國立交通大學

電子工程學系電子研究所碩士班

碩 士 論 文

針對基於壓縮感知訊號的無線網路適應性傳輸技術

Adaptive Transmission for Compressive Sensing Based Signal in Wireless Networks

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摘 要

在未來的無線傳輸系統中，壓縮感知是其中一項具潛力的關鍵技術之一來進一步提高頻帶使用率、傳輸速率或資料安全度等，根據壓縮感知的特殊性質，我們提出了一個優化的壓縮感知測量元子的位元長度，可以使裝置更有效的傳輸資料並且節省傳輸能量消耗。提出的演算法利用資料的特性以及利用最小化l_1解碼，其只需要少量的測量元子就可以還原重建原資料，並且不需要使用重傳機制。優化的測量元子位元長度可以使用比最低全精準位元長度更短的長度傳送，其會產生相對應的溢值機率，針對溢值不有效的測量元子，可以通過收取更多其他的測量元子來補足進行還原; 在傳送端透過調適所需的測量元子以及每個測量元子的位元長度將能使的傳輸更為有效率與靈活，並且最小化在空氣中的傳輸位元。除此之外，適應性無線傳輸也被應用在我們傳輸系統中，根據通道的訊雜比狀況以及錯誤率限制，採用合適的調變與通道編碼，以及拉長訊號週期當通道狀況不佳的時候。

Adaptive Transmission for Compressive Sensing Based Signal in Wireless Networks

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Abstract

We propose an optimal bit-length of measurements for devices that leverages the theory of compressive sensing (CS) to achieve high efficiency and save the energy of devices. Beyond the 4G communication, the CS is one of the potential techniques to further enhance sensor network performance. The proposed optimal measurements of CS exploit the sparse property and l_1-minimization decoding operation that only a relatively small number of measurements are required to be received and no retransmission is necessary. With the target probability of overflow, those optimal measurements are able to be transmitted in fewer bits than full-precision measurements, and they can be recovered by receiving more redundant measurements. This results in an efficient transmission method that decides the number of measurements and number of bits per measurement at transmission side to minimize the expected transmission bits in the air. Besides, the adaptive link is applied to the transmission that uses proper modulation, channel coding scheme (MCS) and repetition according to the signal-to-noise ratio (SNR) and the target outage rate.

誌 謝

時光荏然,從剛大學畢業升碩士的茫然到現在,碩士生活轉眼就過了,求學的階段也即將結束，邁向新的人生階段。感謝黃經堯老師一路上的指導與鼓勵，指引研究方向，與學習面對和解決問題，讓我的研究及人生能更完整與豐富。

除了師長們的教誨外，也感謝實驗室裡東祐學長、烜立學長、勇嵐學長和建銘學長，在我有困難的時候，給予我許多幫助與建議，讓我度過難關。實驗室的同學學弟泓志、仲煒、俊宏、偉生和嘉宏有你們陪伴的碩士學涯,讓生活增加了許多樂事,也因為你們實驗室總是充滿著歡笑,即便是通宵的夜晚。

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Chapter 1
Introduction

Compressive sensing [1] [2] [3] [4] is one of potential key techniques to further improve the performance of wireless communication system in the future. It has been widely studied in various fields of research recently such as medical image, sensor network and signal process. The raw data is compressed or transformed into the "measurements" with proper basis, and the raw data can be reconstructed by capturing a small number of compressive measurements even sampling lower than Nyquist rate. Therefore, it is suitable to apply CS to a large amount of raw data that results in shorter duration of transmission and higher bandwidth-efficiency. In addition, CS provides a higher secure link due to the encoding process that data is encoded by special weighting and a part of information can't obtain the raw data. For the wireless transmission, it means that the transmitted data wouldn't be seen easily without the enough complete packets and the information of encoding weighting. And the targets of compression and higher level of security both can be achieved concurrently by the process of encoding with proper matrix. Moreover, it is possible to provide flexible CS for the users to set the special encoding transform or weighting by themselves if they only want to share something with someone.

