AN ENERGY EFFICIENT CODING AND MODULATION SCHEME FOR WIRELESS SENSOR APPLICATIONS

by

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ABSTRACT

Technological advancements have made it possible to implant a network of Wireless Biosensors inside the human body for applications like prosthesis, health monitoring, telemetry and surveillance. These sensor applications require efficient wireless communication systems that are less complex both at circuit level and systems level. This thesis work involves a detailed study, development and analysis of such a system. An energy efficient coded modulation scheme is developed for low power applications. On/Off keying (OOK) modulation scheme is used here. In OOK, a carrier signal is transmitted for a bit-1 and no signal for a bit-0. Energy is spent whenever a signal is transmitted by the transmitter. Thus, energy consumption can be reduced in an OOK system by reducing the number of high-bits transmitted by mapping a group of source bits to a constant length code word called Minimum Energy Code (ME-Code) which has less bit-1s in it. ME-Codes bring energy efficiency at the expense of bandwidth. They can be made use of in applications with unknown source statistics (probability of occurrence of symbols). Further, the performance is improved by using a simple code-by-code soft decision detection scheme that performs like a Maximum Likelihood detector. Theoretical analysis of probability of error for this coding scheme is provided. Complexity of the coding circuit is estimated and analyzed. A performance metric is developed to quantify the energy consumption by the circuit. The developed scheme was implemented on a Cadence simulator and the circuit energy per processed information bit was determined. It is found that the developed coding scheme has a simple algorithm, is less complex to implement and thus saves energy both at system level and circuit level. This scheme also improves performance of OOK modulation scheme by 6dB and 9dB for an extra bandwidth of 4/3 and 11/4 of original bandwidth, respectively.

Dedicated To My Parents and My Brother

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CHAPTER 1

INTRODUCTION

Telemedicine aims to provide clinical services remotely using telecommunication technologies to deliver vital body information about the patient to the remote physicians and information about the medical treatment back to the patient. One of the important tasks in telemedicine is to gather health data from a patient and transmit it to a distant health center for monitoring, disease curing, surveillance and other health related purposes. Several implantable biomedical devices are currently being used, such as cochlear implants and pacemakers, and many others are being developed, such as cortical and retinal implants for correcting vision. These devices along with other implanted bio-sensors can provide vital biological data from inside the body which can greatly help in improving tele-diagnosis. For medicinal surgical and many other advantages, it is highly desirable that this telemetry of biological data from inside the human body to an external data collection and processing unit should be done wirelessly. FCC has designated some portion of the electromagnetic spectrum, called the ISM bands, to be used for industrial, scientific, and medical applications without the need for license. Its expected that the companies would use these bands to develop wireless biomedical telemetry devices.

In the case of disaster management applications as mentioned in [1] few of the military applications make use of implanted biosensors to collect health data from within the body and transmit to a distant health center. The most crucial, important and difficult task in telemedicine is to obtain the health information or gather data from within the body and transmit it to a recording or displaying device outside the body.

This thesis work involves analysis and development of an important aspects of communication system to establish wireless communication links between chronically implanted in-vivo sensors. This wireless link is called as **bio-link**. An energy efficient coding and modulation is developed to establish a RF Wireless communications in implanted Bio-sensor applications.

A brief overview of the system model and some motivating examples are explained in the next section to facilitate the reader to understand the problem with a better depth and appreciate the solution provided by this research.

1. Biosensors

The system model consists of numerous implants inside the body. These sensors interact with each other and/or with an external body-mounted monitoring device called the base station. The interaction between the sensors and the base-station is generally a two way communication. These implanted sensors usually gather certain data from inside the human body about the health condition. The data gathered can carry information about body temperature, blood glucose level , blood pressure. On the other hand the data flow can be opposite direction, it can be image data to be delivered to the retinal cells from an external source to provide sight to people suffering from retinitis pigmentosa. The sensors and the architecture depends totally on the application. Detailed explanation about these applications are provided below.

Figure 1 shows the schematic diagram of the system. It has an implanted sensor inside the body. An external monitoring device sits on the hand. A tiny wireless transceiver is built on to the in-vivo sensor. The entire sensor and the transceiver resides on one single chip along with the antenna. The information is gathered by the sensor and processed accordingly. The processed information is then transmitted on a high frequency carrier wave by the transceiver into the surrounding tissue medium which propagates in the tissue and then reaches either another sensor or the base-station depending on the application on hand. The implanted bio-sensors or in-vivo sensors are considered to be separated by small distances of the order few centimeters. The receiver then receives this information and required action is taken by the system. It is to be kept in mind that the resources and the system conditions are constrained or limited only inside the body and not outside. However, this thesis work considers a generic system model for wireless communication inside human body which can later be applied or implemented to any application.

The block diagram shown in figure 2 describes the high-level design of the system. In general, a sensor system consists mainly of a sensor module that gathers data from the surroundings. The kind of data gathered depends on the application under consideration. The gathered data is the converted to digital form and processed accordingly catering to the application needs. This digital data is now transmitted by the RF transceiver block. The data travels through the tissue medium and reverse process is performed at the receiver side. The following section will give a brief explanation of few applications of interest. This will add to the motivation of this research work.

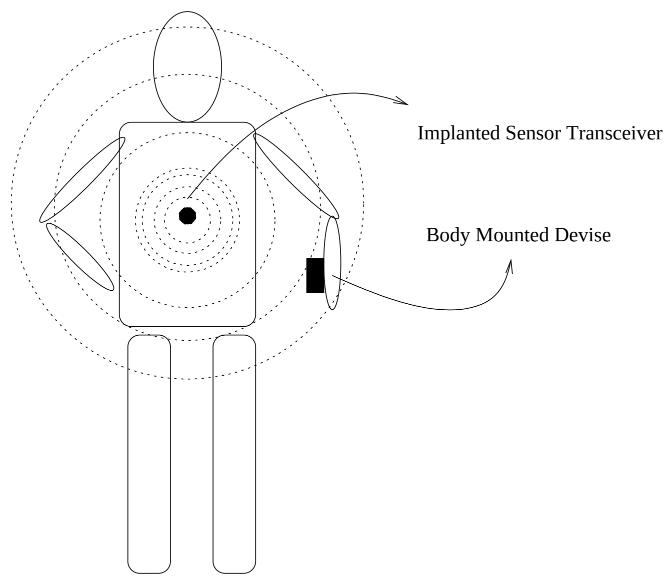

Figure 1. System Model of the Communication Involved

2. Application Examples for Motivation

Many of the in-vivo sensors that are being developed or that are being researched have a similar system model. However, the details and the specifications of the entire system depends totally on the applications. In the following sections few of the examples are described to further motivate the reader.

2.1. Retinal Prosthesis. Many researchers have been working on development of a wireless system that gives sight to people suffering from age-related macular degeneration or retinitis pigmentosa [7]. In this application, few of the diseased rods and cone cells of retina in the eye is artificially stimulated by current from electrodes present on the implanted chip inside the eye. The research team at the Mobile Computing and Wireless Networks Lab at ASU is working on development of such a system which is constrained mostly by power consumption and complexity of operation. A simple and reliable communication system is to be designed to establish a wireless link between a camera/processor outside

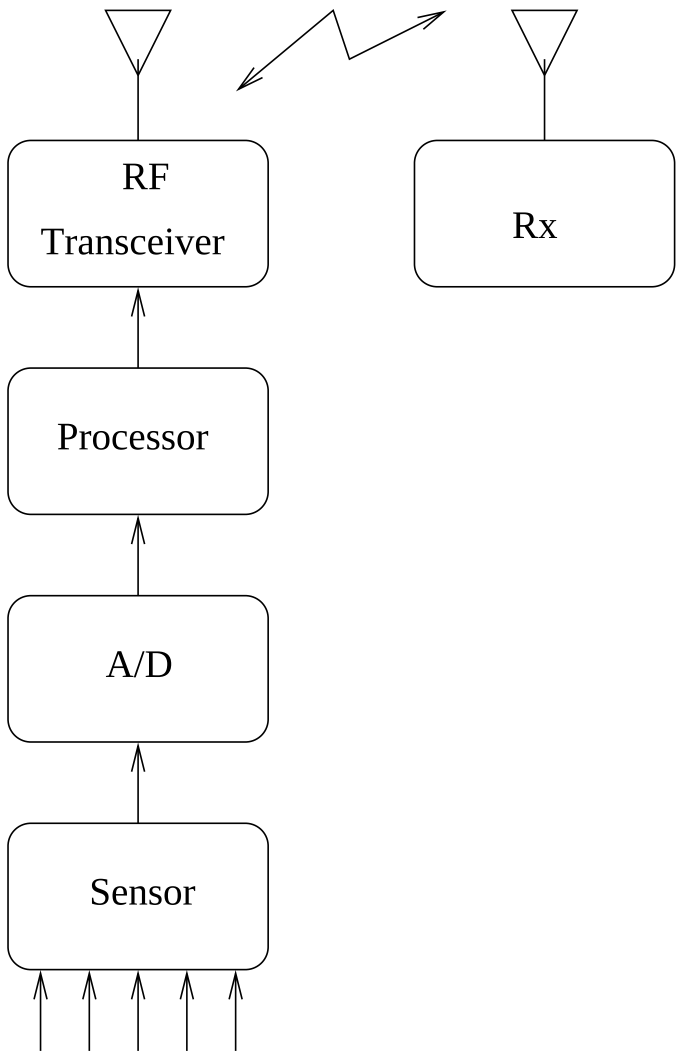

Figure 2. High Level Block Diagram of the System

the eye to a minute chip implanted inside the eye-ball on the retina. The system has to transmit the camera captured/processed video data via a wireless medium. The receiver inside the eye generates signals for stimulation based on the video information received. **This has been the main motivation to develop a communication system that operates at very low power, consuming less energy, simple and less complex to implement**. A channel model for wireless communication inside human body is developed [2]. It behaves like an Additive White Gaussian Noise (AWGN) channel, but with large amount of attenuation due to the presence of water in the tissue. This is the reason to use an AWGN channel for simulation and performance evaluation of the system. Also some of energy efficient techniques to code the data and modulate the carrier before transmitting is designed [3].

There are many such applications that are under research and development which requires an efficient and reliable wireless communication link between the in-vivo sensor and an external agent or device.

2.2. Implantable Glucose Sensors. The development of implantable glucose biosensors has made it possible to track and take care of the glucose level in the human body. There are many ways in which researchers are dealing with this issue. The self-monitoring of blood glucose using finger sticking suffers from the fact that it is discontinuous and is difficult to prevent a hypoglycemic attack if only a limited number of blood glucose determinations are done per day. A continuous glucose monitoring system [4] would therefore provide an alternative to the present discrete method of glucose determination. In principle, an in-vivo glucose sensor provides a basis for insulin administration on a continuous basis. In its simplest form, a sensor measures on-line the glucose concentration and informs the user with the results. On the basis of this information, the patient can anticipate and take the necessary steps to prevent hyper- or hypoglycemia. The advantage of this type of glycaemic control over conventional blood glucose testing is that measurements with a sensor are continuous where blood glucose testing with finger sticking are intermittent measurement. Glucose sensor measurements provide the user not only with the present blood glucose concentration but also with the trend of glucose level variation. A sensor can especially be helpful in the prevention of nocturnal hypoglycemic attacks . In addition, a physician could use the recorded glucose concentration profiles to improve the treatment of the patient. Another form of making use of the in-vivo glucose sensors is to provide an insulin delivery system that is feedback controlled by a continuous glucose measurement (artificial beta cell). In this closed-loop system, a glucose sensor is integrated with an insulin delivery device where insulin administration is based on the on-line measurement of the sensor without or with minimal interference of the patient [4].

3. Problem Statement

There are many existing technologies that can be incorporated in developing efficient systems. However, for such an important application that can revolutionize the field of medicine, an efficient method of transmitting the recorded information to an external monitoring devise is still under research. An energy efficient coding and modulation scheme that is simple to implement, consumes less energy at a circuit level and also systems level that also performs reasonably has to be designed. This is one of the many incentives for this researcher to study about this aspect of wireless communication for in-vivo sensors used for health monitoring Biomedical applications.

3.1. Thesis Goal. The main goal of this research work is to design a communication system to transmit data from one implanted sensor inside the body to another implanted sensor or a receiver residing on the body surface in a very energy efficient manner. The different aspects considered in achieving this goal would be

- Select a simple and efficient modulation scheme.
- Apply coding scheme to improve the performance of this modulation scheme.
- Coding scheme should be such that it is less complex to implement (algorithmically less demanding, less circuit complexity)
- The energy consumed in the circuit by the coding scheme (algorithm) should be very negligible compared to overall energy consumption
- The coding scheme has to have a better performance and provide considerable coding gain.

It is very important to notice that the developed coding and modulation scheme can be used not only for bio-medical applications but for various other applications like telemetry , remote sensing, surveillance and military purposes that require energy efficient communication.

3.2. Thesis Chapters Overview. This thesis is organized into seven chapters to achieve the above mentioned goal considering the various important aspects pointed out.

Chapter 2 gives an overview of the digital communication system and few basic concepts of coding and modulation. This helps the reader to understand some of the key concepts involved in this research work. However, a detailed explanation can be obtained easily from any book describing digital communications fundamentals.

Chapter 3 gives a detailed description of the need for energy efficiency and study, analysis and development of energy efficient codes. This chapter also explains the idea of bringing about error correction mechanism for these designed codes using a soft detection process. Theoretical analysis (Probabilistic Analysis) is also done to quantify the performance theoretically.

It is followed by an introduction to complexity theory and complexity analysis of the scheme. Chapter 4 presents the circuits for implementing the developed codes and estimates the complexity of the designed codes.

In chapter 5 a performance metric called Energy Metric is defined. Encoding/Decoding circuits are realized and is implemented in Cadence Simulator and energy consumption by the circuit is estimated for end-to-end transmission of one information bit.

Analysis of the Bio-Link is done to set up the wireless bio-Link and estimate the amount of transmit power required by the system to set up a reliable link under lossy channel medium like human tissue. Chapter 6 describes the bio-link budget analysis.

Finally, chapter 7 concludes the work and highlights the achievements and accomplishments of this thesis work, also pointing out idea for some future work.

CHAPTER 2

CODING AND MODULATION

In this chapter the researcher gives a very brief overview of a generic point-to-point digital communication system. The source and channel coding idea is briefly explained and few of the concepts of communication system is presented.

1. Introduction

The digital communication industry is an enormous and rapidly growing industry, roughly comparable in size to the computer industry. The objective of this chapter is to study those aspects of digital communication systems that are unique to these systems. That is, key focus is on the fundamental system aspects of modern digital communication. Digital communication is a field in which theoretical ideas have had an unusually powerful impact on actual system design. The basis of the theory was developed 53 years ago by Claude Shannon, and is called information theory. For the first 25 years or so of its existence, information theory served as a rich source of academic research problems and as a tantalizing suggestion that communication systems could be made more efficient and more reliable by using these approaches. By the mid 1970 s, mainstream systems using information theoretic ideas began to be widely implemented, for two reasons. First, by that time there were a sizable number of engineers who understood both information theory and communication system development. Second, the low cost and increasing processing power of digital hardware made it possible to implement increasingly sophisticated algorithms. As we learn about digital communication systems and their conceptual basis in information theory, we will come to appreciate that these ideas require a fairly deep under-standing of somewhat abstract concepts.

2. Generic Point-to-Point Digital Communication System

Here the researcher talks about two fundamental aspects of digital communications: Source coding and Channel coding. The source coding problem is the problem of efficient representation of source signals e.g., speech waveforms, image waveforms, text files as a sequence of bits for transmission through a digital network. Of course it must be keep in mind the paired problem of source decoding: conversion of the bit sequence (possibly corrupted) back into the original source signal.

The channel coding problem is the problem of efficient transmission of a sequence of bits through a lower-layer channel e.g., a 4 KHz telephone channel or a wireless channel. Again it must very much be keep in mind how we intend to recover a more-or-less faithful replica of the original bit sequence from the channel output in the remote receiver, despite the distortions that may be introduced by the channel.

