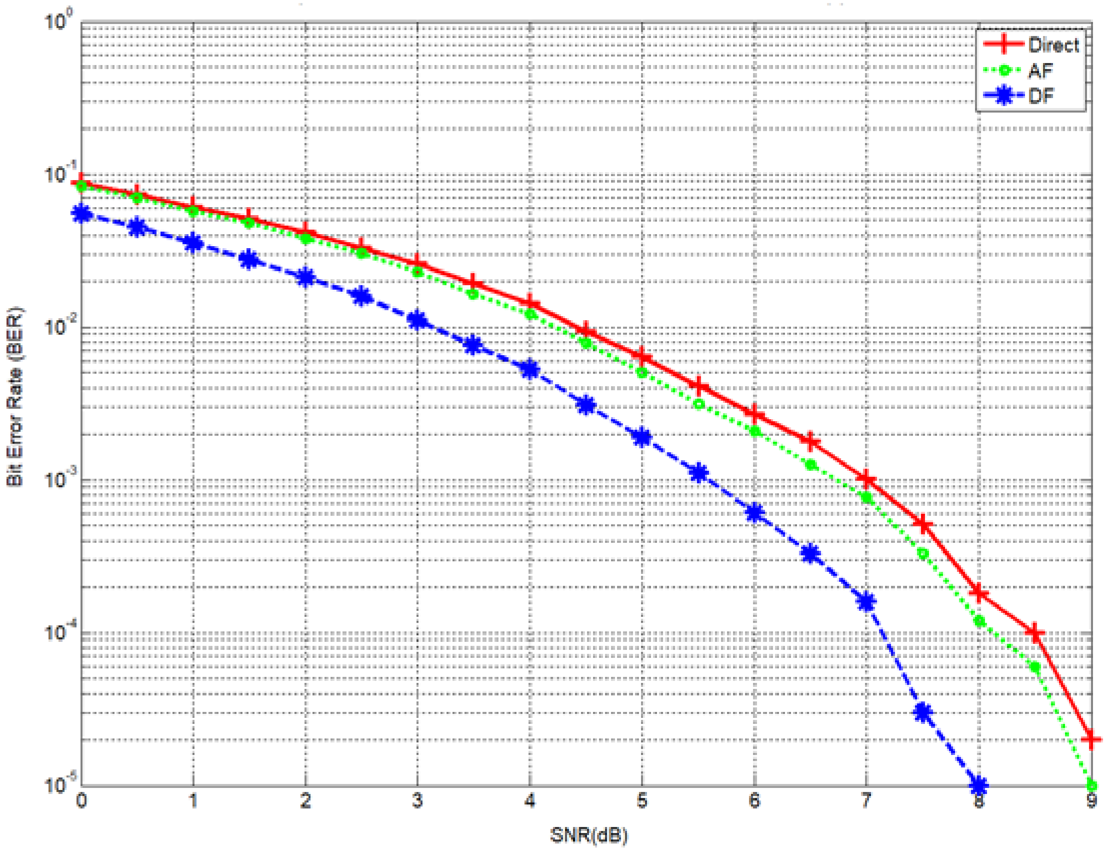


Figure 4.2: BER comparison of direct transmission, AF, and DF protocol

4.3 BER Comparison of DF Protocol with Different Relay Positioning

This section presents the BER comparison of the DF protocol with three different relay positioning which are at the center, near to the source, and near to destination as shown in Figure 4.3. The relay node position that has achieved the lowest BER is highlighted. The observation result performance illustrates that better BER has been obtained when the relay positioned is near to the source node. Contrarily, the BER decreases when the relay is positioned near to the destination node or far away from the source node. This happened because of the data signal transmission through a source node to the relay node that consumed much data signal degradation. The result indicates that the relay node distance from the source node is inversely proportional to the received signal power at the destination node as stated in Equation (4.1).

$$P_r = \frac{1}{d_{sr}} \tag{4.1}$$

where:

P_r= signal power at the destination node

d_{sr} = distance between source to relay node

Therefore, the signal power received at the destination node becomes weaker when the relay distance is far away from the source node that reflected the BER result performance as in Figure 4.3.