In [5], the authors considered the massive MIMO system that channel quality information (CQI) is sparse and capable to be compressed through some transform of appropriate basis. Reference [6] proposed a random access compressive sensing for underwater sensor networks expecting to recover every sensors' data by receiving a small amount of compressed information to achieve fewer collisions and save energy of sensors. In [7] [8], the posterior probability was included, it resulted in decoding correctly with fewer measurements than blind decoding. Some references [9] investigated adaptive compressive sensing to optimize information gain per unit energy by determining the projection vector, but it was difficult to implement in wireless system that the projection weighting must be known for receiver.

Although many applications of CS are proposed in the research area of wireless networks, there is no special transmission mechanism applied to the CS-based data or the measurements to further enhance the efficiency. We wish to build a new system model including the signal process of the CS measurements and the adaptive link with non-retransmission mechanism. Despite the assumption and the environment are simple in this thesis, it is easy to extend our system to more complicated system by the similar process.

We focus on the work of transmission in the air for the devices using CS, and present MAC and PHY layer design selecting the optimal parameters based on CS's characteristic. For the CS-based signal, we can adjust the bit-length lower than minimal sufficient bit-length expressing the CS measurements to further reduce the total required bits of transmission data in spite of it would make some measurements overflow. Due to that CS is sensitive to noise, it is an important issue to protect the transmitted data away from the noise influence by enhancement of signal strength or channel coding, which has the capacity to correct some decision error. There are many adaptive mechanisms proposed to fulfill the different targets of requirements adjusting with the varying channels. Those algorithms consider the error rate of the modulation and channel coding, and use the theoretic error bound to decide the best parameters for transmission. In [10] [11], the authors proposed adaptive payload length, modulation and channel coding scheme (MCS) to maximize throughput, but it required exhaust computation. Hence, a minimum required transmitted time (MRTT) algorithm for video transmission was proposed in [13], to reduce the resource block cost with a simplified calculation. Our work combines these two techniques and can be mainly divided into two parts: (1) Bit-minimization of the transmission data (2) Reliable adaptive link for the minimal transmission energy considering the channel condition. Moreover, the retransmission is not necessary, it indirectly results in fewer hardware of buffer and lower complexity of communication controller on ARQ mechanism. In this thesis, CS is briefly introduced in Chapter 2. The assumption of raw data and the suggestion of CS process setting are also talked in the chapter. The flowchart and the system architecture of proposed design is shown in Chapter 3. And we propose an algorithm for optimal bit-length per measurement to reduce the required total bits for CS recovery in Chapter 4. Besides, in order to save the energy and the transmission time, an adaptive link is proposed and shown in Chapter 5. Finally, we will give a conclusion and further future work in Chapter 6.

CHAPTER 2
BACKGROUND OF COMPRESSIVE SENSING

The CS applying to wireless networks commonly have two parts: (1) Transmit sampling measurements of compressed data at transmitter. (2) Decode to recovery at receiver. For the ideal situation, the sampling process can directly capture the compressed data such as the application of computer tomography (CT) and magnetic resonant imaging (MRI). Unfortunately, it is not common case to sampling directly, we should do extra process to compress the raw data that will be introduced in this chapter. The assumption of the raw data used in our experiment will be talked in section 2.2. In addition, the decoding method and the suggested CS setting for the following work in our experiment will be presented. The CS used in this thesis is just one case that can be changed, and our main contribution is talked in Chapter 4, 5.