In a simple point-to-point channel is illustrated below in the figure 3. The output bit sequence of the source encoder is the input bit sequence of the channel encoder, and the output bit sequence of the channel decoder is the input bit sequence of the source decoder.

Various blocks of the communication system shown in figure 3 will now be discussed. The input is the source signal. It might be a sequence of symbols such as letters from the

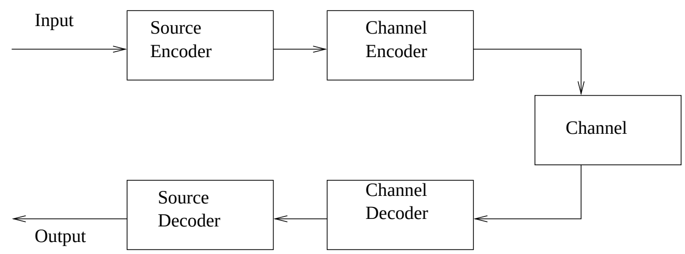

Figure 3. Block Diagram of a Point-to-Point Digital Communication System

English or Chinese alphabet, binary symbols from a computer file, etc. Alternatively, the input might be a waveform, such as a voice signal from a microphone, the output of a sensor, a video waveform, etc. Or, it might be a sequence of images such as X-rays, photographs, etc. Whatever the source signal is, it is modeled it as a sample function of a random process. This is one of the reasons why probability is an essential prerequisite for this subject. It is not obvious why inputs to communication systems should be modeled as random, and in fact this was not appreciated before Shannon developed information theory in 1948. The study of communication before that time (and well after that time) was based on Fourier analysis, which basically studies the effect of passing sine waves through various kinds of systems and components.

3. Source Encoding

The source encoder in figure 3 has the function of converting the input from its original form into a sequence of bits. We have already discussed many of the reasons for conversion- to a bit sequence: standardized interfaces, layering, and the source-channel coding separation theorem. The simplest source coding techniques involve simply representing the source signal by a sequence of symbols from some finite alphabet, and then coding the alphabet symbols into fixed-length blocks of bits. For example, letters from the 27-symbol

English alphabet (including a space symbol) may be encoded into 5-bit blocks. Or, upper-case letters, lower-case letters, and a great many other special symbols may be converted into 8-bit blocks (bytes) using the standard ASCII code. The most straightforward approach to converting an analog waveform to a bit sequence, called analog to digital (A/D) conversion, is first to sample the source at a sufficiently high rate (called the Nyquist rate), and then to quantize it sufficiently finely for adequate reproduction. For example, in standard voice telephony, the voice waveform is filtered to a bandwidth of less than 4 KHz and sampled 8000 times per second; each sample is then quantized into one of 256 levels and represented by an 8-bit byte. This yields a source coding bit rate of 64 kb/s.

4. Channel

We next discuss the channel in a generic digital communication system, before considering channel coding. In general, the channel is that part of the communication medium that is given and not under the control of the designer. Thus, to a source code designer, the channel might be a digital channel with bits as input and output; to a telephone-line modem designer, it might be a 4 KHz voice channel; to a cable modem designer, it might be a physical coaxial cable of up to a certain length, with certain bandwidth restrictions. For a channel code designer, the channel is often a physical channel; e.g., a pair of wires, a coaxial cable, or an optical fiber going from the source location to the destination. It also might be open space between source and destination over which electromagnetic radiation can carry signals. As in the study of signals and systems, we view a channel in terms of its input, its output, and some description of how the input affects the output, which in this course will usually be a probabilistic description. If a channel were simply a linear time-invariant system (e.g., a filter), then it could be completely characterized by its impulse response or

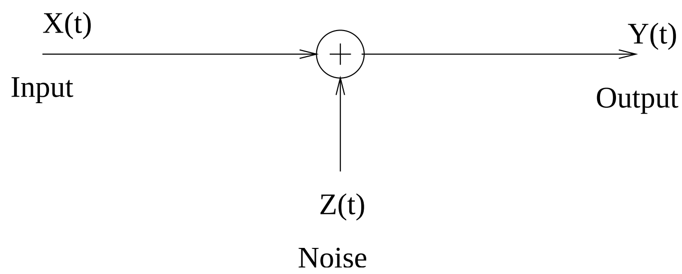

Figure 4. Schematic of an AWGN channel

frequency response. However, the channels that we look at here (and channels in practice) always have an extra ingredient noise. Suppose that there were no noise and a single input voltage level could be communicated exactly. Then, representing that voltage level by its infinite binary expansion, we would in principle be able to transmit an infinite number of binary digits by transmitting a single real number. This is ridiculous in practice, of course, precisely because noise limits the number of bits that can be reliably distinguished. Again, it was Shannon in 1948 who realized that noise provides the fundamental limitation to performance in communication systems. The most common channel model involves a waveform input $X(t)$, an added noise wave-form $Z(t)$, and a waveform output $Y(t) = X(t) + Z(t)$ that is the sum of the input and the noise, as shown in figure 4. Each of these waveforms are viewed as stochastic processes. The noise $Z(t)$ is often modeled as white Gaussian noise. The input is usually constrained in power and in bandwidth.

5. Channel Encoding

The channel encoder box in figure 3 has the function of mapping the binary sequence at the source/channel interface into channel inputs. The channel inputs might be waveforms, or might be discrete sequences, but to be specific here, we view the channel as the linear Gaussian channel of the previous subsection. The general objective here is to map binary inputs at the maximum bit rate possible into waveforms such that the channel decoder can recreate the original bits with low probability of error. One simple approach to this problem is called modulation and demodulation. In the simplest modulators, each bit is independently mapped into one of two possible-ble waveforms. For example, in a binary frequency-shift-keyed (FSK) modem, each bit chooses one of two frequencies. On an optical channel, a laser beam may be turned on or off. In multi-level modulation, a string of m bits may select one of M = 2 m waveforms. In eight-level pulse-amplitude modulation (8-PAM), for example, the input bit sequence is divided into successive triples of binary digits. Each of the eight possible combinations of three binary digits is then mapped into a different numerical signal level (e.g., - 7; - 5; - 3; - 1; 1; 3; 5; 7). The resulting sequence of signal levels then modulates the amplitudes of a certain given modulation waveform. Because of the noise on the channel, the received signal is almost certainly not equal to one of the possible transmitted signals. A major function of the demodulator is that of detection. The detector attempts to choose which possible input signal is most likely to have given rise to the given received signal.

6. Error Correction

Frequently the error probability incurred with simple modulation and demodulation is too high. One possible solution is to separate the channel coder into two layers, first an error-correcting code, and then a simple modulator. As a very simple example, the bit rate into the channel encoder could be reduced by a factor of 3, and then each binary input could be repeated 3 times before entering the modulator. If at most one of the 3 binary digits coming out of the demodulator were incorrect, it could be corrected, thus reducing the error probability of the system at a considerable cost in data rate. The scheme above is a very simple example of error-correction coding, namely repetition coding with majority-rule decoding. Unfortunately, with this scheme, it is possible to get very reliable communication only by greatly slowing down the rate at which the original bits are transmitted. What Shannon showed was the very unintuitive fact that more sophisticated coding schemes can achieve arbitrarily low error probabilities without lowering the data rate below a certain data rate that depends on the channel being used, called the channel capacity. In this subject, the researcher will not prove this result, or even describe it very precisely, although the researcher will provide various types of insight into coding and decoding. For example, for an AWGN channel with bandwidth W and input power P, if the one-sided power spectral density of the noise is N_0, then Shannon showed that the channel capacity in bits per second is

$$C = W log_2 \left(1 + \frac{P}{N_0 W}\right) \tag{2.1}$$

Only in the past few years have channel coding schemes been developed that can closely approach this channel capacity. Until about 20 years ago, channel coding usually involved a two layer system similar to that above, where an error-correcting code is followed by a modulator. At the receiver, the waveform is first demodulated, and then the error correction code is decoded. More recently, it has been recognized that coding and modulation should be considered as a unit, in schemes called coded modulation. Moreover, coding for the AWGN channel is a problem that is best viewed in the geometric signal-space context.

7. Coding Tradeoffs

With a brief over view of the various blocks in a generic point-to-point digital communication system, it is easy to understand a few details about some specific coding schemes.

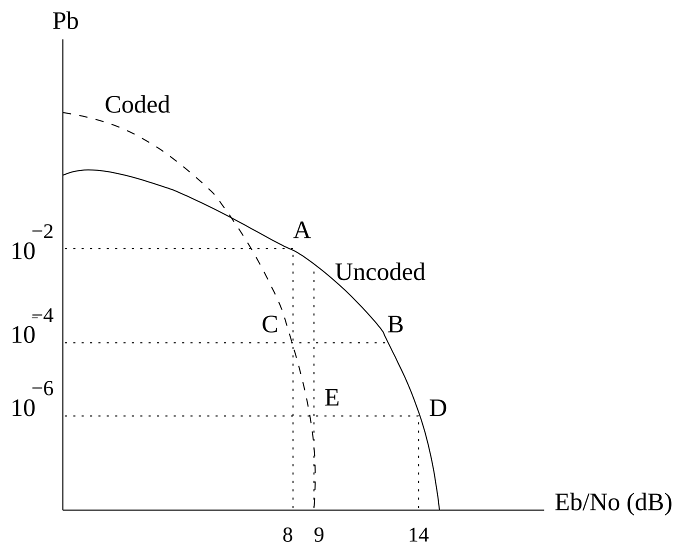

Figure 5. Comparison of Coded versus Uncoded error performance

Channel coding schemes can be partitioned into two areas, waveform coding and structured sequences [16]. Waveform coding deals with mainly transforming into better waveforms to make the detection process less subject to errors. Structured sequences deal with transforming data sequences to better sequences which have better redundancy. These redundant bits can be used in detecting the errors introduced by channel noise. This research work has restricted the studies to structured sequence codes in general and to linear block codes in particular. However, by this procedure, there will be many compromises and gains that can be achieved. In the following few sections some of the tradeoffs are mentioned. Also a brief idea of block codes is presented. It will later be used for comparison with developed coding scheme.

7.1. Error Performance versus Bandwidth. Consider the figure 5 [16]. Suppose initially the operating point for a specific application that uses uncoded modulation scheme is "A" ($P_b = 10^{-2}, E_b/N_0 = 8dB$). If at any point of time there is a request for an increase in the quality of performance, say bit error $10^{-2} to 10^{-4}$. For which, the source has to expend some extra power to mitigate the error, i.e move along the curve to point "B" which requires more power or energy per bit. If there is a restriction on the power, then the only way to satisfy the requirement would be by getting the operating point down to point "C". This is achieved by coding the information bits by adding some redundant bits. Redundant bits leads to increase in bandwidth. Thus, we tend to achieve better performance by the expense of more bandwidth.

7.2. Coding Gain. The coding gain is defined as the difference in the average signal-to-noise ratio per bit E_b/N_0 of coded scheme versus uncoded scheme.

$$G(dB) = \frac{E_b}{N_0}(dB)_{uncoded} - \frac{E_b}{N_0}(dB)_{coded} \tag{2.2}$$

7.3. Data Rate versus Bandwidth. It is to be noted that the data-rate of a system is directly related to the bandwidth of system. As the data rate increases, the number of bits transmitted per unit time increases, i.e there is a decrease in the duration of every bit. Reduction of bit duration T leads to an increased bandwidth (BW = 1/T).

7.4. Capacity versus Bandwidth. Shannon's channel capacity theorem sets a limit on the amount of data transmitted (Data rate) for a given channel condition and transmit power. It is seen in the above Shannon's channel capacity theorem, that the bandwidth occupied by the communication system has to be always lesser or equate to the channel capacity for a given transmit power and channel condition.

8. Block Codes

A block code is a code in which k bits (or, more generally, symbols) are input and n bits (or, more generally symbols) are output. The code is designated as an (n, k) code. For a k bits input, there would be 2^k distinct messages. Each message of n symbols associated with a with each input block is called a codeword. In general, simply a lookup table with k inputs and n outputs can be used. However, the lookup table seems infeasible for very large values of k. A block code C of length n with 2^k codewords is called a linear (n; k) code if and only if its 2^k code words form a k-dimensional subspace of the vector space of all n-tuples over the field GF(2). More generally, with a bigger field, a block code C of length n with q^k is called a linear (n; k) code if and only if its q^k code words form a k-dimensional subspace of the vector space of all n-tuples over the field GF(q).

Hamming codes are simplest form of block codes, for $m \geq 2$: $n = 2^m - 1; k = 2^m - m - 1; n - k = m$; error correction = 1.

The sum of any two codewords is a codeword. Being a linear vector space, there is some basis, and all codewords can be obtained as linear combinations of the basis. Let $g_0, g_1, g_2 ......, g_{k-1}$ be designated as the basis vector. In a nutshell, it means that we can represent the coding operation as matrix multiplication, as we have already seen. A generator matrix **G** of (kXn) with elements $g_0, g_1, g_2 ......, g_{k-1}$ can be formulated. We observe that the all-zero sequence must be a codeword. Therefore, the minimum distance of the code C is the codeword of smallest weight. Comment on circuits to implement encoding. We have a vector space of dimension k embedded in a vector space of dimension n, the set of all n-tuples. Associated with every linear block code generator G is a matrix **H** called the parity check matrix whose rows span the null-space of **G**. Then if c is a codeword, then $c\mathbf{H}^T = 0$, That is, a codeword is orthogonal to each row of **H**. From this it is observed that $\mathbf{G}\mathbf{H}^T = 0$.

For example, the generator matrix for a (7,4) Hamming code is

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

and the parity check matrix is

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

Syndrome: Let the columns of H be designated as $d0, d1, ..., dn$ Then since $c\mathbf{H}^T = 0$ for any codeword c, we have $0 = c_0d_0 + c_1d_1 .... + c_{n-1}d_{n-1}$. Let c be the codeword of smallest weight $= d_{min}$. Then the columns of **H** corresponding to the elements of c are linearly dependent. Based on this, a bound on the distance of a code: $d_{min} \leq n - k + 1$ can be determined since **H** has $n - k$ linearly independent rows. For a received vector r, the syndrome is $S = rH^T$. Obviously, for a codeword the syndrome is equal to zero. We can determine if a received vector is a codeword. Furthermore, the syndrome is independent of the transmitted codeword. If $r = c + e$. Therefore $S = eH^T$. the received code word can be corrected by using the error pattern i.e $c = r + e$.

CHAPTER 3

ENERGY EFFICIENT CODES

The first two chapters of this report gives a brief overview of the biosensor applications, about few of the motivating application examples for this technology and few aspects of digital communication system in general. This chapter will give a detailed explanation of the need for energy efficiency and design of energy efficient codes, performance evaluation, performance enhancement due to soft detection and trade-offs of energy efficient codes designed. A theoretical analysis is also conducted towards the end of this chapter.

1. Need for Energy Efficiency

Current advancement in the semiconductor industry has made it possible to have wireless microsensor applications [7][8], especially related to the civil and military operations. These sensors are mainly used for sensing, data gathering or surveillance use. They involve very low data rate of the order of few kilo bits per second (Kbps) and of transmission range of the order of few meters, unlike other wireless applications. Deploying the sensors and frequent replacement of the battery is a major issue. For some specific bio-sensor applications, over heating due to excess of power consumption leads to the damage of tissues [7]. Thus the wireless communication system for such sensitive applications have to be designed with a different perspective altogether. It demands energy efficient design of the radio systems in order to minimize the battery power consumption of the device. This energy efficiency must be brought about at every stage of the design. Power efficiency at system level must be brought about by keeping in mind the circuit complexities and the circuit power consumption. Every design comes with a trade-off, hence, we have to compromise either with power, bandwidth or error. Sensor applications with very low data rates of the order of few KBPS operating in the ISM Band (unlicensed) can afford to compromise on bandwidth requirements of the system but definitely not on the power consumption. This is the main reason for us to think in terms of developing a most energy efficient wireless communication system at the expense of bandwidth that performs considerably good with least circuit complexities.