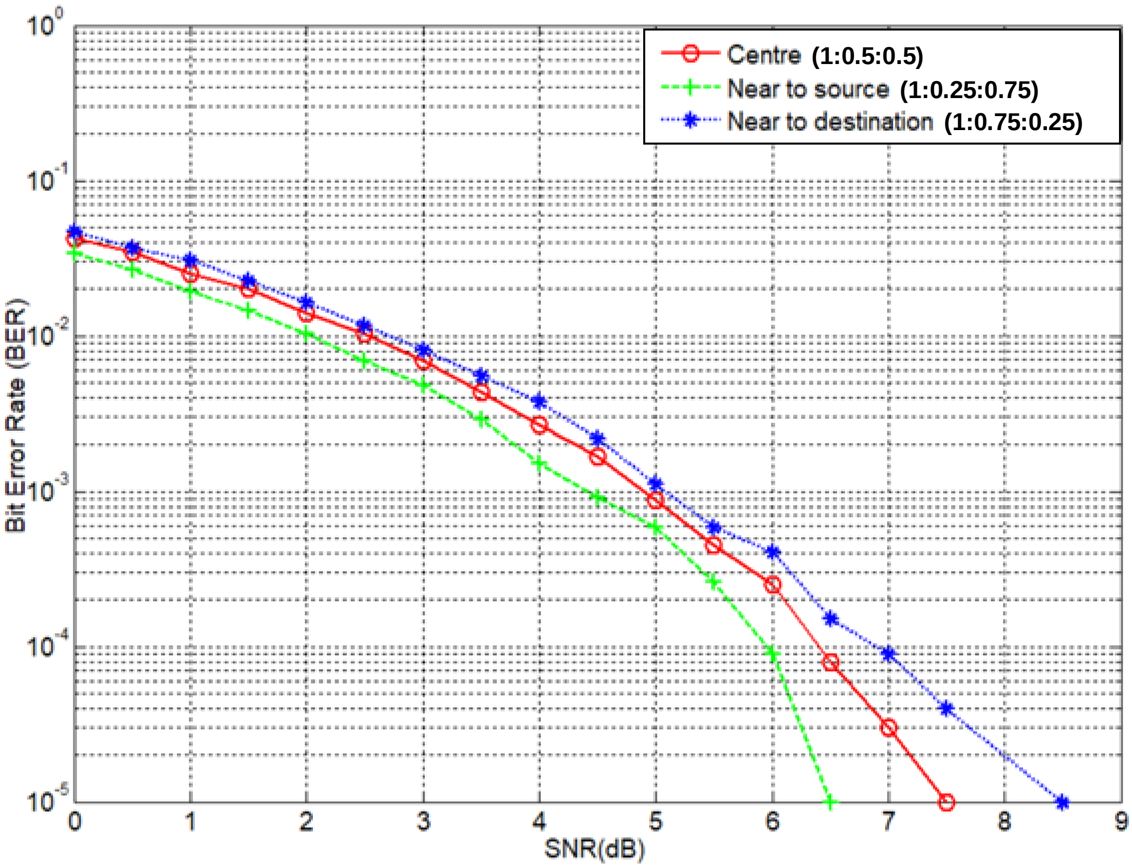


Figure 4.3: BER comparison of the DF protocol with different relay positioning

4.4 BER Comparison of LDPC Code Against Non-Cooperative, AF, DF, and Turbo Code

The BER comparison for DF relay protocol using LDPC code against non-cooperative, AF, DF, and DF relay protocol using the Turbo code is shown in Figure 4.4. The result shows that the DF relay protocol using the LDPC code performs better results than other relay protocols (non-cooperative, AF, DF, and Turbo code). LDPC codes achieve lower decoding complexity than Turbo codes. Non-cooperative shows the highest BER performance as there was no relay considered in this transmission. While AF and DF using Fixed DF is much better BER than non-cooperative, but high BER than DF using Turbo code and LDPC code. The result in other studies that have been done in [141] also found that LDPC code gives better BER for the Rayleigh channel for low SNR and the difference in dBs increases for the higher value of SNR. The result in Figure 4.4 also shows the error floor tends to occur at a lower BER by DF using LDPC code. The BER of DF using LDPC codes is slowly dropped from 0 to 3 dB. BER at 3.5 dB suddenly dropped and this characteristic is known as 'error floor'. 'Error floor' is characterized by the phenomenon of an abrupt decrease in the slope of code's error performance curve from moderate SNR water-fall region to high SNR region. The error probability of a code in the SNR region suddenly dropped at a rate much slower than that in the region of low to moderate SNR or even stops to drop.

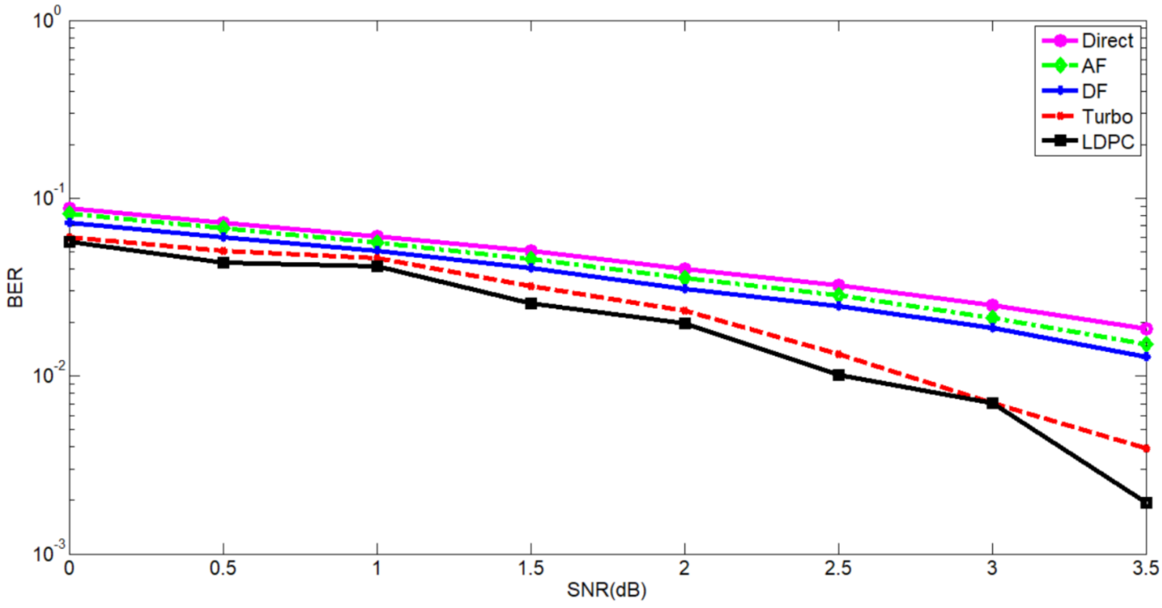


Figure 4.4: BER comparison for non-cooperative, AF, DF, DF using Turbo code and DF using LDPC code

The DF using LDPC codes operates lower complexity in terms of parallel decoder computational operation and gives lower BER performance compare with Turbo codes decoders that operate in serial as stated in [142]. Turbo codes also have a fixed number of iterations in the decoder which implies that the time spent in the decoding and the bit rate out of the decoder, are constant entities. In contrast, the LDPC decoder stops when a legal codeword is found, implying that there is potential for significantly reducing the amount of work to be done relative to Turbo codes. The LDPC decoder decodes much faster at a higher SNR value. An advantage of LDPC codes is that the decoders implemented in parallel. This has significant advantages when considering long codes.

LDPC code was found to be the best candidate for the DF protocol relay system as it can perform lower complexity operation and error rate performance [142]. Thus, further investigation on the low complexity LDPC code decoding algorithm is needed in balancing the trade-off between complexity operation reduction and error correction performance.

4.5 Variable Global Optimization Min-Sum Algorithm

a) Simulation 1: Scaling factor, x

The variation of BER for scaling factor, x for 1 dB SNR is shown in Figure 4.5. In this simulation, for 1 dB SNR value, the scaling factor, x is determined to obtain the minimum BER. For 1dB SNR, the scaling factor, the x value of 0.9560 is selected to obtain the minimum BER, 7.50×10^{-2} as shown in Figure 4.5. The same procedure is used to obtain the optimal scaling factor in achieving the minimum BER for different SNR. The result in other studies that have been done in [143] found PSO can give better decoding performance and shows a wide field of application with good prospects in LDPC codes decoding where is strict with decoding performance and complexity.