2.1 Overview of Compressive Sensing

At transmission side, the raw data is divided into many partitions that each of them contains an *N*-dimensional vector $\boldsymbol{x} = [x_1\ x_2\ \cdots x_N]^{\mathrm{T}}$ and sparse property through some transform with appropriate basis such as FFT. The compressive process can be viewed as projecting $\boldsymbol{x}$ onto *M*-dimensional space, and the normal form is given as:

$$\boldsymbol{y} = \boldsymbol{\Phi x} \tag{2-1}$$

where $\boldsymbol{\Phi}$ is a *M*-by-*N* random matrix called encoding matrix and $\boldsymbol{y}$ is a $M\times1$ vector called measurements in which $M \ll N$. In order to reconstruct the raw data at decoder, *M* must be larger than a minimal number of required measurements that depends on the raw data and decoding method to ensure having enough information.

To obtain the original data with enough number of measurements, the decoding operation at receiver can be $\boldsymbol{l_o}$-minimization or $\boldsymbol{l_1}$-minimization that both can find a unique solution. Since $\boldsymbol{l_o}$-minimization is a NP-hard problem, $\boldsymbol{l_1}$-minimization, the computational complexity of which is convex, is more often used for recovery. $\boldsymbol{l_1}$-minimization can find

TABLE 2-1 Notation Summary

Parameter	**Explanation**
N	Number of original sparse signal
L	Bit-length of each original signal
S	Sparsity(number of nonzero term)
s	Sparsity ratio (S/N)
H	Size of overhead in bits
A	Number of measurements per packet
m_{req}	Number of required measurement for recovery
M_{req}	Number of required packet for recovery
γ_s	SNR per symbol in dB
P_{out}	Outage rate constraint
m	m-ary QAM
r_c	Code rate of channel coding
r_p	Number of repetition bit

the unique solution subjecting to that $\boldsymbol{\Phi}$ satisfies the restricted isometry property (RIP) given below:

$$(1-\delta)\|\boldsymbol{x_1}-\boldsymbol{x_2}\|_2^2 \le \|\boldsymbol{\Phi x_1}-\boldsymbol{\Phi x_2}\|_2^2 \le (1+\delta)\|\boldsymbol{x_1}-\boldsymbol{x_2}\|_2^2 \qquad \text{(2-2)}$$

holds for all sparse vector $\boldsymbol{x}$, where δ has a small value. It can be viewed as that the process of projection between different domains wouldn't change the Euclidean distance. There are some matrixes that has been proven fulfilling the RIP, such as Fourier, Bernoulli and Gaussian matrix. $\boldsymbol{l_1}$-minimization and blind decoding method excluding prior probability is used as following:

$$\min_{\boldsymbol{x}} \ \|\boldsymbol{x}\|_1 \qquad s.t. \quad \boldsymbol{y}=\boldsymbol{\Phi x} \qquad \text{(2-3)}$$