Many new coding and modulation schemes like Turbo codes can be employed to bring about power efficiency at system level. The system can be made to operate with less SNR for a given error performance, but these are complex codes and circuit power consumption of the algorithms are more.

There has been many recent works in the field of wireless microsensors to bring about energy efficiency at both system level and circuit level. Wang et al. [11] have discussed the issues of many low power wireless microsensor applications. They have proposed energy efficient modulations and MAC protocols for asymmetric RF microsensor systems. Comparison of various modulation techniques with respect to transmit power and bandwidth efficiency is discussed. Methods to over come the transmitter complexities and also the MAC protocols are described for microsensor applications. They compare the transmit power of M-PSK, M-QAM and M-FSK and their bandwidth efficiencies for different values of M in a fading channel. It is found that as M (no. of symbols) increases, M-PSK/M-QAM sacrifices transmit power to achieve higher bandwidth efficiency and M-FSK on the other hand sacrifices bandwidth efficiency to achieve less transmit power. Thus, FSK can be used for power constrained applications. However, it is noted that M-FSK consumes less transmit power compared to M-PSK/M-QAM only for M>8. M-FSK is less energy efficient for M<8 as it requires 6 dB more RF power to achieve the same error performance [11]. For applications involving RF wireless microsensors where either the bandwidth required is low or when there are limited number of users, B-PSK which consumes less power looks like a reasonable choice. Simple digital modulation technique like OOK is totally ignored due to its bad error-performance. Typically uncoded OOK requires double the power (3 dB more SNR) to perform as much as BPSK/BPAM.

A simple and energy efficient source coded On/Off Keying modulation and near optimal error detection scheme for wireless applications is presented in this paper. Many low-power battery operated radio systems, especially for microsensor applications, has a need for saving power both at the system level and circuit level implementation. Our main objective in this paper is to come up with energy efficient coded modulation scheme that consumes comparatively less power both at system and circuit level. A simple On/Off keying (OOK) digital modulation scheme is used for this purpose. The basic idea of Minimum Energy coding (ME-Coding) for source with known statistics (probabilities of occurrence of symbols) is obtained from [9]. In ME-Coding scheme, source bits are mapped to constant length codes (ME-Codes) which has less number of high-bits in it. Since the OOK transmitter consumes energy only when transmitting a high-bit, mapping to ME-Codes reduces the total energy consumed in RF transmitter. In this thesis work, the researcher has come up with ME-Coding scheme for sources with unknown statistics and further a new method of code-by-code detection that can detect and correct certain errors in the codeword received

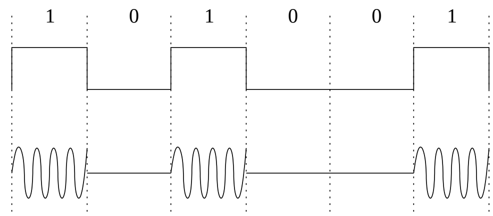

Figure 6. Typical OOK Modulation Scheme

is proposed. The inferior performance of OOK when compared to other simple modulation schemes is overcome by ME-Coding. A total of about 6 dB improvement in signal-to-noise ratio (SNR) per bit is observed when a 3-bit message symbol is mapped to a 7-bit ME-Code. It also performs 3 dB better than a Hamming(7,4)-coded BPSK. Further it is observed that these ME-Codes can be applied to sources with known statistics

Erin and Asada [10], have discussed many approaches towards optimizing the energy consumption problem and have proposed efficient source coding scheme for information transmission in wireless environment. The basic idea of minimum energy source coding scheme proposed by them [9] is used in this work.

In the course of this thesis the basic idea of Minimum Energy Coding is explained in section 2. Section 3 describes the approach in improving the error-performance of ME-Coding.

2. Minimum Energy Coding (ME-Coding)

For low data-rate wireless applications, simplest form of digital modulation technique like On/Off keying (OOK) can also be considered. In OOK, the base band signal modulates a carrier wave at a higher frequency f_c and transmits it as RF waves. That is, a carrier signal is transmitted when a bit-1 is to be sent and no signal is transmitted when a bit-0 is to be sent. Figure 6 shows OOK transmitted signals for a sequence of bits. Hence transmitter expends energy only when transmitting a signal for bit-1. Thus, for a system that uses OOK modulation technique, the obvious way to reduce the energy consumed would be to reduce the number of bit-1's transmitted compared to the bit-0's. Since there is no control over the information source, the only way to reduce the high bits (bit-1s) would be to map a set of information bit sequence to a constant length codeword (ME-Code) which has less number of bit-1's in it. This is originally based on the idea proposed by Erin and Asada [9]. They have formulated the power optimization problem for wireless communication applications with message source of known statistics. They bring about the reduction in energy consumption in two steps. Firstly, use a set of codes that have less number of high bits in it. Secondly, assign these set of codes to the messages in such a way that, codes with lesser number of ones are assigned to messages of higher probabilities. They have also taken one step towards improving the performance of these codes by simple concatenation process. Their approach of ME-Coding cannot be applied to sources with unknown statistics. Keeping the basic idea of ME-Coding (source-bits mapped to code-bits) for source with unknown statistics (unknown probabilities of occurrence of symbols) and using a very simple near optimal detection process to improve the performance of ME-Coding, the researcher proposes a new approach towards ME-Coding.

2.1. Our Approach Towards ME-Coding. The basic transmitter-side block diagram is as shown in Figure 7. Information source produces information bits 1's and 0's. The info-bits are fed to the source encoding block or the ME-Coding block. The ME encoder gives out a sequence of bits that has a reduced number of bit-1s in it. These source encoded bits are now OOK modulated in the modulator block and then transmitted by a RF transmitter bit-by-bit.

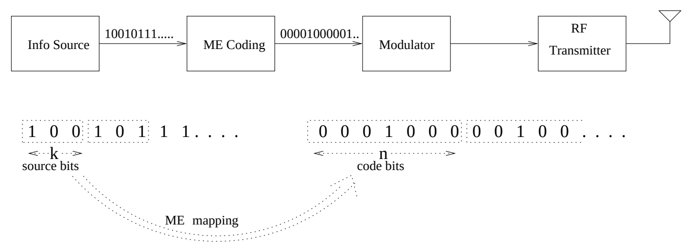

Figure 7. Block Diagram of ME Mapping Scheme

2.1.1. *Codes considered.* Consider k binary bits (1's and 0's, with $k > 1$) from the source. ME-encoder groups these k bits together and maps it to a ME-Code word of length n, where $n > k$. Thus, there can be a total of $M = 2^k$ possible incoming symbols mapped on to M codewords that are predetermined. As already mentioned these codewords have less number of high bits compared to the original information sequence but with more number of bits in it. Our main idea is to apply the ME-Coding to sources with unknown statistics. That is, say, a source symbol 1011000 or 1101011 can be mapped only to a code with not more than two ones or four ones in it respectively. Otherwise, the whole idea of reducing the number of ones in the transmitted bit sequence is lost. Figure 7 also shows the mapping of k source bits on to a codeword of n bits.

The extreme form of coding is used here where a maximum of one high bit is present in the entire codeword sequence. The reason being, firstly, it satisfies the criteria of having less number of ones in the transmitted codeword bit sequence compared to source bit sequence. Secondly, this codeword can safely be assigned to any of the M source symbols occurring at any probability. Finally, this results in the maximum reduction of total number of ones in the transmitted codeword bit sequence.

Table 1 shows the source symbol and their corresponding mapped codewords for $M =$ 4 and 8. For mapping of $M = 2^k$ source symbols, a codeword of length $n = M - 1$ is required. This is because the all-zero source symbol is mapped to an all-zero codeword sequence and

Table 1. Minimum-Energy Code table for $k = 2$ and 3

$Sourcebits$ $ME(3,2)$	$Codeword$ $ME(3,2)$	$Sourcebits$ $ME(7,3)$	$Codeword$ $ME(7,3)$
00	000	000	0000000
01	001	001	0000001
10	010	010	0000010
10	100	011	0000100
		100	0001000
		101	0010000
		110	0100000
		111	1000000

the remaining $M - 1$ source symbols can be mapped to codeword with $M - 1$ bits in it, with each codeword having one of its bit high. In general, for grouping k bits a code length of $2^k - 1$ is needed. The code rate for this form of source coding is $k/n = k/(2^k - 1)$. The codes are represented in the standard form as ME(n, k), where n represents the codeword length assigned to message symbol of k bits. The minimum euclidean distance between any two ME-Code is $d_{min} = 1$. Thus, these codes have no capability of correction or detection of errors. However, the basic characteristic of the code (maximum of one high bit in the codeword) makes it possible to detect errors when the receiving codeword has more than one high bit in it. ie. if a bit-by-bit hard decision with 0.5 threshold is made on the demodulated signal, and if any codeword is detected with more than one high bit, then it can be considered as code in error and hence, all the final k message bits corresponding to that codeword at the receiver is considered to be in error. Figure 8 shows an example of the process of error detection for a ME(3,2) code.

2.2. Energy Saving in ME-Codes. Assume the OOK transmitter consumes E Joules of energy to transmit a high bit. If n_{Si} is considered as the number of high bits in a source symbol Si that occur with a probability of P_{Si} and N as the total number of symbols

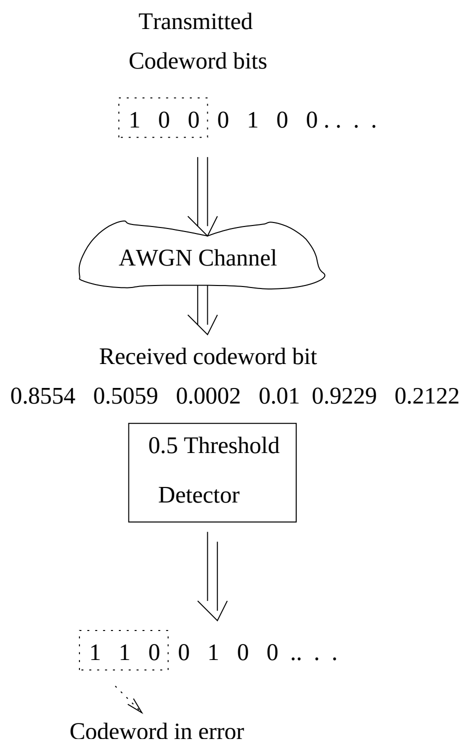

Figure 8. Flow of bit-by-bit detection process

transmitted by the transmitter, then the total amount of energy consumed in an uncoded OOK scheme would be

$$\sum_{i=1}^{M-1} E * n_{Si} * (P_{Si} * N) \tag{3.1}$$

By mapping the non-zero source symbol Si to ME-Code, the total amount of energy consumed now would be $\sum_{i=1}^{M-1} E * P_{Si} * N$. This is due to the fact that all the non-zero ME-Codes have exactly one high bit. Thus, the percentage saving of the total energy of ME-Coded OOK scheme compared to an uncoded OOK scheme is given by

$$\begin{aligned} Saving &= 1 - \frac{\sum_{i=0}^{M-1} E * (P_{Si} * N)}{\sum_{i=0}^{M-1} E * n_{Si} * (P_{Si} * N)} * 100 \\ &= \frac{\sum_{i=0}^{M-1} n_{Si} * P_{Si} - 1}{\sum_{i=0}^{M-1} n_{Si} * P_{Si}} * 100 \end{aligned}$$

For sources with equal probability of occurrence of symbols the above equation reduces to

$$Saving = \frac{\sum_{i=0}^{M-1} n_{Si} - M}{\sum_{i=0}^{M-1} n_{Si}} * 100 \tag{3.2}$$

With the increase in number of source symbols M, there is an increase in the percentage saving of total energy spent in this scheme. Therefore energy saving becomes 100% for infinite number of source symbols M. However, in practical systems, M cannot be increased arbitrarily to reduce energy consumption as it increases the bandwidth and is limited by the channel capacity.

However, the above formulated ME-Coding scheme can be used to argue that the codes used by this researcher is the most efficient in terms of total energy consumed by the transmitter. Every non-zero coded/uncoded OOK symbol has at least one high bit in it. We consider the number of high bits as $n_{Si} = 1 + n'_{Si}$. We know that the total amount of energy (E_{total}) spent by the system is proportional to the number of high bits in the symbol.

$$E_{total} \propto \sum_{i=0}^{M-1} n_{Si} * P_{Si} \geq 1 \tag{3.3}$$

Since there is no transmission for an all-zero code word, we can write

$$\begin{aligned} \sum_{i=1}^{M-1} (1 + n'_{Si}) * P_{Si} \geq P \\ P + \sum_{i=1}^{M-1} n'_{Si} * P_{Si} \geq P \end{aligned} \tag{3.4}$$

In the case of ME-Codes used in our scheme, there is only one high bit in every non-zero codeword, i.e. $n'_{Si} = 0$. Thus $P + \sum_{i=1}^{M-1} n'_{Si} * P_{Si} = P$. Achieving the lower bound for energy consumed, our scheme of ME-Codes proves to be most energy efficient and can be safely implemented for many low data rate wireless applications.

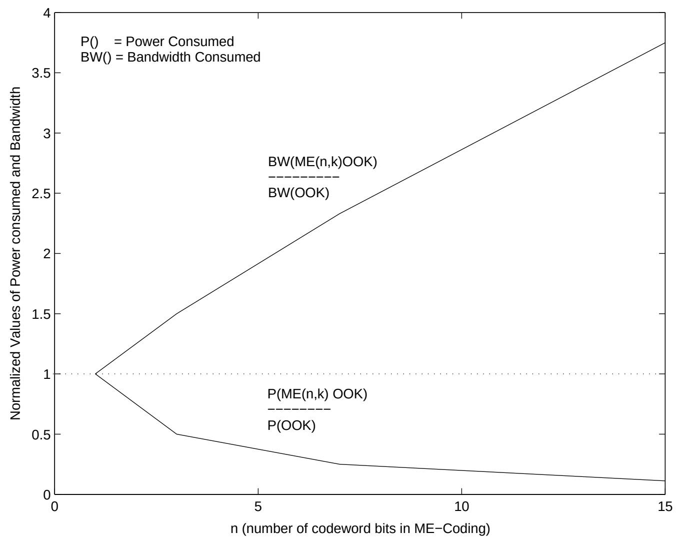

Figure 9. Normalized Bandwidth and Power Consumption

2.3. Power and Bandwidth Requirement of ME-Coding. This simple ME-Coded OOK modulation scheme now performs better (in terms of power consumption) than scheme like BPSK. Figure 9 shows the amount of decrease in the normalized power and an increase in the bandwidth requirement of the system for increasing values of n. However, a trade-off must be done between power and bandwidth consumption of the system. For applications operating in the unlicensed ISM band, there is a scope for using higher bandwidth to achieve power efficiency. ME-Coding being a simple mapping technique, can be implemented with less power requirement. Further, a scheme is presented which improves the performance of this non-optimal bit-by-bit detection by using a simple code-by-code detection process.