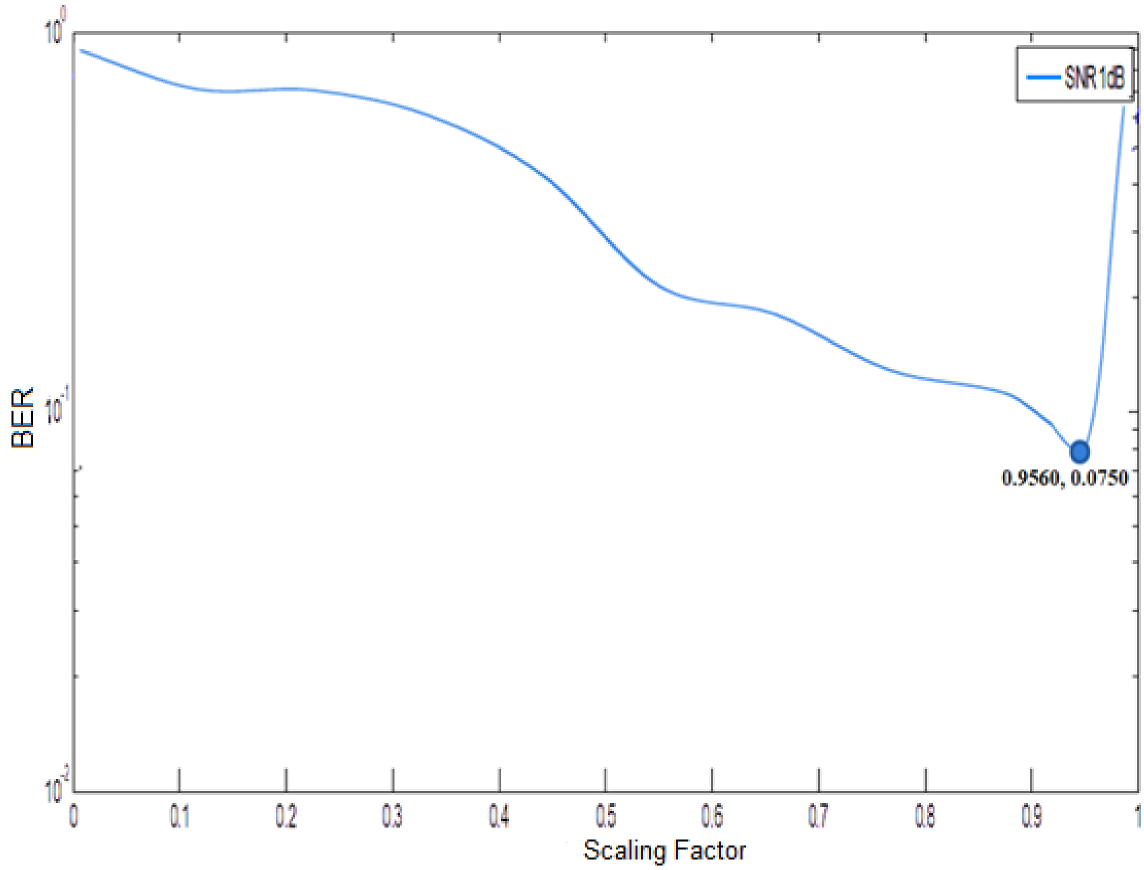


Figure 4.5: The effect of the scaling factor, *x* in the VGOMS on the BER under 1dB SNR value

b) Simulation 2: Performance comparison between the VGOMS algorithm against four existing decoding algorithms: MS, OMS, NMS, and SP

The BER comparison of VGOMS against four other existing LDPC code decoding algorithms: original MS, OMS, NMS, and SP under cooperative channel are presented in Figure 4.6. The result in Figure 4.6 shows the VGOMS outperforms well known existing LDPC code decoding algorithm original min-sum, comparable with Normalized min-sum (NMS) and Offset min-sum (OMS) and close to ideal Sum-Product (SP) algorithm at higher SNR in terms of error rate performance. This indicates that the proposed VGOMS algorithm demonstrates great potential for the LDPC decoder at the relay node.

The limitation of the VGOMS is that at a lower SNR (0 – 3dB), the error correction operation at the check node is less optimized compared to the NMS, OMS, and SP algorithms. This causes the received signal to be higher in BER. However, at higher SNR (more than 3dB), the optimization of VGOMS at the variable node caused lower BER in the received signal. The optimization of the VGOMS variable node involved the calculation of the bits from the estimated posterior probability for each bit of the message and validating the decoding test decision at the bit node processing of the variable node. The PSO method is used to optimize the bit processing of the variable node to improve BER.

The result of the VGOMS also shows that the error floor tends to occur at a lower BER. The BER of VGOMS is slowly dropped from 0 to 3 dB. Then, the BER suddenly dropped at 3.5 dB, while this characteristic is known as the 'error floor'. 'Error floor' is characterized by the phenomenon of an abrupt decrease in the slope of code's error performance curve from moderate SNR water-fall region to high SNR region. The error probability of a code in the SNR region suddenly drops at a rate much slower than that in the region of low to moderate SNR or even stops to drop.

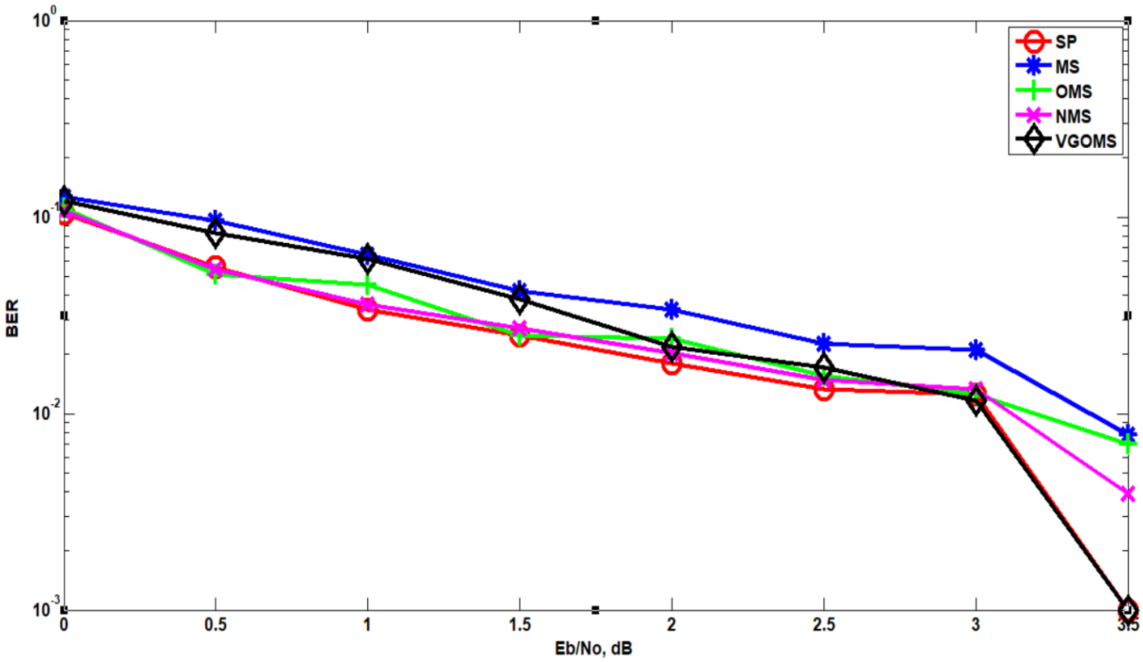


Figure 4.6: BER comparison of the VGOMS against original MS, NMS, OMS, and SP decoding algorithm

Due to the high check node operation complexity of NMS, OMS, and SP algorithms, VGOMS has been developed to solve this limitation. The check node operation complexity comparison of VGOMS against the original MS, NMS, OMS, and SP decoding algorithm is shown in Table 4.1. The check node operation complexity comparison was determined by multiplication and addition operations. VGOMS only required $d_c + \lceil \log d_c \rceil - 2$ additional operations compared with NMS and OMS which required two extra multiplications and extra addition operation respectively. NMS required two extra multiplications for normalized factor, α operation while OMS required for the offset factor, β.

Table 4.1: Check node complexity comparison of the VGOMS against original MS, NMS, OMS, and SP decoding algorithms [144]

Algorithm	Multiplication	Addition
MS	N/A	$d_c + [\log d_c] - 2$
OMS	N/A	$d_c + [\log d_c]$
NMS	2	$d_c + [\log d_c] - 2$
VGOMS	N/A	$d_c + [\log d_c] - 2$
SP	$4d_c - 2$	$4d_c - 2$

Indeed, as the VGOMS scaling factor, x only at the bit node processing of variable node operation, the computational complexity of the algorithm is reduced. The bit node processing is observed to have significantly less complexity as compared with the check node operation. Moreover, the check node operation also performs the message error correction operation that consumes most of the decoding calculation operations. Meanwhile, the bit node processing only involved the calculation obtaining the bits from the estimated posterior probability for each bit of the messages, and validating the decoding test decision, which is significantly less in computation calculation complexity. The scaling factor is determined by the PSO method with $\mathrm{nt} \log n$ computational complexity where t is time for the condition to become true and n is the number of iteration.