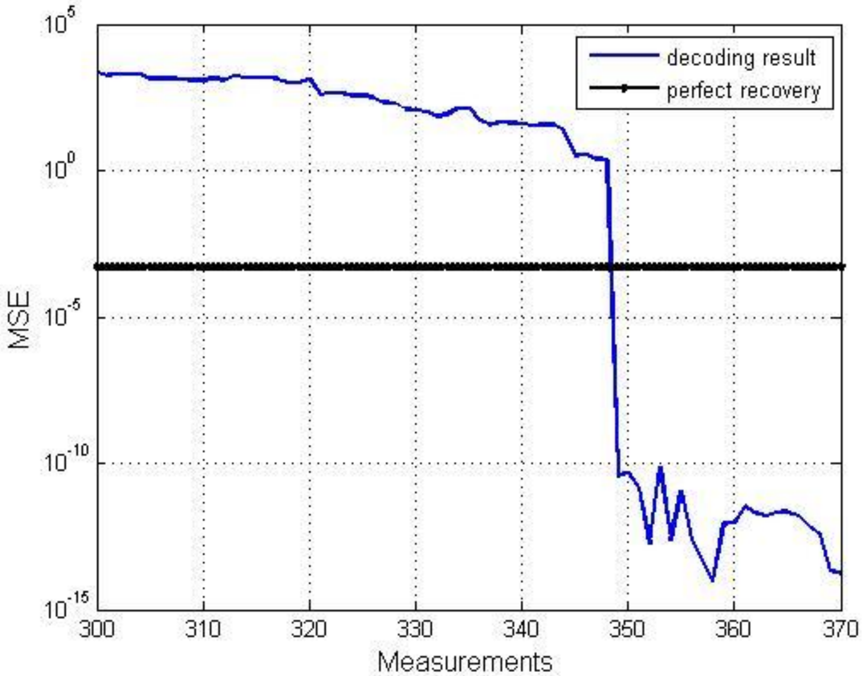

Figure 2-1 Performance of MSE using unsigned raw data, Bernoulli encoding matrix and blind decoding algorithm. (N=500, L=8, s=0.5)

The common notations here are listed in Table 2-1. The performance of MSE with different numbers of measurements is shown in Figure 2-1, the MSE can dramatically decrease to achieve perfect recovery with enough number of measurements for decoding.

Perfect recovery means that recovery is 100% correct, and the MSE is resulted from decoding result including float point that hasn't used corresponding precision. The extra process and comparison will be talked in next section.

2.2 Hypothesis and Compressive Sensing Setting

In order to implement and simplify the CS design, it is reasonable to compress some specific fixed dimensions of raw data. Hence, the raw data are divided into many segments, and each segment is an N-by-1 vector, in which each element is an L-bits data. We process the raw data using a segment each time in the following work, and the "raw data" mentioned in the following chapter indicates a segment of raw data. We assume the raw data that is generated randomly by us has the sparse property, and the nonzero part is

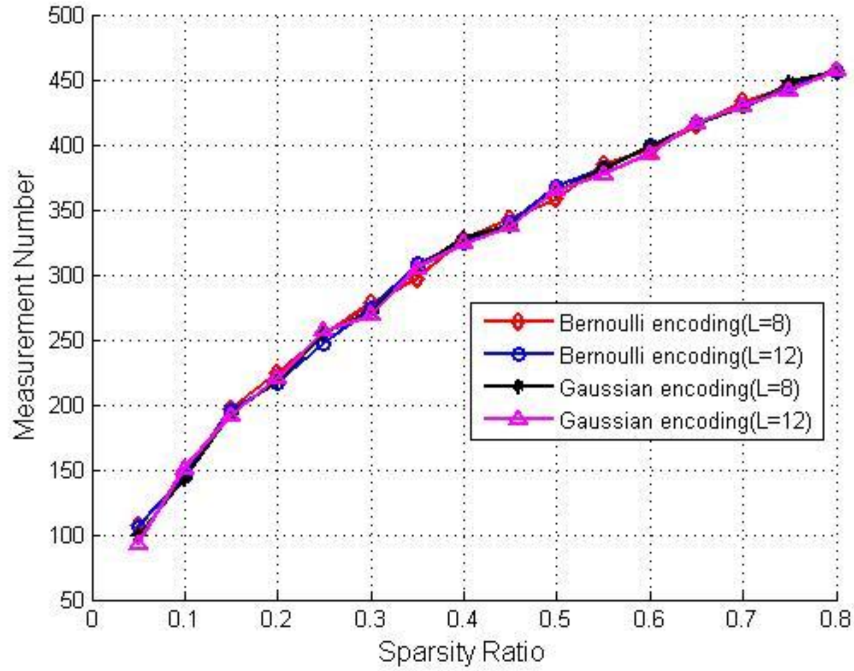

Figure 2-2 Measurement number comparison between various signal length and encoding matrix. (*N*=500, *s*=0.5, 50 samples, *L*: raw data bit-length)