2.4. Performance of ME-Code with bit-by-bit hard decision decoding. For simulation purpose, a source generating binary bit sequence (1's and 0's) and additive white gaussian noise (AWGN) channel is considered. Matlab 6 was used for simulation purpose. When ME(3,2) code from the table 1 is applied to the source symbols, and a bit-by-bit hard

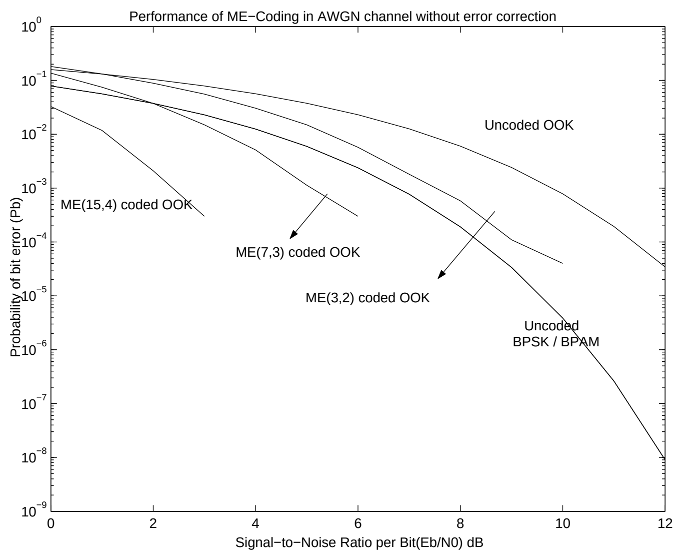

Figure 10. Performance Comparison and Evaluation of ME-Coding

decision with 0.5 threshold is made without any error correction at the receiver, there is an improvement of 2 dB in the SNR per bit for a probability of error of 10^{-4}. An improvement of 5 dB and 7 dB is seen with a ME(7,3) and ME(15,4) codes respectively. Figure 10 depicts the same. The code rates of these code sets are 2/3, 3/7 and 4/15 respectively. With the increase in value of k, there is a remarkable increase in the bandwidth requirements of the system. The performance of ME(7,3)-coded OOK and ME(15,4)-coded OOK are 2 dB and 4 dB better than the uncoded BPSK/BPAM.

3. Error correction in ME-Coding

The sensor applications have transceiver with limited computing capabilities, memory resources and reduced processor speed. Another important factor to be considered is the delay in the receiver processor. There are many efficient codes with higher code gains like turbo codes to achieve energy efficiency at a system level [12][15]. It is complicated to generate and detect these codes. Complex algorithms take up more power in computing.

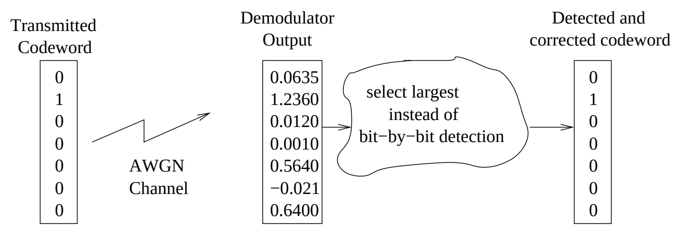

Figure 11. Error Correction with Code-by-Code Detection

Computation time also increases with complexities. Moreover, our sole idea of having less number of bit-1's in the transmitted code bit sequence must be maintained. The main objective here is to bring about a considerable conservation in the energy at a system level with algorithms of least complexities, demanding less resources and consuming lower power in the circuit level implementation.

Error correction schemes like Convolution codes and Block codes can be adopted to have an improvement in the error performance of the ME-Coding scheme. Convolution codes are tough to be combined with ME-Codes as they are generated in a finite-state machine and they do not allow a direct concatenation with ME-Codes [9]. Block codes like Hamming code are used for error performance improvement in ME-Coding [9]. For example, Systematic binary Hamming block code scheme, say a standard (7,4) Hamming code can be combined with the ME-Codes using the parity check equation $C_m H' = 0$ (C_m is the codeword and H' is the transpose of parity check matrix). This effort of improving the error performance of ME-Code by combining it with Hamming Code proves unsuccessful as the basic approach of ME-Coding to have a reduced number of ones in the transmitted codeword bit sequence is lost. The coding gain provided by Hamming codes for smaller values of n is small and also has a higher circuit complexities for syndrome detection at the receiver [15]. It also increases the length of the ME-Codeword.

3.1. Error Correction in ME-Codes with Code-by-Code Detection. The performance of the bit-by-bit detection explained in the earlier section can be further increased by code-by-code detection. The problem of uncorrected ME-Code bits faced by the bit-by-bit detection process was explained in the previous section. Also the limitations of using ME-Codes along with other simple error correcting codes like Hamming codes is discussed. Hence, other energy efficient approach is proposed in improving the performance of the ME-Coding scheme .

The signal strengths of the demodulated bits vary due to the presence of noise in the channel, the bits may not be the same as it was sent from the transmitter. Consider AWGN with zero mean and unit variance. After a bit-by-bit 0.5 threshold detection is made, a codeword bit sequence say, 0 1 0 0 0 0 0 might be sent and may be detected as 0 1 0 0 1 0 1. As already discussed, the basic property of the codeword has made it possible to detect an error in the codeword. Instead of declaring this codeword as one to be in error, a different approach is followed for codeword detection.

Before a bit-by-bit hard detection is made, we observe the energy levels of all the incoming n bits of the codeword. Then make the bit with highest strength as a high-bit and the rest as low-bit. Figure 11 shows the process of our code-by-code detection for a codeword. It shows a transmitted codeword 0 1 0 0 0 0 0. This is demodulated as 0.0635, 1.236, 0.012, 0.001, 0.564, -0.02, 0.64. In the earlier approach of bit-by-bit detection with 0.5 threshold, it would have been detected as 0 1 0 0 1 0 1. Now, by this approach we look at the bit with highest strength in the entire codeword. The original high-bit of energy 1.236 is set as bit-1 and the rest is made as bit-0's. Thus, it is detected as 0 1 0 0 0 0 0. Since the noise is AWGN, the probability of energy of genuine bit-1 being greater than the energy of the error bit-1 is more. ie. if energy of genuine bit-1 is e_i and that of the error bit-1 is e_j, then, $P(e_i > e_j)$ is more than $P(e_j > e_i)$. This fact is clear from a Gaussian distribution curve.

By code-by-code detection process we accomplish two things. Firstly, eliminate the occurrence of an invalid codeword at the receiver and improve the error performance of ME-Coding. Secondly, this method performs exactly like an optimal detector.

In an optimal decoding scheme, the demodulator output produces the receiver codeword of length n as $\mathbf{r} = [r_1, r_2, ...r_n]$. An optimal detector maximizes the probability of detecting a correct codeword $C_m = [c_{1m}, c_{2m}, ...c_{nm}]$ from the codeset $\mathbf{C}$, given, received code $\mathbf{r}$. ie. $argmax_{m=1,2,...8} P_r(\mathbf{C}_m/\mathbf{r})$ [15]. It maximizes the correlation metrics $C(\mathbf{r}, \mathbf{C}_m)$. The correlation metrics $C(\mathbf{r}, \mathbf{C}_m)_{m=1,2,3...8} = r.C_m = (r_1C_{1m} + r_2C_{2m} + r_3C_{3m}..... + r_nC_{nm})$. Since our codeword has only one high bit in it, $MAX[C(\mathbf{r}, \mathbf{C}_m)_{m=1,2,3...8}]$ is nothing but considering the highest energy bit. This method of code-by-code detection proves to be simpler than the optimum detection.

3.2. Performance of ME-Coding with Code-by-Code Detection. It is noted that ME-Coded OOK modulation scheme when detected with code-by-code detection, performs better than the bit-by-bit detection. Figure 12 shows the relative improvement in the error performance. In the Figure 12, ERCN represents the code-by-code detection which has error correction capability. For an error probability of 10^{-4}, a total of about 3 dB, 6 dB and 9 dB improvement in SNR per bit was seen with ME(3,2), ME(7,3) and ME(15,4) respectively compared to uncoded OOK. ie. ME-Coded OOK can now perform a given probability of error with lesser SNR per bit value. ME(7,3)-coded OOK is about 2 dB better than Hamming(7,4)-coded BPSK/BPAM. The main reason for such a comparison is to emphasize the fact that ME-Coded OOK is more energy efficient than other simple

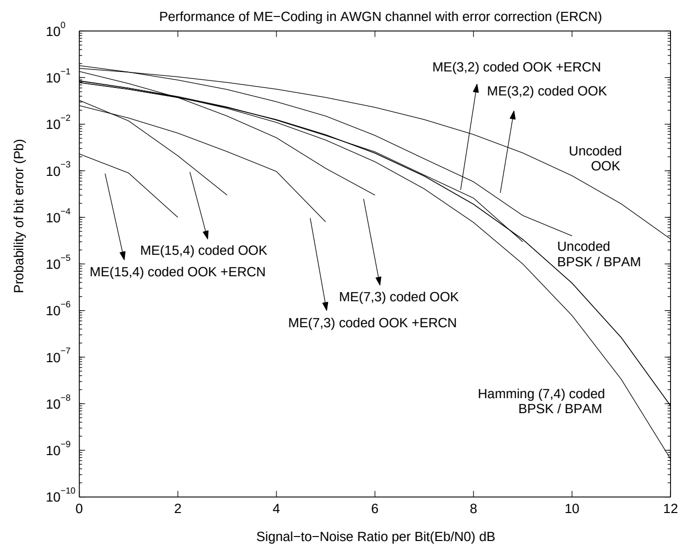

Figure 12. Performance of ME-Coding with Error Correction

schemes like block-coded BPSK/BPAM and also to propose a new and simple approach of improving the inferior error performance of the OOK scheme.

Although this scheme is based on On-Off Keying modulation technique, the characteristic of the code makes it look like an orthogonal signaling scheme [15], except for the presence of an all-zero code. As a matter of fact, it is quite different compared to orthogonal signals in terms of transmission / reception techniques and also performance. In orthogonal signal scheme, each symbol (group of k bits) is transmitted as one of 2^k orthogonal signals and received as one of 2^k orthogonal signal vector. However, in ME-Coding scheme used here, a code representing a group of k bits is transmitted bit-by-bit and received bit-by-bit.

The theoretical performance of orthogonal signals has already been dealt in detail [15]. Say, for probability of bit error 10^{-4}, SNR per bit required is about 7.5 dB, 6.5 dB and 6 dB for $M = 2^k = 8, 16, 32$ respectively. Simulations show that in the case of ME-Coding, the same probability of bit error performance can be achieved at a lesser average SNR per bit value.

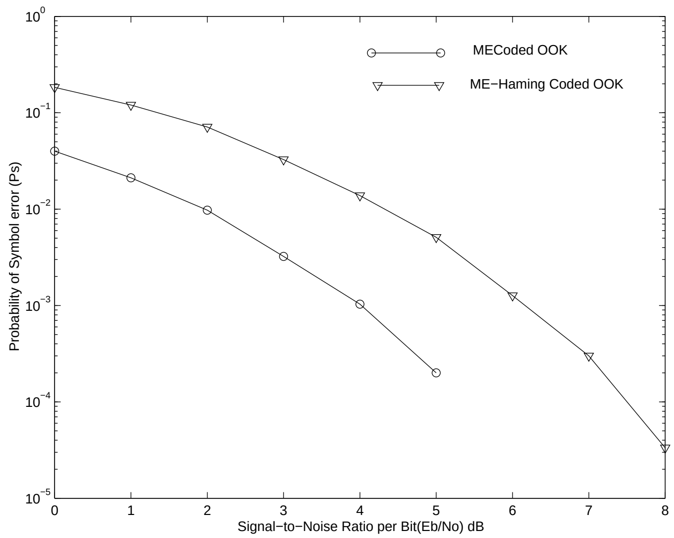

Figure 13. Comparing Symbol-Error of ME-Codes with that of ME-Hamming codes presented in [9]

4. Performance of ME-Codes with ME-Hamming Codes(MEH-Codes)

In this section a direct comparison of ME-Codes presented in Table 1 is made with that of a MEH-Codes presented in Table 1 of [9] for source with known probability of occurrence of symbols. ME-Codes presented here have a maximum of one high-bit. However, the minimum energy codes in [9] have unequal number of high-bits in them. Due to the presence of unequal number of high-bits in them, it can be applied to only sources with symbols of known probability of occurrence to achieve energy efficiency as described in section 2. However, the ME-Codes presented here can be applied to sources with both known and unknown statistics. In [9] efforts are made in combining minimum energy codes with Hamming codes resulting in MEH codes for better performance in the presence of channel noise. However, it has limited error correction capability. Table 2 shows MEcodes presented in this paper and the ME-Hamming codes presented in [9] for sources with known probability of occurrence. For sources occurring with the probability as shown in the table,

Table 2. ME(7,3) and the ME-Hamming codes for known symbol probability

Prob.of Occr.	*Source Symbols*	*ME(7,3) Code*	*MEH Code*
0.2	$S1$	0000000	0000000
0.18	$S2$	0000001	0010110
0.13	$S3$	0000010	0011001
0.12	$S4$	0000100	0100101
0.11	$S5$	0001000	0101010
0.10	$S6$	0010000	1000011
0.09	$S7$	0100000	1001100
0.07	$S8$	1000000	1110000

a performance comparison was made.

Inspite of error correcting capability of Hamming codes in MEH-Codes in [9], the presence of more number of high-bits reduces it's performance. A higher average energy-per-bit is required compared to our ME-Codes. Figure 13 shows that for a BER of 10^-5, about 2.5dB less SNR per bit is required when compared to that of MEH-Code. Since matrix multiplication and syndrome detection is involved in Hamming decoding, it is more complex than the ME decoding presented here.

4.1. Comparing ME-Codes, MEH-Codes and Hamming. The ME(n,k) codes presented here has a coding rate of k/n which is different compared to that of a Hamming codes and MEH codes. In the above example, the coding rate of ME(7,3) is 3/7 and that of MEH and hamming codes is 4/7. A direct comparison of schemes with different transmission rates will be unfair. Thus, in order to prove the better performance of ME-Codes compared to that of MEH-Codes and Hamming-Codes, we use their respective channel capacities and see how much closer they are to their respective channel capacities.

Shannon's information capacity theorem states that the channel capacity of a continuous channel of bandwidth W Hz, perturbed by band-limited Gaussian noise of power

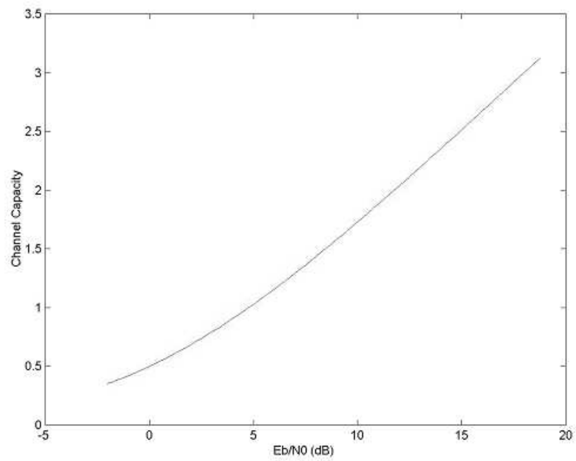

Figure 14. Shannon's Capacity curve

Table 3. Comparison with Shannon's Capacity

$@10^{-5}BER$	$Eb/N0$ used	$Bits/$ $Channel$	$Eb/N0for$ $Shannon'sCapacity$	$Distancefrom$ $Capacity$
$ME(7,3)$	$6dB$	$3/7$	$-0.9074dB$	$6.9dB$
$MEH(7,4)$	$8.6dB$	$4/7$	$0.8213dB$	$7.77dB$
$Hamming(7,4)$	$11.5dB$	$4/7$	$0.8213dB$	$10.67dB$

spectral density $n_0/2$, is given by [16]

$$C = Wlog_2\left(1 + \frac{S}{N}\right) bits/sec \tag{3.5}$$

where S is the average transmitted signal power and the average noise power is $N = N_0W$. For binary symmetric channel it can be written as [16]

$$C = \frac{1}{2}log_2\left(1 + \frac{E_b}{N_0}\frac{R}{W}\right) \tag{3.6}$$

Example, it takes 0dB to achieve 1/2 bits per channel usage. The variation of the channel capacity with respect to E_b/N_0 is plotted as shown in the figure 14.

A descriptive table for comparison, Table 3 is presented. It compares the actual values of energy-per-bit required by all the three coding schemes. table it is clear that ME-Codes require 6dB of E_b/N_0 to achieve a BER of 10^{-5}. Similarly, MEH codes [9] and Hamming codes require 8.6 dB and 11.5dB respectively. It is found out from the channel capacity curves that the actual used E_b/N_0 values by these three schemes are away from the capacity curve by 6.9, 7.77 and 10.67dB respectively. It is very clear that to achieve a certain BER (say 10^{-5}), the code which uses lesser E_b/N_0 value is a better code. Thus, it can be stated that ME(7,3) is 0.87dB better than the MEH(7,4) [9] and 3.77dB better than a Hamming(7,4) code.