The computational complexity for PSO based on the VGOMS algorithm is as follows:

For the check node operation

$d_c + [\log d_c] - 2$ Addition

For the variable node operation

$(d_v - 1)$ Addition

1 Multiplication

$(\text{nt} \log n)$ PSO

So, the total complexity

$d_c + [\log d_c] - 2 + (d_v - 1) + 1 + (\text{nt} \log n)$

$$d_c + [\log d_c] - 2 + d_v + (\text{nt} \log n) \tag{4.2}$$

where t is time for condition becomes true, n is number of iteration, d_c is the average row weight and d_v is the average column weight.

PSO is more computationally efficient that uses less function evaluations than the Genetic algorithm optimization method [145]. PSO optimization method is a simple, easy implementation, low algorithmic complexity, and low computational burden. This significantly improved the performance and efficiency of the VGOMS algorithm. From the error rate in Figure 4.6 and computational complexity result observation in Table 4.1 and the Equation (4.2), VGOMS has shown a better compromise between better error rate performance and low computation operational complexity.

c) Simulation 3: BER Performance with BPSK and QPSK

The simulation in 4.5(b) was carried out using BPSK modulation. In this simulation, the BER comparison is performed between BPSK and QPSK modulation schemes under the cooperative channel. The comparison is carried out to obtain a practical view of the VGOMS algorithm.

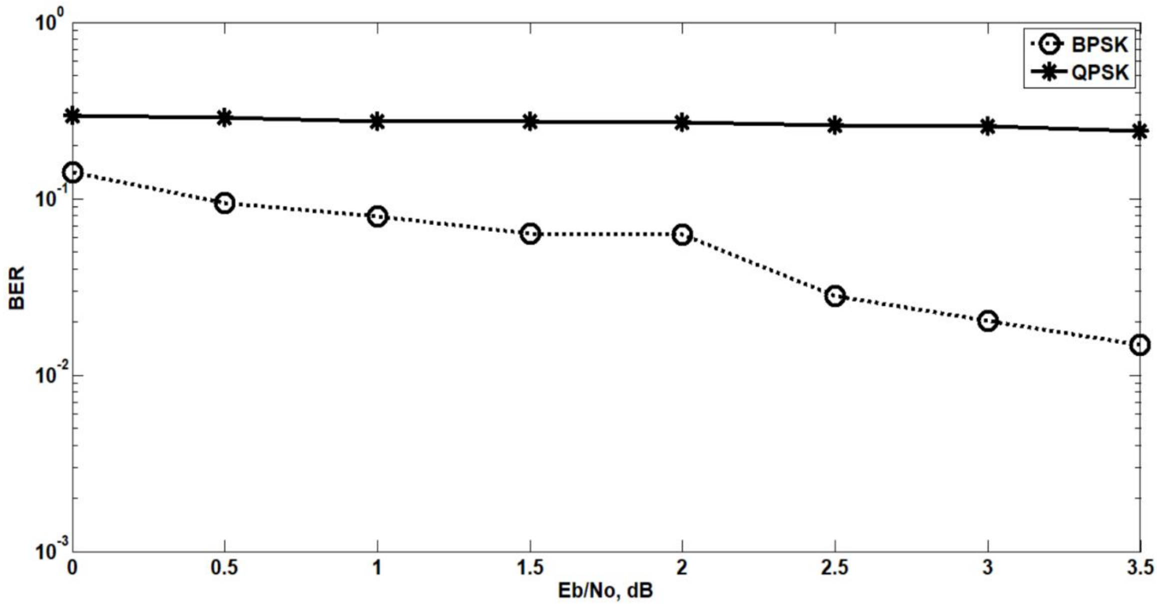


Figure 4.7: BER comparison of VGOMS with BPSK and QPSK modulation schemes

The BER comparison of VGOMS with BPSK and QPSK modulation schemes under the cooperative channel is shown in Figure 4.7. As the SNR increases, the BER of VGOMS with the BPSK modulation scheme reduces below 10^{-1}, while the BER of

VGOMS with QPSK is between 10^0 and 10^{-1}. The BPSK modulation scheme improves VGOMS performance with less BER compared with QPSK. The BER of VGOMS is better with BPSK because BPSK can handle the highest noise level or distortion, such as a cooperative channel that is used in this simulation. BPSK is considered to be a robust modulation scheme compared to QPSK as it easy for the receiver to receive the original bits [146]. BPSK also provides high immunity to noise to the signal moving through the channel [147]. Therefore, higher distance coverage can be achieved from the base station cellular cell of the fixed station to the mobile subscribers by using BPSK compared with QPSK.

d) Simulation 4: BER comparison of VGOMS under AWGN, Rayleigh fading, and cooperative channel

In the previous simulation 1 until 3, the VGOMS algorithm was examined under the cooperative channel. To gain a further view of the VGOMS algorithm, the error performance of the algorithm in AWGN, cooperative, and Rayleigh fading channels are compared.

The BER comparison of the VGOMS algorithm under AWGN, Rayleigh fading, and cooperative channel illustrate in Figure 4.8. The curve for BER values decreases faster starting from 2 dB. The result under AWGN shows the BER reaches $10^{-1.7}$at 3.5 dB, but Rayleigh fading and cooperative fading take 2.8 dB and 2.4 dB respectively to reach the same BER value. That is 1.1 dB differences for cooperative fading BER to reach $10^{-1.7}$as AWGN, while 0.4 dB differences for cooperative fading BER to reach $10^{-1.7}$as Rayleigh fading. The result simulation shows that the BER response over AWGN is faster than the response over Rayleigh fading and cooperative fading. This is because a Rayleigh detector depends on the magnitude and phase of the received signal which is formed from different amounts of scattered signals during transmission [148], while a cooperative fading is the channel model that combines the large scale effect and small scale effect. The large-scale effect is a common path loss exponent for urban cellular radio channel with a path loss component of 3 is considered [66], while the small scale effect modeled as quasi-static Rayleigh block fading channels [134-135]. This fading combination makes the cooperative fading considered the worst BER compared to the AWGN and Rayleigh fading channels.