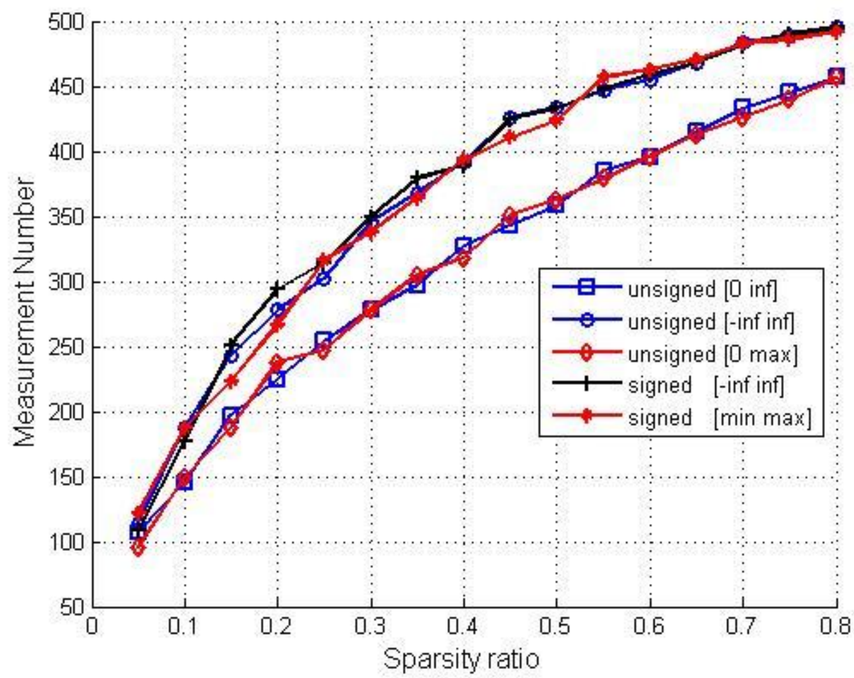

Figure 2-3 CS required measurements comparison based on different decoding constraint. (*N*=500, *s*=0.5, 50 samples, **signed** or **unsigned**: original signal format; [ ] indicates the CS decoding constraint)

distributing uniformly. In this thesis, we consider three cases of the dimensions of the raw data segments: N=250, 500 and 1000.

Although our work is based on the CS-based signal, we still took a series of CS verification and comparison. According to the result of the comparison, we suggest a CS setting, and the following proposed algorithm is based on the suggested CS setting. It is important to know the CS setting is just one case, our proposed method can further extend to other cases of CS.

In our experiment, the Gaussian encoding matrix for CS causes longer bit-length per measurement than Bernoulli encoding matrix that both require the near numbers of measurements for CS decoding and different precisions of raw data cause the same result (see Figure 2-2). Each points in the figure took 50 times of experiments and recorded the largest value of numbers of required measurements with perfect recovery. In addition, we found that unsigned data results in fewer necessary CS measurements for recovery, the comparisons of which are shown in Figure 2-3. We also applied different decoding constraints to obtain the raw data. From the result of experiment, the bit-length of each raw data doesn't need to be known for receiver in advance. Consequently, the unsigned-data format and Bernoulli encoding matrix are employed to minimize the required information according to the experimental results, and we use L=8 bits for our all following work The data are transformed to unsigned value, and then encoded through Bernoulli encoding matrix that the elements in matrix are either 1 or -1 with p=0.5. Hence, the decoding algorithm becomes to have more constraint shown as following:

$$\min_{\boldsymbol{x}} \quad \|\boldsymbol{x}\|_1 \qquad s.t. \quad \boldsymbol{y} = \boldsymbol{\Phi x}\,,\ \boldsymbol{x} \geq 0 \qquad \text{(2-4)}$$

2.3 Recovery Bound

To obtain the raw data successfully, a minimal number of measurements is necessary to be reached for decoder that may differ by various elements of encoding matrix, raw data and decoding method. It is impractical to verify the required measurements at transmitter or device that decoding costs power, time and extra hardware. In order to efficiently process the fast adaptive transmission, a valid recovery bound that must ensure having enough