5. Implementation of the Scheme

This scheme was implemented and simulated in Matlab. The block diagram of the whole system is as shown in the Fig7. For studying the performance of ME-Coding with source of unknown statistics, the Information Source Module generates source bits such that the ones and zeros have a normal distribution. That is, there are equal number of zeros and ones in the source bits. These bits are then grouped into symbols of length k bits resulting in a total of $M = 2^k$ possible symbols. This source symbols are fed to the ME encoding module which maps the k-bit length symbols on to ME-Codes of length n from a look up table stored in the memory. This operation leads to increase in the data rate of the system in turn increasing the bandwidth of the system by a factor or n/k. The transmitter module receives these series of code bits which are transmitted to the AWGN channel. AWGN channel module now adds the noise to each and every bit transmitted in such a way that the noise is a random variable with variance $N_0/2$ (N_0 = Noise Spectral Density) and mean as zero and one for bits zero and one respectively. The noise power is maintained such that the signal to noise power ratio is maintained to a particular level so that a comparison

```
begin
    for SNR 0:10 dB
        for bit 1:total_length
            Generate uniformly distributed rand( ) bits 'X_i' (0's and 1's)
            Store 'k' bits in a buffer
            map ('k'bit symbol to 'n'bit code)
            Transmit code bits C_i
            Add AWGN channel noise N_i normally distributed and with variance σ^2 = N_0/2
            Received bits Y_i = C_i + N_i * σ
            Store 'n' code bits in a buffer
            Perform a soft decision decoding to correct errors in the code bits.
            Re-Map codebits back to source bits X'_i
            Compare received X'_i bits with transmittedX_i to estimate the error.
        end
    end
    Plot graph of error Vs SNR
end
```

Figure 15. Algorithm of Minimum Energy Coding

can be made. In the Receiver module, the noise corrupted code-bits are received and the bits are detected accordingly. For a code-by-code soft detection, the received code word of length n bits are placed in a buffer before detection. Codeword is then determined based on the scheme explained in section 11. Once the code word in determined, a re-mapping of the codeword to source symbol and in turn into source bits is performed in the receiver. Finally the received bits at the receiver are compared with the original transmitted source bits and the number of error bits are counted to make an estimate of the error. The algorithm of the ME-Coding scheme is as shown in Fig 15

6. Theoretical Analysis of Performance of ME-Codes

Consider a codeset $\mathbf{C}$ with M constant length ME-Codewords each of length n bits. Let the all-zero code be represented by $C_0 \in \mathbf{C}$ and the non-zero codes by $C_i = [c_{i1}c_{i2}c_{i3}.....c_{in}]$; $C_i \in \mathbf{C}$ for $i = 1, 2, 3....M-1$. ie. c_{ij} represents the j^{th} element in the i^{th}

code. For any ME(n,k) code C_i, we consider $c_{ii} = 1$ and $c_{ij} = 0; j \neq i, j = 1, 2, ...n$. Due to the AWGN noise introduced by the channel, a ME-Code sent as $C_i = [c_{i1}\ c_{i2}\ c_{i3}...c_{in}]$ is received at the receiver as $r_i = [r_{i1}\ r_{i2}\ r_{i3}.....r_{in}]$.

An OOK bit-by-bit detector at the receiver detects the bits based on the threshold of 0.5. In a code-by-code detection process for detecting ME-Codes, we consider the entire code word received before making a decision. In this codeword, the bit with largest strength is detected as bit one and the rest as zeros, this eliminates occurrence of non-existent code (with more than one high-bit). This procedure might result in any of the other $M-1$ codes which results in error-bits that go undetected. Errors can occur due to any of the following four reasons: (consider bit-detection threshold of $\sqrt{E_b}/2$ for any received bit r_{ij}),

- $r_{ij} \geq r_{ii}; j \neq i$ with $r_{ii} \geq \sqrt{E_b}/2$.
- $r_{ij} \geq \sqrt{E_b}/2; j \neq i$ and $r_{ii} < \sqrt{E_b}/2$(one non-zero code detected as another non-zero code).
- $r_{ij} < \sqrt{E_b}/2$ and $r_{ii} < \sqrt{E_b}/2$ for any $j = 1, 2, 3....n$ (non-zero code detected as all-zero code).
- $r_{0j} \geq \sqrt{E_b}/2$; for any $j = 1, 2, 3....n$ (all-zero code detected as non-zero code).

For a given code C_i, r_{ij} and r_{ii} are Gaussian distribution random variables with mean zero and $\sqrt{E_b}$ respectively. Figure 16 shows the same for means zero and one with unit variances. The total probability of error can be evaluated as follows,

$$P(e) = P(e/C_0)P(C_0) + P(e/C_i)P(C_i) \tag{3.7}$$

$$P(e/C_0) = 1 - P(correct/C_0)$$

$$P(e/C_0) = 1 - P(r_{01} < \sqrt{E_b}/2, r_{02} < \sqrt{E_b}/2, ...r_{0n} < \sqrt{E_b}/2/C_0)$$

Since each bit in the code is statistically independent, the joint probability can be written as a product of individual probabilities. Thus,

$$P(e/C_0) = 1 - [P(r_{01} < \sqrt{E_b}/2)]^n = 1 - \left[1 - Q\left(\sqrt{E_b/2N_0}\right)\right]^n \qquad (3.8)$$

where $Q(x) = 0.5erfc(x/\sqrt{2})$. Now consider a non-zero code,

$$P(e/C_i) = 1 - P(correct/C_i)$$

$$P(e/C_i) = 1 - P(r_{i1} < r_{ii}, r_{i2} < r_{ii}, ...r_{in} < r_{ii}/r_{ii} > \sqrt{E_b}/2)$$

$$P(e/C_i) = 1 - \int_{\sqrt{E_b}/2}^{\infty} \left[P(r_{i1} < r_{ii}/r_{ii} > \sqrt{E_b}/2)\right]^{n-1} P(r_{ii} > \sqrt{E_b}/2) dr_{ii}$$

$$P(e/C_i) = 1 - \int_{\sqrt{E_b}/2}^{\infty} \left[\int_{-\infty}^{y} \frac{1}{\sqrt{2\pi}} exp(-X^2/2) dX\right]^{n-1} \frac{1}{\sqrt{2\pi}} exp\left[-\frac{1}{2}(y - \sqrt{2E_b/N_0})^2\right] dy$$

$$P(e/C_i) = 1 - \frac{1}{\sqrt{2\pi}} \int_{\sqrt{E_b}/2}^{\infty} \left[\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{y} exp(-X^2/2) dX\right]^{n-1} exp\left[-\frac{1}{2}(y - \sqrt{2E_b/N_0})^2\right] dy$$

The total probability of error is given by

$$P(e) = \frac{1}{M}\left[1 - \left(1 - Q(\sqrt{E_b}/2)\right)^n\right] + \frac{M-1}{M}[P(e/C_i)]$$

Figure 17 shows the comparison of theoretical analysis and the implemented ME codes.

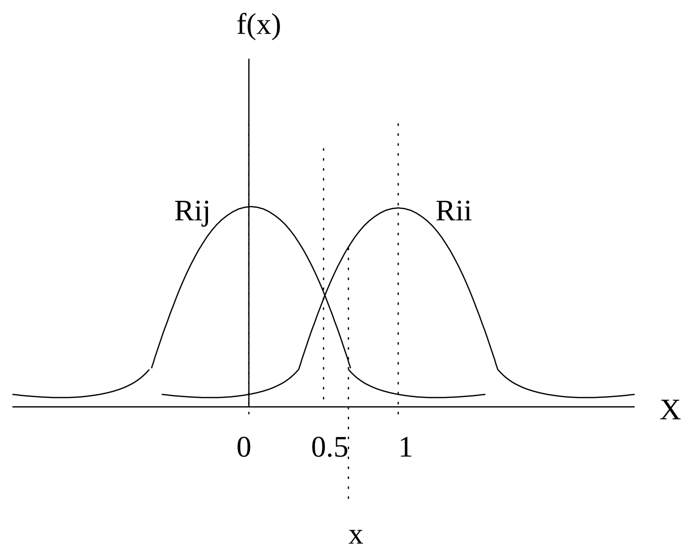

Figure 16. Gaussian PDFs for bit-0(R_{ij}) and bit-1(R_{ii})

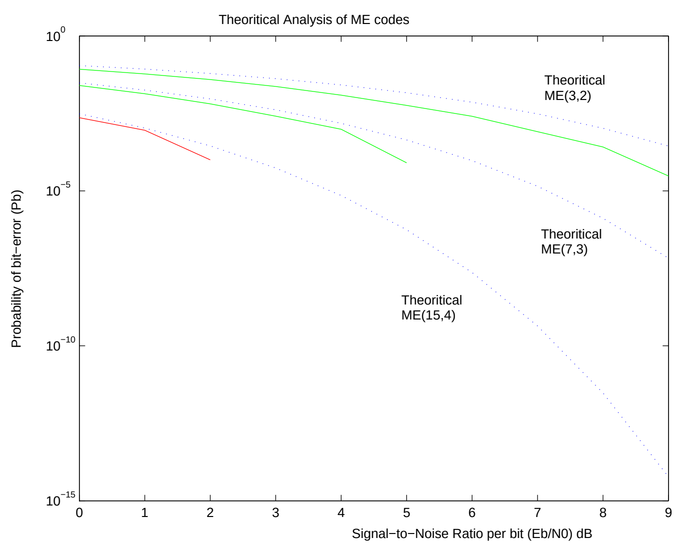

Figure 17. Theoretical Analysis of ME codes

CHAPTER 4

CODING COMPLEXITY

In the previous chapters different aspects of the minimum-energy codes were studied. Researcher showed the Power-Bandwidth requirement, quantified and formulated the amount of energy saving achieved by ME-Codes. ME-Codes were also implemented and it was verified that it saves energy and there is a reduction of average energy consumed per bit. However, throughout the argument so far, it is stated that actual implementation of this scheme would be simple and also consumes less power. In this chapter, the circuit for the ME-codes are given and complexity of ME-Codes are analyzed along with hamming codes for comparison purposes.

A very important issue in the implementation of any channel and/or source coding/decoding scheme is the coding/decoding complexity of the algorithm i.e. the computational complexity required to code and decode the noisy received data at the receiver. There are many coding and decoding schemes developed to achieve the requirements. In common, when designing communication systems, we achieve optimizing one parameter while compromising on the other one. The other important parameters considered in common when designing a communication system are coding rate, coding gain, coding complexity, bandwidth efficiency of the modulation scheme, bit-error-rate, power consumed or average energy spent per information bit. An improvement or optimization of one leads to the compromise in the other. The system with parameter that best suits the needs of an application will be designed accordingly. For very high data rate applications, power is usually compromised to obtain better channel usage or better bandwidth efficiency. However, the main goal of this thesis work has always been to achieve power efficiency at the expense of bandwidth and with less circuit complexity.

It was demonstrated that ME-coding scheme can achieve good saving in energy at the expense of bandwidth. About 3dB, 6dB, and 8dB of average SNR per bit was saved when OOK scheme was coded with ME(3,2) (7,3) and (15,4) respectively. It was also shown that ME coding performs better than a (7,4) hamming coded BPSK.

In this chapter It will be demonstrated that the circuit implementation of the ME-Code is simple and the circuit involves less complexity. The circuit complexity will be compared with that of the hamming coding scheme.

1. Complexity

Let $\Psi : X \to Y$ be some Boolean function, where X and Y are sets of binary words or symbols of length n_1 and n_2 respectively. It is obvious that encoding and decoding can be viewed as such a Boolean function. Assume that the Boolean function is constructed by means of logic elements (AND, OR, NOT). A suitable combination of these elements can be represented as a directed graph which will be referred to as a logic circuit. In such a graph or logic circuit there are n_1 input points and n_2 output points. There are many points in a logic circuit which are neither input nor output points. They are referred to as functional points. In each functional point there is a logic element.

There are two important ways of estimating the complexity of any given circuit or algorithm or a function. Namely, Computational complexity and Delay complexity. Both these complexities play a very important in estimating the overall complexity of any system (Coder/Decoder).

The complexity $C(S)$ of a circuit S is defined as the sum of the complexities of the single elements in all the functional points. The circuit S is said to realize the function $\Psi : X \rightarrow Y$ if for every word $x \in X$ fed to the circuit, the word $y = \Psi(x) \in Y$ is obtained at the output points. Now, let $G(\Phi)$ be the set of all circuits which realize the function Φ.

Definition of Computational Complexity: The complexity $C(\Phi)$ of a function Φ (Computational work involved) is defined [17, 19, 20, 18] by $C(\Phi) = minC(S)$; where $S \in G(\Phi)$. Thus, the complexity of a function is the complexity of the simplest circuit which realizes this function.

Definition of Delay complexity: Assume there exists a path from some input point to some output point of a circuit. The length of this path is defined as the number of functional points lying on the path [17, 19, 20]. Let L_s be the longest path in the circuit S. Then Computational Delay $L(\Psi) = minL_s; forS \in G(\Psi)[17,\ 19,\ 20,\ 18]$.

Delay complexity can also be referred to as circuit depth. Since, not all circuit elements are active for encoding/decoding a single bit, it would not be right to consider the entire circuit complexity to evaluate the complexity of any algorithm. Thus circuit depth will help us to estimate the number of circuit elements (functional points) that the signal has to traverse through or the number of gates which are active to encode/decode one single information bit.

Keeping the above definitions in mind, the complexity of the devised coding scheme is evaluated to quantify the circuit complexity. It is fair enough to assume that the total complexity of a system can be considered as the sum of complexity of implementing both the coder as well as the decoder. This is because the encoding schemes are generally simpler than the decoding scheme, for example a simple channel coding scheme like convolution scheme can be implemented by the use of a shift register and X-OR ing few elements of the shift register. However, the decoding scheme for a convolution scheme is a very complex process which involves lot of computation and processing delay. However, a compromise on high complexity results in robust codes which has very good performance. This scope of this thesis work will restrict the complexity analysis to ME-Codes which can be considered as a form of block-codes.

2. Complexity of ME-Codes

Now that a brief introduction of analyzing the coding/decoding algorithm is given in the previous section of this chapter, we proceed with estimating the complexity of the ME-Coding scheme. Before we estimate the complexity, it is very much required to discuss the method of implementing the circuit for the scheme. The complexity of any coding/decoding scheme will not only depend on the algorithm but also on the implementation method. Optimizing the implementation method is also an important factor. In this section ME-Code is implemented and finally the complexity is estimated.

The basic operation of ME-Code is explained in detail in Chapter-3. Figure 18 shows the diagram of different blocks involved in implementing ME-Coding scheme. The serial input data is given to a serial to parallel converter. This converts serial data of length k to a parallel data. Now the parallel data is fed to the ME-Coding block which does a one-to-one mapping to generate a n bit parallel data or a n bit code word. Finally the parallel data is further converted to serial data before being transmitted. It is assumed that this scheme is used for real-time applications, so that there are no storage elements involved to store data either at the input or the output. If the data transmission rate at the output is less than that of the input, then there will be a need for storing the data at the output for later delivery, which obviously does not serve the purpose of real-time applications like Bio-Sensors or any other real-time sensor applications.