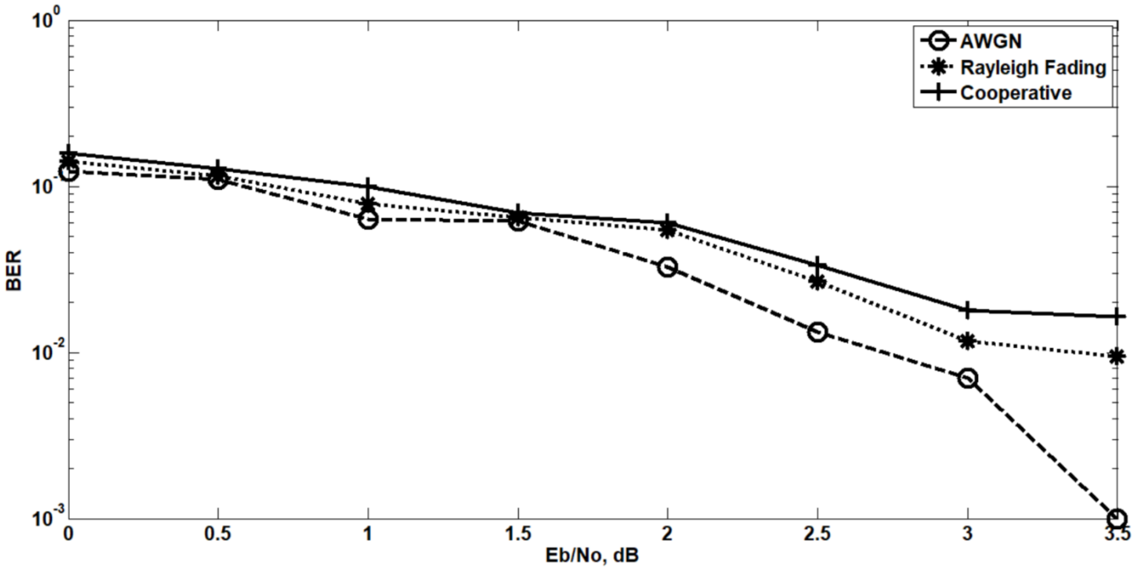


Figure 4.8: BER comparison of VGOMS under AWGN, Rayleigh fading, and cooperative fading

4.6 LDPC Encoder Model

In this simulation, eight LU and QR algorithms at the source node of the DF protocol relay system using LDPC code were investigated. Each encoding algorithm was examined and the lowest complexity encoding algorithm was determined for the DF protocol relay system using LDPC code. The complexity comparison was carried out using execution time, a number of nonzero, and a pattern of nonzero. Figure 4.9 illustrates the execution time comparison of LU (Lower Upper Triangular) and QR (Orthogonal Upper Triangular) encoding methods. The result from Figure 4.9 shows the LUPQ encoding algorithm achieved the lowest execution time with 0.000076 s among LU and QR encoding methods while the Householder Reflection encoding method yielded the lowest execution time with 0.00648 s among QR encoding methods. The encoding algorithms execution time could be ranked in descending order as follows: For LU encoding algorithms: LU (0.000244 s), LUP (0.000232 s), LUpvector (0.000221 s), LUPQ (0.000076 s), and for QR encoding algorithms: Given Rotation (0.081264 s), Modified Gram Schmidt (0.007815 s), Classical Gram Schmidt (0.007649 s), Householder Reflection (0.00648 s).

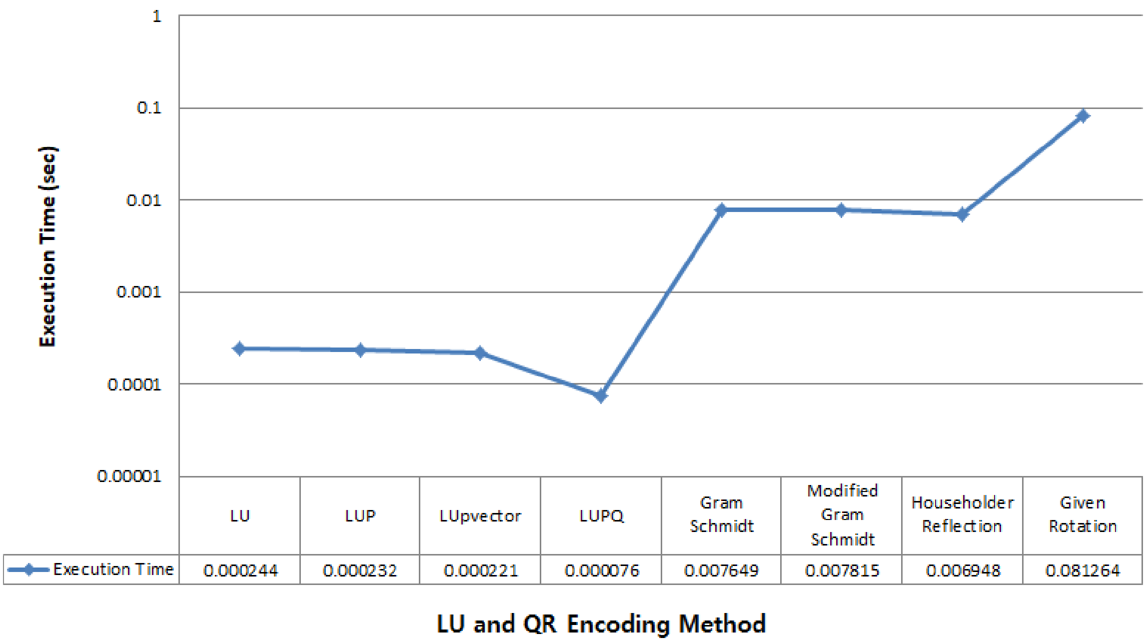


Figure 4.9: Execution time comparison of LU and QR encoding method

NNZ of the encoding algorithm indicated each row and column elements of the matrix number of nonzero and dots indicate the structure of the nonzero element. The spy plots of the L and U factors of the LU algorithm, as well as Q and R factors of the QR algorithm, generate to present the number and pattern of nonzero in the factors. The result in Figure 4.10 shows the LUPQ encoding algorithm achieved the lowest number of nonzero with LU factor: (150,726) among LU and QR encoding methods while the Householder Reflection encoding method yields the lowest number of nonzero with QR factor (1052, 3861) among QR encoding methods. The encoding algorithms number of nonzero could be ranked in descending order as follows: For LU encoding algorithms: LU (183,1002), LUP (183,1002), LUpvector (183,1002), LUPQ (150,726), and for QR encoding algorithms: Classical Gram Schmidt (2272, 4788), Modified Gram Schmidt (2262,4786), Given Rotation (1187, 4007), Householder Reflection (1052, 3861). The result in Figure 4.10 showed that the time complexity of LUpvector and LUPQ is proportional to the number of nonzero.