2.0.1. *ME-Encoder Complexity.* For implementing the function of one-to-one mapping digital circuits with AND gates are used. The whole circuit is built in the most optimum manner using a Karnaugh's Map [22] to reduce number of gates involved. Figure 18 shows the circuit diagram of an ME(7,3)-Encoder. It is clear from the figure that the Implementation of ME coder is quite simple. As shown a ME(7,3) Encoder circuit requires three NOT gates and seven AND gates. That is a total of ten gates is required for a ME(7,3) Encoder circuit. In general to implement a ME(n,k) Encoder circuit we can visualize the fact that we need k NOT gates and n AND gates, i.e a total of $k+n$ gates. in the above discussion of method to estimate the complexity of a circuit, we know that the complexity of any circuit is defined by the number of gates used to realize the boolean function. The function performed by an ME-Encoder is to map a k bit input (from the possible 2^k tuple) on to a n bit output code word(chosen from 2^k codewords). As illustrated we need a total of $k+n$ gates to perform this function $\Psi : X \rightarrow Y$. Thus the complexity of the ME-Encoder circuit is

$$C(S)_{ME-Encoder} = k + n \tag{4.1}$$

2.0.2. *ME-Decoder Complexity.* Proceeding in a similar fashion, the computational complexity for the ME-Decoder can also be evaluated. Figure 19 shows the circuit implementation of a ME(7,3) Decoder. The implemented ME(7,3) Decoder requires seven NOT gates, sixteen AND gates and three OR gates. It is optimized for the usage of minimum number of gates. Thus the complexity of the circuit C(S) shown in the figure is twenty-six.

x	y	z	a	b	c	d	e	f	g
0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	1
0	1	0	0	0	0	0	0	1	0
0	1	1	0	0	0	0	1	0	0
1	0	0	0	0	0	1	0	0	0
1	0	1	0	0	1	0	0	0	0
1	1	0	0	1	0	0	0	0	0
1	1	1	1	0	0	0	0	0	0

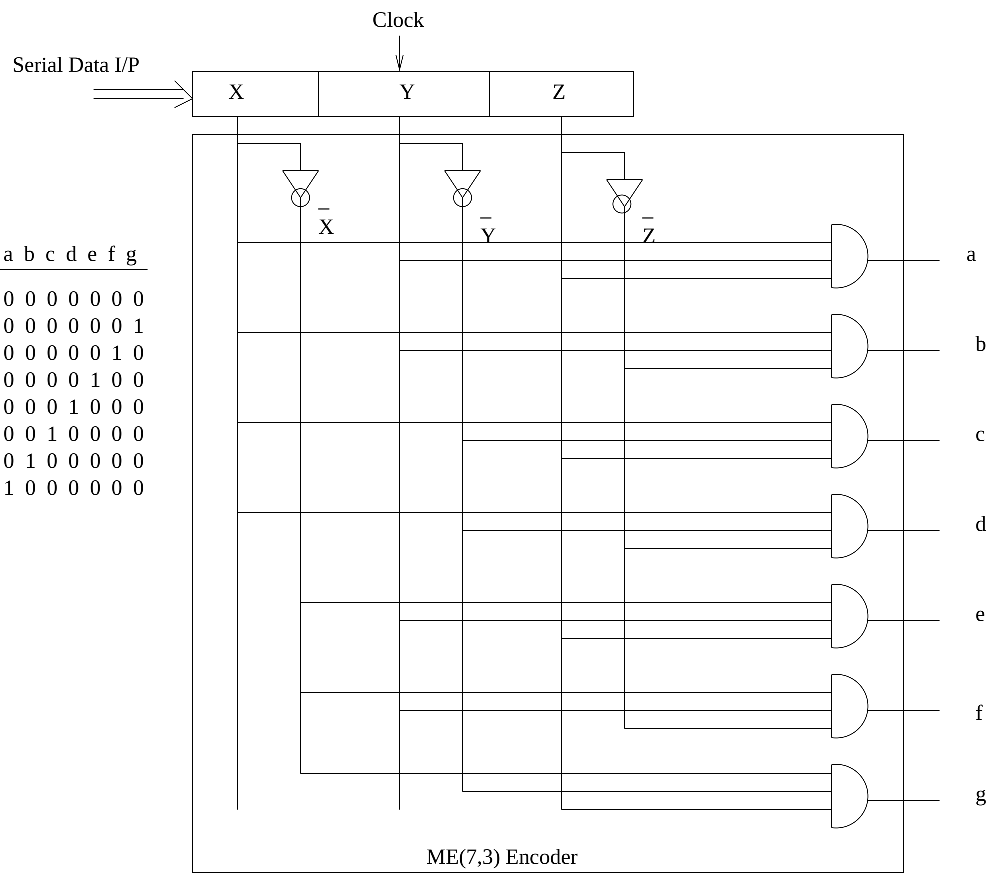

Figure 18. ME(7,3) Encoder

However, a generic way of expressing the complexity of a ME(n,k) Decoder is as follows. It was studied and verified that it requires n number of NOT gates, k number of $2^k/2$-input-OR gates and $2^k/2$ number of n-input-AND gates. That is a total of $n + k + 2^{k-1}$ elements or gates. Thus, the complexity of ME-Decoder is estimated as

$$C(S)_{ME-Decoder} = n + k + 2^{k-1} \tag{4.2}$$

However, since the availability of 2^{k-1}-input-gate is not possible for larger values of "k" ,the circuit can be constructed with the available elements. For example a eight-input AND/OR gate can be constructed by two four-input AND/OR gates and one two-input AND/OR gates.

3. Complexity of Hamming Block Codes

In the previous chapters, it was shown by simulations that ME-Codes perform better that a Hamming coded scheme or the ME-Hamming codes (MEH Codes) presented in [9, 10]. In this section the complexity of implementing a Hamming code is discussed in order to make a comparison of the over all performance of the two schemes.

Figure 20 shows a generic block diagram of a Hamming Encoding and Decoding procedure. As explained earlier in previous chapters, Hamming codes involve generation of n-bit codes or block-codes by multiplying a block of k-bits with a kXn generator matrix. On the other hand in the case of a Hamming decoder, the incoming code of n-bit long is multiplied with the transpose of a Parity matrix. At the decoder, there is a syndrome detector and an error corrector to correct a single bit error as shown in the figure 20. Thus, the syndrome detector and error corrector adds to the complexity of Hamming decoding scheme.

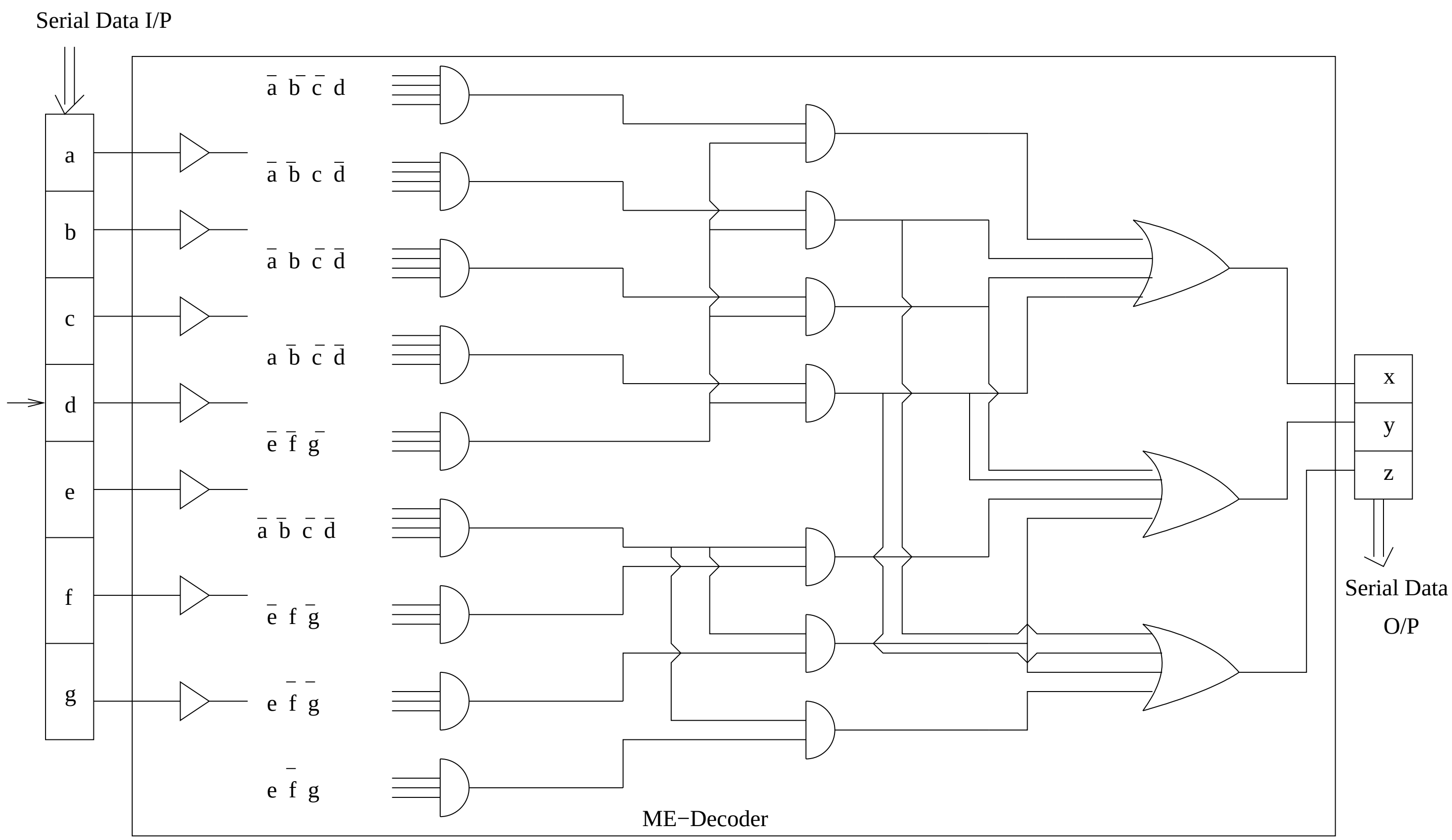

Figure 19. ME(7,3) Decoder

The circuit of a matrix multiplication is as shown in the figure 21. The matrix multiplier shown in the figure is a generic multiplier . The columns of the matrix to be multiplied is store in the ROM as shown. The incoming serial bits are converted to parallel and then multiplied and added to do the function of a matrix multiplication. Thus a matrix multiplication in Hamming(n,k) encoder has $k * n$ AND gates and n X-OR gates. Thus a total of $(k + 1) * n$ gates are required for matrix multiplication. Thus in general the complexity of Hamming encoder is

$$C(S)_{Hamming-Encoder} = (k + 1) * n \tag{4.3}$$

In the case of a Hamming Decoder, a transpose parity matrix of size $nXn - k$ is multiplied with the n bit code word. It requires $(n - k) * n$ AND gates and $n - k$ number of OR gates. Thus it requires a total of $(n - k) * n + n - k$number of logic elements. Hamming decoder thus has a complexity of $(n-k)*(n+1)$ + Complexity of syndrome detector (s) and error corrector (e). The scope of this research work is limited to determining the complexity of matrix multiplication only. However, it is seen in the example described below that the complexity of a matrix multiplication by itself is more complex than the ME-Decoding. Thus,

$$C(S)_{Hamming-Decoder} = (n - k) * (n + 1) + s + e \tag{4.4}$$

4. Complexity Comparison

ME-Codes has a coding rate defined by $(k/n) = (k/2^k - 1)$ and Hamming codes have coding rate defined by $(k/n) = (2^m - 1 - m/2^m - 1)$ for m = 2,3,... Compared to the complexity of a ME(n,k)-Encoder which has a complexity of $k + n$, the Hamming encoder has a complexity of $(k+1)*n$. For example, for ME(7,3) Encoder the complexity is $k+n=10$ and Hamming(7,4) has a complexity of $(k+1)*n=(4+1)*7=35$. However, though ME(7,3) or ME(15,4) so on, has a higher Coding Gain and lesser complexity than a Hamming(7,4) or Hamming(15,11), a direct comparison of both the schemes would be an unfair method of comparison as the coding rates of both the schemes are different. Thus, a performance metric is defined in the next chapter which takes care of these inequalities to make a fair comparison of the two schemes. In comparing the complexity of a scheme it is fair enough to consider a combined complexity of both encoding and decoding together [19, 18]. That is sum of complexities of Encoder and Decoder.

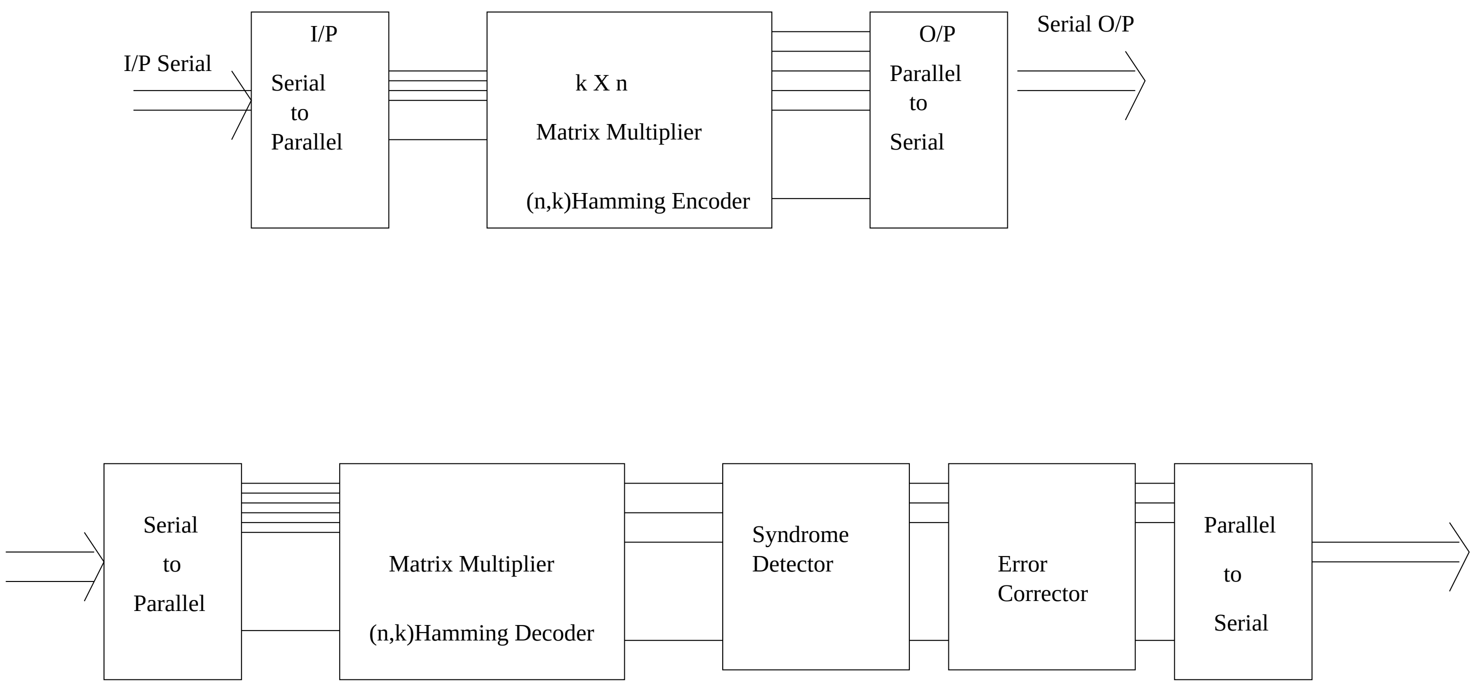

Figure 20. Hamming Encoder/Decoder

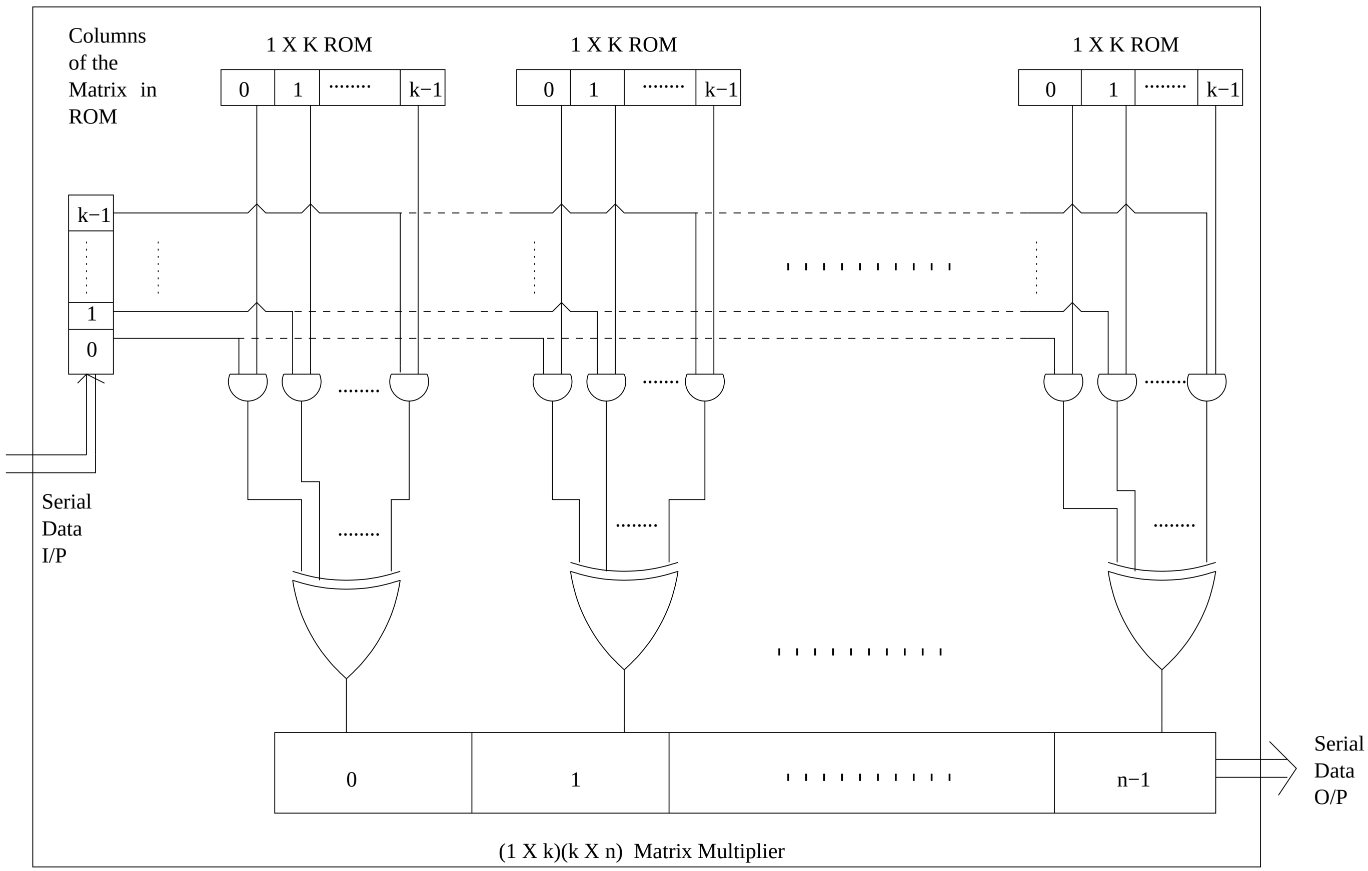

Figure 21. Matrix Multiplication

CHAPTER 5

PERFORMANCE METRIC

In common, a communication system design will involve various issues to be considered. A detailed explanation of various factor involved in the trade-offs and gains of coding modulation schemes were discussed in chapter 2. In order to compare ME-Codes with other codes say Hamming codes, a performance metric is defined in this chapter.

The whole idea of defining this metric is to make a fair comparison of ME-Coding with that of Hamming Codes. The metric is called as Energy Metric. Circuit for ME-Coding scheme presented in the previous chapter is implemented using a Cadence simulator. The average energy for encoding/decoding one information bit ME scheme is estimated and compared with that of Hamming block code scheme.

In the previous chapter, it was described that the total complexity of a circuit is the sum of all the functional elements (gates) in a circuit that is implemented in the optimum manner. However, it is very intuitive to say that not all functional points or gates are active at any point of time. The number of elements active at any point of time depends on the input data and the circuit activity. Current drawn by the encoder/decoder circuit from the source supply depends purely on the switching activity. Thus the current consumption and in turn the power used by the circuit is dependent on the circuit depth [23, 24]. Hence, the circuit depth is used here for coming up with the energy metric.

1. Energy Metric for ME-Coding

Energy Metric is developed here in order to compare ME-Code with the other schemes at a circuit level. The energy metric will estimate the amount of energy consumed in terms of complexity or circuit depth.

Energy metric for the ME-Coding scheme is defined as the sum of energy to encode and decode one information bit. Since, the energy metric evaluates the energy consumed for encoding and decoding one information bit end-to-end, it does not really matter what encoding rate is used. Thus, even if two schemes with two different coding rates are compared, the total amount of energy to encode/decode one information bit end-to-end will determine the energy usage by the coding system.

Energy Metric = Average energy consumed by the circuit to encode one information bit (E_E)+ Average energy consumed by the circuit to decode one information bit (E_D)

$$Metric = E_E + E_D \tag{5.1}$$

In chapter 3, it was demonstrated that there is more saving in the average energy per bit in the case of ME-Coded OOK scheme compared to a Hamming coded scheme. Hence, this chapter will concentrate in estimating the ME-Code's circuit energy consumption.

For comparing two schemes, i.e to compare the energy consumption of two schemes we evaluate the total energy consumed by the two schemes to encode/decode one information bit at a certain BER. It is assumed that both system will provide the same level of probability of error. Now, since the two systems are assumed to perform the same, the coding system that consumes less energy is obviously the better scheme in terms of energy consumption for a given performance level.

It was seen in the previous chapter that the total amount of energy consumed in a circuit depends on the current drawn by the capacitors in the circuit elements (Gates). The number of capacitors in the circuit is proportional to the number of gates in the circuit. Thus a circuit with more number of gates or a circuit with higher complexity will drain more current from the source and thus consumes more energy.

It is seen that total number of gates that are active to encode k information bit is $n+k$ and total number of gates to decode k bits from n bits is $n+k+2^{k-1}$. Thus total number of gates active to encode and decode k information bits is $2(n+k)+2^{k-1}$. Thus, average number of gates active to encode and decode one information bit is $\frac{2(n+k)+2^{k-1}}{k}$; $k = log_2(n+1)$.

Energy consumed to encode/decode one information bit is proportional to the number of gates active. Thus, Energy consumed in the ME-Encoder(E_E) + energy consumed in the ME-Decoder(E_D) is

$$ME - Code(E_E + E_D) = constant * \frac{2(n+k)+2^{k-1}}{log_2(n+1)} \tag{5.2}$$

Similarly, the number of gates active in Hamming code to encode k information bits is $n(k+1)$. Number of gates required to decode k information bits is $(n-k)(n+1)+s+e$; s= complexity of syndrome detector, e= complexity of error corrector and $k = 2^m - 1 - m$ for m=2,3,....

Thus, total amount of energy consumed in encoding and decoding one information bit by Hamming scheme is

$$Hamming(E_E + E_D) = constant * \frac{n^2 + 2n - k + s + e}{2^m - 1 - m} \tag{5.3}$$

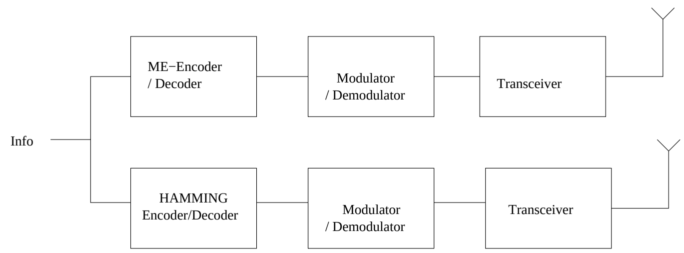

Figure 22. Block Diagram of ME-Coded and Hamming Coded Scheme

2. Energy Metric Comparison

We can now perform a fair comparison of ME-Coding with that of Hamming Coding. Consider the block diagram shown in the figure 22. For the system shown, it is clear that both at the transmitter and the receiver the total performance in terms of complexity and coding gain depends on the coding / encoding scheme and the modulation / demodulation scheme. For the sake of comparison purposes we shall assume the modulator/demodulator block to be same in both upper and lower schemes. The only block that differs would be the coding/decoding scheme. Thus, among the two systems to be compared the system with a better metric will obviously be better than the other.

From the Energy metric formula obtained in the previous section, values of energy metrics for both ME-Coding and Hamming coding scheme for encoding/transmitting/decoding one information bit is presented in the table 4. The first column of the table has various values of n for which the metric is compared. The second column gives an estimate of the energy consumed by ME-Codes encoder/decoder circuit and the third column shows the energy consumed by Hamming encoder/decoder circuit.

Similarly a comparison of ME-Coding can be done with several other coding scheme. However, it would be more appropriate to do a comparison on similar block codes. Thus it can now be clearly stated that ME-Coding scheme has a better performance and has less

Table 4. Energy Metric Comparison for various values of n

	$ME - Code(E_E + E_D)$	$Hamming(E_E + E_D)$
n	$= constant * \frac{2(n+k)+2^{k-1}}{log_2(n+1)}$	$= constant * \frac{n^2+2n-k+s+e}{(2^m-1-m)}$
3	$ME(3,2) = constant * 6$	$Hamming(3,2) = constant * \frac{13+s+e}{2}$
7	$ME(7,3) = constant * 8$	$Hamming(7,4) = constant * \frac{59+s+e}{4}$
15	$ME(15,4) = constant * 11$	$Hamming(15,11) = constant * \frac{244+s+e}{11}$

complexity and in-turn consumes less energy in the circuit to implement the scheme.

The analysis made so far shows that ME-Coding is less complex and consumes less energy both system and circuit level. However, a definite value or the actual value of energy consumed at circuit level is not determined. This is accomplished by implementing the transistor level circuit of the scheme in a hardware simulator and estimating the current consumption.

3. Estimation of System's end-to-end Energy Consumption

The system of interest consists of an Encoder, an OOK transmitter, OOK receiver and a Decoder block. It is demonstrated that ME-Coding saves energy in an OOK transmitter. In this section the total energy consumed by the system is determined. Energy consumed by the ME-Encoding/Decoding circuit and Hamming circuit is determined by implementing it on a hardware circuit simulator. The estimate of energy consumed in an OOK transceiver is determined from the data-sheet of the off the shelf transceiver chips available market.

3.1. Energy Consumption in ME-Encoder/Decoder. ME Encoder/Decoder and Matrix multiplication for Hamming code was simulated in "Cadence Virtuoso Schematic Composer" at a transistor level and the static power dissipation of the circuits were estimated. The technology used was AMI 1.6 μm CMOS technology with a Vdd of 3.3V. The

Table 5. Energy Consumption in a ME(7,3) Encoder/Decoder Circuit

Input	*Output*	*I(PicoAmps)*	*Encoder(PicoWatts)*	*Decoder(PicoWatts)*
000	0000000	47.53	156.84	229.4
001	0000001	54.15	178.69	216.5
010	0000010	54.99	181.46	215.4
011	0000100	55.79	184.10	210.1
100	0001000	55.00	181.50	210.4
101	0010000	55.78	184.07	206.2
110	0100000	56.19	185.42	200.1
111	1000000	56.31	185.82	198.6

CMOS technology provides lower power dissipation and is the commonly used technology for low power applications.

The software is used to estimates the current drawn by each 'ON' transistor for a particular input. Total current drawn by the source can also be found out to estimate accurate value of average current used in the circuit. Thus, average power and average energy consumed can be estimated by using these values. The basic schematic circuitry was developed for mapping/re-mapping of ME(7,3) codes and Matrix multiplication of Hamming(7,4) codes. The Shift registers and other memory units have not been considered.The circuit diagrams of the implemented schemes were presented in chapter 4. The power dissipation was calculated by looking at the total current drawn from the 3.3V DC source for various inputs.

The total current consumed and the power used by the ME Encoder/Decoder circuit is estimated in Cadence and the data is presented in the table 5

From the table we determine the average power consumed by ME(7,3) Encoder and Decoder to Encode/Decode '3' bits to be 179.738 and 210.837 Pico Watts respectively. Thus, on an average, 59.9127 pico watts of power is consumed in the ME(7,3) encoder circuit to encode one information bit and 70.279 pico watts for decoding one information

Table 6. Energy Consumption in a Hamming(7,4) Matrix Multiplier Circuit

$Input$	$I(PicoAmps)$	$P(PicoWatts)$
0000	776.4	2562.12
0001	778.9	2570.37
0010	781.6	2579.28
0011	790.4	2608.32
0100	781.5	2578.95
0101	789.2	2604.36
0110	792.0	2613.60
0111	800.7	2642.31
1000	784.4	2588.52
1001	789.5	2605.35
1010	792.2	2614.26
1011	803.6	2651.88
1100	798.2	2634.06
1101	803.4	2651.22
1110	806.1	2660.13
1111	812.2	2680.26

bit. Hence a total of $59.912 + 70.279 = 130.192$ pico watts is required to encode and decode one information bit end-to-end.

Similarly, the matrix multiplication circuit presented in chapter 4 was also implemented in cadence. The power consumption for a Hamming (7,4) matrix multiplier is as shown in table 6 From the table it is seen that on an average 2615.31 pico watts of power is required for encoding '4' bits by matrix multiplication. Therefore to encode one information bit it requires 653.82 pico watts of power. Thus a Hamming (7,4) encoder decoder circuit will consume $1307.64+P_s+P_e$ pico watts of power. Where P_s and P_e are the power consumed in syndrome detector and error corrector circuit respectively.

Knowing the power consumed by the ME-Code circuit and the Hamming circuit, we can now estimate the average energy consumed in both the cases. If both the circuits are assumed to operate for a period of T seconds, then the total energy consumed by ME encoder/decoder circuit is 130.192*T pico Joules per info-bit. The ME circuit encodes /

Table 7. Power Consumption per Info Bit in ME-Coding

	$EncoderCircuit(pW)$	$DecoderCircuit(pW)$	$Total(pW)$
$ME(7,3)$	59.912	70.279	130.192
$Hamming(7,4)$	490.365	$490.365 + P_s + P_e$	$980.73 + P_s + P_e$

decodes once every 3 bits and hamming circuit encodes / decodes once every 4 bits. Thus both the circuits are used unequal number of times. Hence to make a fair comparison a factor 3/4 is multiplied to Hamming scheme to scale the switching activity. The total energy consumed by the Hamming scheme is 980.73*T + $E_s + E_e$ pico Joules.

3.2. Energy Consumed in OOK Transceiver. Many low power wireless applications utilizes OOK for very low power wide band transceiver radio modules, which are designed for short range (¡50m) wireless application by making full use of many commercially available chips. OOK is used in low speed applications typically 2400bps and is ideal to short range remote control application [25]. High speed type applications with data-rate of about 115.2KBPS utilize ASK (Amplitude Shift Keyed) modulation and is ideal for data communication application.

It is believed that OOK modulation scheme are energy efficient for they put the transceiver chip to sleep state during transmission of zeros. Examples of applications that generally use this would be [25]

- Handy terminal
- Wireless card reader / bar code reader
- Short distance remote control
- Telemetry system

Table 8. Few of the Commercially Available OOK Transceiver Chips

	$Chip$	$f(MHz)$	$Rb(Kbps)$ $(Typical)$	$RxSensitivity(dBm)$ $(@10^-3BER)$	$SupplyVtg$
1	$RFMTR1000$	916.5	2.4	$-104to-100$	3.3
2	$RFMDR4000$	916.5	2.4	$-104to-100$	$2.7-3.5$
3	$RFMDR5000$	916.5	2.4	$-104to-100$	$2.7-3.5$
4	$TRF6901$	$868-915$	2.4	$-104to-30$	$1.8-3.6$
5	$WiseNet$	868	2.0	-102	$0.9-1.5$
6	$TDA5250D2$	868		< -109	$2.1-5.5$
7	$CC1000$	868/915		$-110to-109$	$2.1-3.6$
8	$CC1020$	868/915		-121	$2.3-3.6$
9	$CCD-TR-01$	868.35	2.4	-98	$2.7-3.5$

- Wireless security system

Here few examples of the commercially available very low-power transceiver chips are presented along with their specifications. The data was obtained from the product's data sheet available online. It is to be noted that the comparison made here is purely for academic purpose and to provide an estimate of the amount of energy consumed in a commercially available fully functional OOK transceiver chip. The choice of the transceiver chip has got nothing to do with the marketing strategies of the companies.