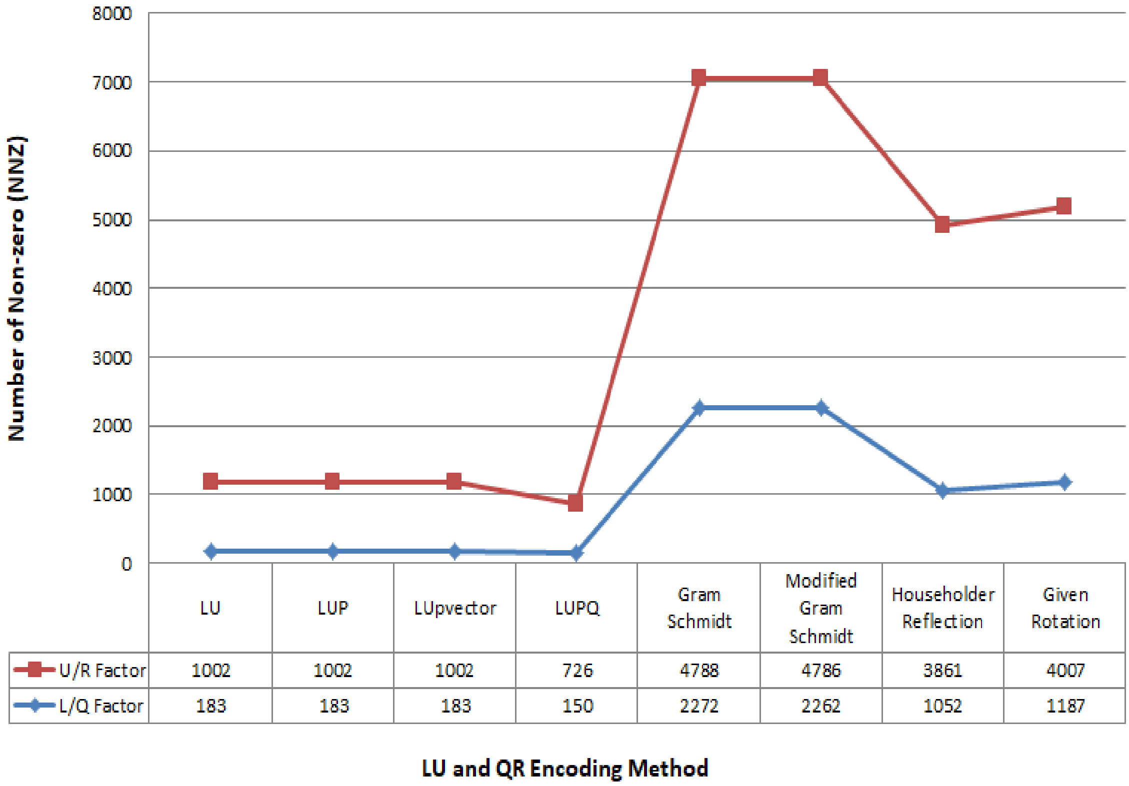


Figure 4.10: Number of nonzero comparison of LU and QR factor

The pattern of nonzero LU and QR encoding methods is shown in Figure 4.11 until Figure 4.18. The results presented in Figure 4.11 until Figure 4.18 showed that the nonzero pattern distribution of LUPQ is the most near to the diagonal and symmetrical compared with other LU encoding algorithms (LU, LUP, LUpvector). While basic LU encoding showed the most unsymmetrical nonzero distribution and much denser compared with other LU encoding algorithms (LUP, LUpvector, LUPQ). This is because less number of nonzero symmetrical fill-ins structures and the non-zero scattered distributed during the elimination process as basic LU used Gaussian elimination without permutation. The nonzero pattern distribution of Householder Reflection is the most near to the diagonal and symmetrical compared with other QR encoding algorithms (Classical Gram Schmidt, Modified Gram Schmidt, Given Rotation). The encoding algorithms nonzero pattern distribution could be ranked in descending order from wide distribution are LU, LUP, LUpvector, and LUPQ and for QR encoding algorithms are Classical Gram Schmidt, Modified Gram Schmidt, Given Rotation, and Householder Reflection.

The NNZ of the LU factor is reduced by using row permutation (NNZ of LUP less than LU). LUpvector saves memory space by making the row permutation as a vector rather than a matrix. The use of permutation in a larger matrix can achieve more efficient memory use. For subsequent operations, the use of a permutation vector often saves on execution time. The execution function process takes a little less time with the use of the permutation vector even though the number of nonzero generated from the permutation vector and the permutation matrix is similar. The numbers of nonzero in the LU factors of LU, LUP, and LUpvector are maintained while the execution time was decreasing respectively. The number of nonzero in the LU factors will be further be reduced by using LUPQ that uses column permutation. The less NNZ in L and U factors has significant advantages in terms of computational efficiency. The resulting efficiencies will result in significant performance improvements in the number of floating-point operations and execution processing time. It also greatly reduces the amount of memory needed to store the data.

QR variants performed higher execution time compared with LU variants because it requires as many floating-point operations and more complicated update step. Among QR encoding algorithms, Householder consumes less execution time compared with others. This is due to the less computational cost of Householder with $2mn^2 - 2n^3/3$. The Householder Reflection algorithm is also more easily vectored. Hence, Householder Reflection is labeled as a greedy algorithm because it tries to zero more nonzero elements at the same time. Meanwhile, Given Rotation operates at the highest execution time which