In the tabular column 8, the general characteristics of the transceiver chip is presented. It is noted that all the chips considered here have similar characteristics. Table 9 shows the amount of current consumed in each of the chips under transmitting and receiving conditions. The chips numbered from 1 to 3 are products of company RF Monolithic Inc. Chip 4 in the table is a product of Texas Instruments. Products 6 and 7-9 belong to Chipcon and Circuit Design, Inc. respectively.

It is observed that many of the above presented commercially available very-low power OOK transceiver chips consume 1.8mA of current from the source for reception and 12mA for the transmission operation. In other words, the power consumed in an OOK

Table 9. Power consumed in OOK Transceiver Chips

$Chip$	$RxI(mA)$	$TxI(mA)$	$Prx(mW)$ @$2.4kbps$	$Ptx(mW)$ @$2.4kbps$
$RFMTR1000$	1.8	12	5.94	54.45
$RFMDR4000$	1.8	12	5.94	54.45
$RFMDR5000$	1.8	12	5.94	54.45
$TRF6901$	$18-21$	$32-40$	59.4	105.6
$WiseNet$	$1.8-2(max)$	< 30	5.94	99.0
$TDA5250D2$	9	12	29.7	54.45
$CC1000$	9.36	26.7	30.8	88.11
$CC1020$	17.6	35	58.08	115.5
$CCD-TR-01$	1.8	12	5.94	54.45

Table 10. End-to-End Power Consumption per Info Bit

$ME-Encoder$ (pW)	OOK $Transmitter(uW)$	OOK $Receiver(uW)$	$ME-Decoder$ (pW)	$Coding$ $Gain(dB)$
59.912	16.5	2.475	70.279	6

transceiver chip alone is 13.8*3.3 = 45.54mW of power. For a continuous operation, the total power consumed in these OOK transceiver chips would be 45.54mW @2.4Kbps or 18.975micro watts per transmitted bit. Table 10 shows the power consumed at every block in the system.

Thus, from the simulations in Matlab, implementation of the circuit in cadence, it is found out that ME-Coding scheme brings about considerable amount of energy-saving

Table 11. Summary of ME-Code and Hamming code Performance

	$ME(7,3)$	$Hamming(7,4)$		$ME(15,4)$	$Hamming(15,11)$
$Complexityperinfobit$	8	$59+s+e/4$		11	$244+s+e/11$
$PowerConsumed$	$130pW/bit$	$> 980.73pW/bit$		$250pW/bit$	$> 5.57nW/bit$
$Eb/N0required$ @$BER10^-5$	$6dB$	$11.5dB$		$3dB$	$10.5dB$
$CodingRate$	3/7	4/7		4/15	11/15
$ExtraEb/N0required$ $toachieve$ $Shannon'scapacity$	$6.9dB$	$10.67dB$		$6.49dB$	$9.74dB$

(say 6dB for ME(7,3)) in the transmission, for a very negligible amount of increase in the circuit complexity and power consumption (say 130pJ per bit for ME(7,3)). It is also proved that, ME coding performs better than the Hamming coding scheme in terms of coding-gain, circuit complexity and circuit-power consumed.

The overall performance is summarized in the table 11. A better performance, is clearly achieved at a lesser complexity, and lesser energy consumption in the encoding/decoding circuit.

CHAPTER 6

BIO-LINK BUDGET ANALYSIS

FCC regulations require the use of Spread Spectrum techniques for most applications in the unlicensed ISM bands (Industry Science and Medicine Band). It is necessary to perform a top level analysis of a wireless link to understanding some of the system design issues. The implantable biosensors application has to comply with FCC regulations for unlicensed operation in the ISM band. These regulations permit radiated RF power of up to 1W when spread spectrum modulation techniques are used. However, Part 15 of FCC regulations [26] also specifies the use of non-spread spectrum techniques for transmit powers less than 1mW. The usual value of RF transmit power is about -1.25dBm or 0.75 mW. For such applications the complexities imposed by the use of spread spectrum radios are more than offset by the interference rejection properties and higher RF power permitted by FCC regulations. First step an engineer will take in order to determine the feasibility of any given system is to do an analysis of link budget. This part of the thesis presents a brief note on a high level link budget analysis of the bio-link and also compare it with the other schemes discussed.

1. Link budget analysis

For analyzing the Bio-link, a set of details about the different aspects of the link is briefly mentioned here. There are several bands available for operation in the ISM band. Available bands are 900MHz, 2.4 GHz, 5.275GHz. Higher the frequency, higher is the path loss and also less complex and less expensive to build wireless radios. Keeping in mind the above conditions, 900MHz band is the easy choice, also taking the advantage of many commercially available off-the-shelf RF chips and components.

In the link budget analysis here, source information bandwidth of 1 KHz is considered. For this source information, link transmit power is estimated for schemes with and without coding schemes (transmitting just 'k' information bits per symbol Vs transmitting 'n' coded information bits per symbol). A comparison of uncoded OOK scheme, ME(7,3) coded OOK scheme and ME-Hamming(7,4) coded scheme is made. As the coding rate is different for each of these schemes, the bandwidth of the transmitted information is different and thus the noise quantity is different for different bandwidths. Thus we calculate noise floors for each of these schemes and compute their respective link transmit power for transmitting bits that originate from a common source with and without using coding schemes. For comparison purposes let us consider a source transmitting uncoded OOK signals at 1 kH bandwidth. Now if this is coded by ME(7,3) scheme, the bandwidth is going to be (3/7)* 1 KHz . And (4/7)* 1 KHz for ME-Hamming(7,4) scheme.

1.1. Path Loss or Channel Loss.

The system model of the bio-link was explained in chapter 1. The bio-link is considered to be established inside the human body. The initial bio-link will be considered to be surrounded by tissue of the same type. The distance of operation is very small of the order of about 5-10mm. The propagation loss or the Path loss will be determined by the model developed (PMBA) by Prakash et. al. [2]. PMBA was specifically developed by the authors for such bio-medical implantable applications.

PMBA was developed for a di-pole in a homogeneous lossy human tissue medium with conductivity σ (S/m), permitivity ϵ (F/m), permeability μ (H/m). This model was developed by estimating the average SAR in the tissue medium. SAR-Specific Absorption Rate is defined as the amount of energy absorbed in watts by a unit mass of the tissue. It's unit is Watts/Kg.

As per the developed model PMBA, the amount of RF power received (P_R) inside a homogeneous tissue at a distance d from the dipole antenna transmitting RF power of P_T is given by

$$P_R = \frac{(P_T - P_{NF} - P_{FF})\lambda^2 G_T G_R}{(4\pi d)^2} \tag{6.1}$$

where G_T and G_R are the gain of the transmitting and receiving antenna respectively. P_{NF} and P_{FF} are the amount of power absorbed by the human tissue in the nearfield and farfield of the transmitting antenna respectively. Where,

$$\begin{aligned}
P_{NF} &= \sigma\mu\omega\frac{|\eta|}{|\gamma|}\frac{I^2 dl^2}{6\pi}[A + B + C], \text{where} \\
A &= e^{-2\alpha r}\left(\frac{|\gamma|^2}{2\alpha} + \frac{d_0 - r}{4r^2} + \frac{|\gamma|(d_0 - r)}{2r}\right), \\
B &= e^{-2\alpha d_0}\left(\frac{-|\gamma|^2}{2\alpha} + \frac{d_0 - r}{4d_0^2} + \frac{|\gamma|(d_0 - r)}{2d_0}\right), \text{and} \\
C &= e^{-\alpha(d_0 + r)}\left(\frac{2(d_0 - r)}{(d_0 + r)^2} + \frac{2|\gamma|(d_0 - r)}{(d_0 + r)}\right)
\end{aligned}$$

The antenna dimensions depend on the wavelength of the wave in the medium given by $\lambda_m = \frac{2\pi}{\beta}$ [27].

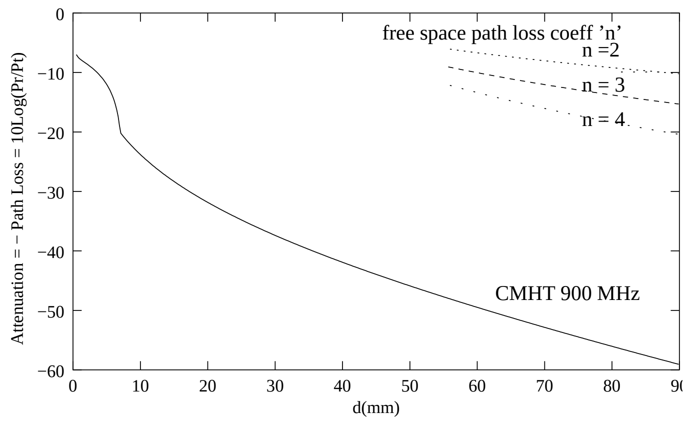

Figure 23. Bio-Link path Loss estimated by PMBA for 900MHz ISM band

$$P_{FF} = \sigma|\eta|^2|\gamma|^2 \frac{I^2 dl^2}{12\pi\alpha}(e^{-2\alpha d_0} - e^{-2\alpha d}) \tag{6.2}$$

and $\eta = \frac{\gamma}{\sigma + j\omega\epsilon}$ is the complex intrinsic impedance, $\gamma = \alpha + j\beta$ is the propagation constant of the tissue medium and d_0 is the extent of nearfield surrounding the dipole antenna or radius r and length L operating at an angular frequency ω. A detailed explanation of the derivation, analysis and validation of PMBA is presented in [2].

Figure 23 shows the estimation of total path loss for a 900MHz ISM band using PMBA.

It is estimated that the total path loss for a distance of 60 mm is about 50dB. This estimated path loss is now used for doing the link budget analysis for the bio-link under consideration.

1.2. Noise Floor. Receiver noise floor is determined mainly by the bandwidth of the application using the bio-link. For an application like retinal prosthesis or blood glucose monitor, the typical data-rate is very low of the order of 1 kHz. Now, the channel noise is

$$
\begin{aligned}
N &= kTB \\
&= 1.38X10^{-23}J/KX309.81KX1000s^{-1} \\
&= -143.69dBm
\end{aligned}
$$

Noise Figure (NF) of the receiver is the measure of the noise added by the receiver [15] and is typically 15dB. Thus, the receiver noise floor is -128.69dBm. On the other hand, it is -125.01dBm and -126.25dBm for ME(7,3) and ME-Hamming(7,4) scheme respectively.

1.3. Receiver Sensitivity. The receiver sensitivity basically determines the amount of the Signal-to-Noise Ratio (SNR) required by the receiver to achieve a certain Bit-Error-Rate (BER). 12dB of SNR is required for an uncoded OOK scheme and from the design and analysis made so far in this thesis work, it was determined that the amount of E_b/N_0 required by the ME(7,3) coded OOK scheme is 6dB at a BER of 10^{-5} and 8.5dB for a ME-Hamming(7,4) coded OOK. $SNR = E_b/N_0XR/B$. Therefore $SNR = 12dB, 6dB, 8.5dB$ respectively for uncoded OOK, ME(7,4) and ME-Hamming(7,4) schemes.

Thus, receiver sensitivity of uncoded OOK scheme is

$$
\begin{aligned}
P_{rx} &= ReceiverNoiseFloor + SNR \\
&= -128.69dBm + 12dB \\
&= -116.69dBm
\end{aligned}
$$

-119.01dBm and -117.75dBm for ME(7,3) and ME-Hamming(7,4) respectively.

1.4. Link Transmit Power. We can now determine the link budget or the transmit power required for the above considered example. For a simple dipole antenna the antenna gain can be assumed to be 0dB.

$$
\begin{aligned}
P_T &= P_{rx} - G_{tx} - Grx + pathloss \\
&= -116.69dBm - 0dB - 0dB + 50dB \\
&= -66.69dBm \qquad (6.3)
\end{aligned}
$$

The link transmit power is computed similarly for the other two schemes. For ME(7,3)-OOK it is -69.01dBm (-119.01+50) and for ME-Hamming(7,4) it is -67.75dBm. Even though the proposed ME(7,3) scheme has higher bandwidth than ME-Hamming(7,4) scheme (i.e. higher noise floor), overall energy is reduced because the amount of coding gain provided by ME(7,3) scheme is greater than the ME-Hamming(7,4) scheme at a lesser cost of circuit power and complexity.

This link budget analysis shows an approximate amount of power transmitted by the transmitter in the bio-link established in a lossy human tissue to achieve a reliable communication with a BER of 10^{-5} at a source data rate of 1KBPS. It is to be noted that the transmit power estimated is well below the FCC regulation of -1.25dBm. However, if air is used as a channel medium then approximately the same transmit power can establish an efficient link upto about 8 meters.

CHAPTER 7

CONCLUSION

Wireless sensor applications have a wide-spread growth in the industrial marketplace because of a technological and economic driving forces. The sensors in general and wireless sensors in particular have countless advantages compared to wired telemetric sensors or data-gatherers. The use of wireless sensors especially in the field of bio-medical devices has more advantages and has more capabilities to contribute for a better society and a better standard of living. The different applications of wireless sensors in implantable devices and their advantages and limitations were discussed in detail throughout this research work.

Main goal of this thesis work has been to contribute a better system for such applications which can change tomorrows world. This thesis work contributes an important aspect in the field of wireless communication for biosensors in biomedical applications and various other low-power wireless sensors. It proposes a simple energy efficient coding and modulation for sensor applications. Many low-power battery operated radio systems, especially for microsensor applications, has a need for saving power both at the system level and circuit level implementation. The main objective in this research work was to come up with an energy efficient coded modulation scheme that is easy to implement and consumes comparatively less power both at system and circuit level.

On-Off Keying (OOK) modulation scheme has been used to keep the system simple.

The inferior performance of OOK scheme is also improved by using the Minimum Energy Codes (ME-Codes) developed specifically for this purpose. Simple process of mapping in involved in this coding scheme making it simple. Simulation and implementation in Matlab has justified the fact that transmitted codes consumes less energy than an uncoded-OOK scheme. The inherent nature of presence of only one high-bit in the code has made it possible to be used for applications not only for sources with known statistics but also with sources of unknown statistics. A detailed study of the performance improvement and the power-bandwidth requirement of the scheme is discussed explaining the tradeoffs of power vs bandwidth. A probabilistic theoretical analysis is presented to verify the performance of the implemented scheme. The circuit for the implementing the scheme is designed and the circuit complexity is determined. It was proved that the complexity of ME-Code is less compared to a similar block code; Hamming code. The circuit is implemented in Cadence software and average energy consumption per information bit is estimated. A performance metric called Energy Metric is developed to study and analyze the performance of the developed ME-Codes. A fair comparison of the performance of ME-Codes and Hamming codes is done using this metric. Many commercially available OOK transceiver chips are presented and the end-to-end energy consumption is determined. It was found out that the developed scheme improves the performance of the OOK modulation scheme with a considerable coding gain and also with a very negligible expense of energy in the circuit. Finally the bio-link budget analysis shows the amount of energy or power required by the implanted bio-sensor system to establish a reliable wireless bio-link.

The developed scheme in this thesis work is published in IEEE Wireless Communication and Networking Conference 2003 [3]. In future, this work can be extended to wireless mobile sensors that are used in mobile and fading environments.

Developed system's performance can be studied under sever fading channels in slow and fast moving mobile wireless sensors. Different methods can be designed to mitigate the fading effects and improve the performance of the system. Many other new innovative technologies can be applied to make the system suit for other mobile applications.

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