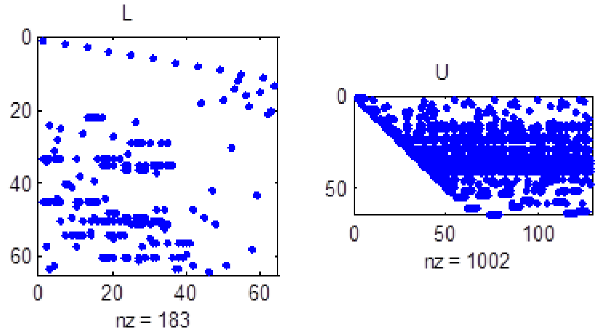


Figure 4.11: Non-zero pattern of LU algorithm

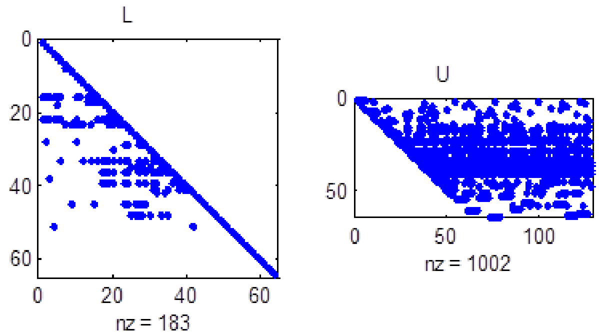


Figure 4.12: Non-zero pattern of LUP algorithm

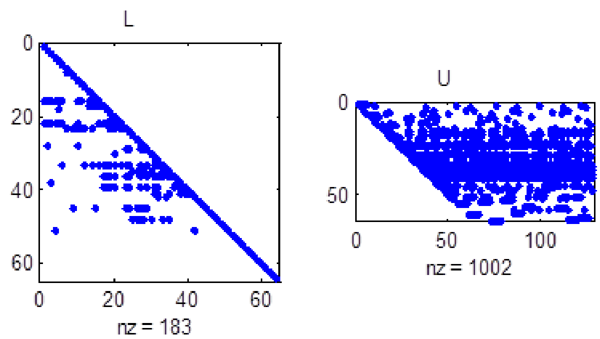


Figure 4.13: Non-zero pattern of LUpvector algorithm

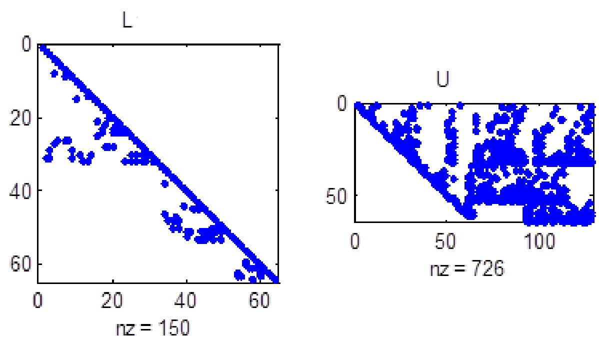


Figure 4.14: Non-zero pattern of LUPQ algorithm

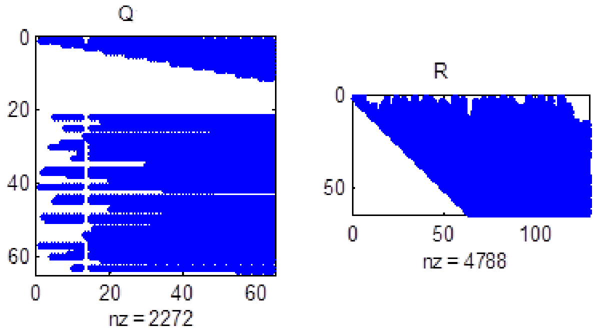


Figure 4.15: Non-zero pattern of gram schmidt algorithm

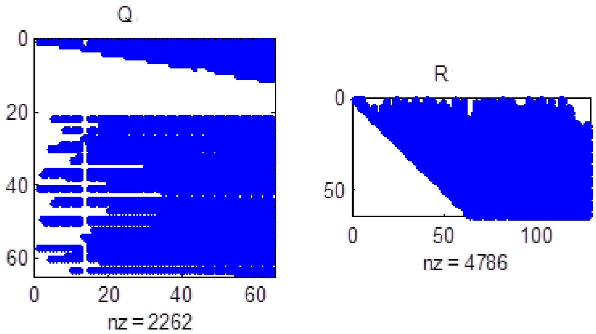


Figure 4.16: Non-zero pattern of modified gram schmidt algorithm

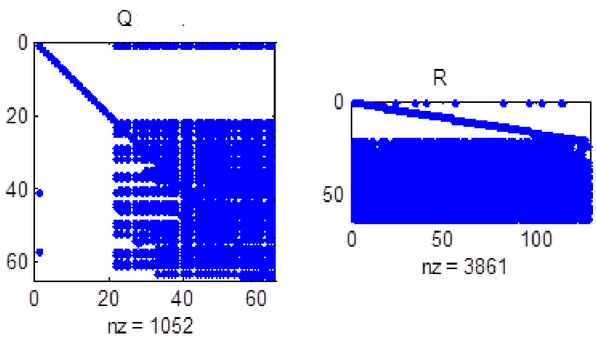


Figure 4.17: Non-zero pattern of householder reflection algorithm

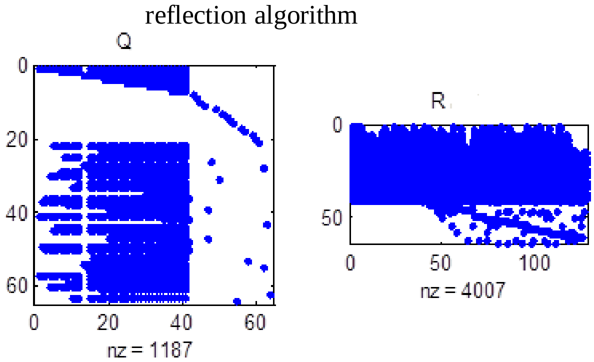


Figure 4.18: Non-zero pattern of given rotation algorithm

is 50% more than Householder Reflection. This is due to the Given Rotation need as the highest number of mathematical operations compared to the three other QR variant algorithms. Given Rotation is slow and suffers from high intermediate storage demand.

There is no particular single encoding algorithm that is perfect for all problems. The performance of the encoding algorithm depends on the size of the parity check matrix, H, and the performance criteria for the target. In this research thesis, the lowest complexity encoding algorithm of the LDPC code for the DF protocol relay system is investigated. The comparison in terms of complexity was carried out using encoding execution time, number, and pattern of nonzero for LU and QR encoding algorithms. QR algorithm is a very powerful algorithm to stabilize compute eigenvalues and the corresponding eigenvectors. QR encoding algorithms can make very good use of the sparsity of the problem. The main drawback of QR algorithms for solving encoding compared to LU algorithm is that the QR algorithm requires much more computational cost, $2n^3$ than Gaussian elimination of LU computational cost, $2n^3/3$. LU algorithm is not stable but computes low cost and high CPU efficiency. LU algorithm, despite being one of the slower methods available for encoding matrices, is still faster than the QR algorithm because QR computes lots of norms, square roots, and other things. LU applicable for any matrix finds all solutions and easy to program. The performance result highlighted that LUPQ is the most suitable encoding algorithm for the DF protocol relay system using LDPC code as it performs low processing time of the LDPC encoder component. If stability and productive efficiency are desired, Householder Reflection can establish the required criteria. The householder encoding algorithm has shown remarkable potential for application in this area.

4.7 Summary

This chapter describes the result and discussion of this research. The result and discussion of this research are divided into three parts. In the first part, the performance of the decode and forward relay system using LDPC code is evaluated. The BER performance of the decode and forward relay system using LDPC code against non-cooperative, AF, DF, and DF relay protocol using Turbo code presented. From the simulation result, the DF protocol achieved much better bit error rate result performance than the AF protocol. This is because of the employment of the error correction code method to DF protocol whereas there is no noise amplification involve as the operation process in AF protocol. However, the high amount of computing operation power is needed is the major drawback of the DF protocol. Therefore, a low complexity error correction method is required for DF protocol working operation. Thus, a low complexity decoding algorithm is developed to solve this major drawback of the DF protocol.

In the second part, a low complexity LDPC code decoding algorithm based on a min-sum algorithm called Variable Global Optimization min-sum (VGOMS) at the relay node is evaluated. The Particle Swarm Optimization (PSO) technique was adopted in the VGOMS algorithm to determine the optimized scaling factor at bit node processing of the variable node operation. From the result, VGOMS outperforms well known existing LDPC code decoding algorithm original min-sum, comparable with Normalized min-sum (NMS) and Offset min-sum (OMS) and close to ideal Sum-Product (SP) algorithm at higher SNR in terms of error rate performance. The VGOMS check node operation that consumes most of the decoding calculation operations complexity is less against NMS, OMS, and SP decoding algorithm. From the error rate and computational complexity result observation, VGOMS has shown a better compromise between better error rate performance and low computation operational complexity. VGOMS algorithm is more straightforward to implement compared to the optimized min-sum algorithm [14] and the 2D correction min-sum algorithms [102].

In the third part, the LDPC code encoder model is evaluated to identify the low complexity LDPC code encoding method for the DF protocol relay system using eight different encoding algorithms. The comparison in terms of complexity was carried out using encoding execution time, number, and pattern of nonzero for LU and QR encoding algorithms. The result shows the LUPQ encoding algorithm achieved the lowest execution time with 0.000076 s among LU and QR encoding methods while the Householder Reflection encoding method yielded the lowest execution time with 0.00648 s among QR encoding methods. the LUPQ encoding algorithm achieved the lowest number of nonzero with LU factor: (150,726) among LU and QR encoding methods while the Householder Reflection encoding method yields the lowest number of nonzero with QR factor (1052, 3861) among QR encoding methods. The nonzero pattern distribution of LUPQ is the most near to the diagonal and symmetrical compared with other LU encoding algorithms (LU, LUP, LUpvector). While basic LU encoding showed the most unsymmetrical nonzero distribution and much denser compared with other LU encoding algorithms (LUP, LUpvector, LUPQ). The nonzero pattern distribution of Householder Reflection is the most near to the diagonal and symmetrical compared with other QR encoding algorithms. There is no particular single encoding algorithm that is perfect for all problems. The performance result highlighted that LUPQ is the most suitable encoding algorithm for the DF protocol relay system using LDPC code as it performs low processing time of the LDPC encoder component. If stability and productive efficiency are desired, Householder Reflection can establish the required criteria. The householder encoding algorithm has shown remarkable potential for application in this area.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

This chapter concludes with its findings and contributions, highlights some recommendations, and outlines the direction for future recommendations that might lead to an improvement in decode and forward protocol relay system error rate performance and its computational complexity operations.

5.1 Conclusion

The research on DF relay protocol using LDPC code has shown a significant advantage in reducing decoding implementation complexity and less error propagation. The thesis finding and contribution are as follows:

a) The development of the proposed model of the DF protocol relay system using LDPC code has shown better error rate performance against non-cooperative and other existing relay protocol systems which are AF, DF, and DF protocol relay system using Turbo code in terms of error rate performance. The development of this model brings along new techniques and perspectives to reduce error rate system performance and at the same time reduce decoding processing time.

b) A new LDPC code decoder algorithm used an optimization min-sum based belief propagation approach called Variable Global Optimization Min-Sum (VGOMS) to provide a good characteristic to balance the trade-off problem between complexity reduction and error correction performance of the DF protocol relay decoder. This algorithm applies the optimization scaling factor at the bit node processing of the variable node operation only which significantly consumes less in computation calculation complexity of decoding operations. The Particle Swarm Optimization (PSO) search method is utilized to search the optimized scaling factor to obtain optimal error rate performance. The employment of the PSO method as an optimization scaling factor searching method has shown a better achievement to obtain optimal error rate performance. VGOMS outperforms the well-known existing LDPC code decoding algorithm original min-sum, comparable with Normalized min-sum (NMS) and Offset min-sum (OMS) and close to ideal Sum-Product (SP) algorithm at higher SNR in terms of error rate performance. VGOMS also outperforms NMS, OMS, and SP in terms of check node operation complexity that consumes the most complex of decoding operations. From the error rate and computational complexity result, VGOMS has shown a better compromise between better error rate performance and low computation operational complexity.

c) The development of the LDPC code encoder model is to identify the lowest complexity encoding algorithm of the LDPC code encoder which is the DF protocol relay system using the LDPC code component. Low complexity encoding is to ensures low complexity and good performance of the subsequent decoding stage. LUPQ encoding algorithm achieved the lowest execution time and the number of nonzero among LU and QR encoding methods, while the Householder Reflection encoding method yields the lowest execution time and the number of nonzero among QR encoding methods. The nonzero pattern distribution of LUPQ is the most near to the diagonal and symmetrical compared with other LU encoding algorithms. While basic LU encoding showed the most unsymmetrical nonzero distribution, it is much denser compared with other LU encoding algorithms. The nonzero pattern distribution of Householder Reflection is the nearest to the diagonal and symmetrical compared with other QR encoding algorithms. The performance result highlighted that LUPQ is the most suitable encoding algorithm for the DF protocol relay system using LDPC code as it performs low processing time of the LDPC encoder component. If stability and productive efficiency are desired, Householder Reflection can establish the required criteria. The householder encoding algorithm had shown remarkable potential for application in this area.

5.2 Recommendations

Following the issues addressed in this research thesis, several possible future research recommendations in this area are highlighted. There are a lot of opportunities to expand and improve the proposed system method and to try to discover a possible potential problem issue. These are used to ensure that the proposed system methods will operate to their best to benefit the cooperative communication areas.

The potential and effectiveness of the LDPC code for the DF protocol relay system in this thesis have been thoroughly investigated. Min-sum based LDPC code offers low computational complexity operation and better error-correcting performance. In this research thesis, the min-sum based optimization at bit node processing of variable node operation is designed. The research work in the future can be expanded to different types of min-sum based algorithms, such as offset min-sum decoding algorithm for LDPC code DF protocol relay system. The OMS algorithm can also apply the PSO optimization method to find the optimal offset factor to get better error-correcting result performances and low complexity computational operation. Some basic PSO modifications that can be done in this field of future research work, focus on improving the PSO method performance, such as a reduction in error rate result performance. Numerous optimization methods concentrate on how to increase the convergence speed and manage the trade-off between exploration and exploitation. The significant aspect of the PSO algorithm, such as the initial and stopping conditions, the problem in boundary value, and the velocity clamping technique should be practiced to solve the premature convergence and stagnation problem. As the proposed algorithm is tested using the cooperative channel model and the lower order modulation (BPSK and QPSK modulation schemes), further expense and analysis can be conducted with other types of channel models and higher-order modulation methods. Besides, expanding the proposed decoding method architectures is preferable to deal with different types of code rates, codeword length, and multiple modes of operations. The encoding and decoding processes in this research work used the regular LDPC code. Thus in the next research stage, it is recommended to explore irregular LDPC code behavior to see their system performance changes. Besides that, VGOMS can be applied to a variety of applications, such as digital magnetic recording. BF and BP algorithms can be integrated into a single algorithm to improve error-correcting performance and reduce operating speed that would be interesting. This could also reduce the system's execution time. Future work in this research area may include a multi-user scenario exploring the possibility of making the relay operates with more than one single signal source. Optionally, when a single signal source works with two or more relays, a multiple relay methodology could also be employed. Additionally, the observation of the output performance having a constantly moving signal source or relay may also be interesting to explore.

Future work on LDPC code encoder, the modification of the householder can be explored to form a new encoding algorithm for the proposed system to obtain computation efficiency with significantly low complexity operation. More broad innovations include integrating both LU variants and QR variants algorithms that can be explored to produce a significantly better compromise between the implementation of low computational complexity and efficiency as well as numerical stability. For LUPQ as well as other LU variants, the numerical stability operations of the algorithm are still a concern. Thus, further analysis of the encoding algorithms is also needed in terms of the numerical stability operation of the algorithms.

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APPENDIX

Journal Publication

a) Suud, J., Zen, H., Othman, A. B. H., & Hamid, K. A. (2018). Decoding of decode and forward (DF) relay protocol using min-sum based low density parity check (LDPC) System. *International Journal of Communication Networks and Information Security*, 10(1), 199–212.

b) Suud, J., Zen, H., Othman, A. B. H., & Hamid, K. A. (2020). Variable global optimization min-sum (VGOMS) algorithm of decode-and-forward protocol for the relay node in the cooperative channel. *The Journal of Mobile Communication, Computation and Information, Wireless Networks, Springer*, 26, 531-541.

c) Suud, J., Zen, H., Othman, A. B. H., & Hamid, K. A. (2021). An empirical comparison of encoding algorithms of the low density parity check code for decode and forward protocol relay system. *Wireless Personal Communications, Springer*, 117, 2007-2026.

Colloquium Paper

d) Suud, J., Zen, H., Othman, A. B. H., & Hamid, K. A. (2015). Cooperative relaying protocol communications in wireless system. In: *Faculty of Engineering Post Graduate Research Colloquium 2015*, 14 April 2015**.** UNIMAS Publisher.