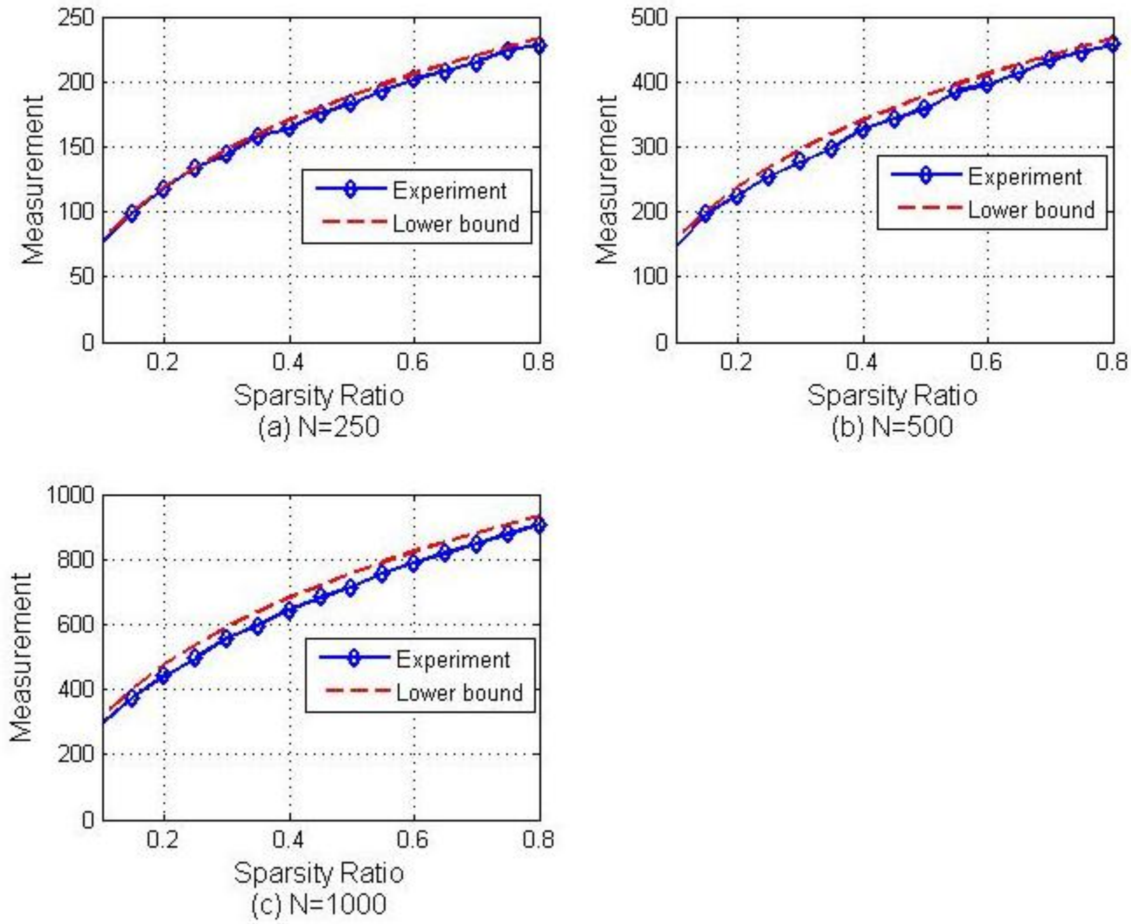

Figure 2-4 The largest value of minimal numbers of experimental required measurements and expected recovery bound. (L=8, 50 samples)

measurements and information is applied to our process. We took a series of test to find out a proper bound that can be expressed by some simple variables, so it can be applied to the latter work easily with guarantee of accurate decoding.

First, we took 50 times of experiments using the raw data of assumption and blind decoding algorithm talked in section 2.2 and recorded the largest value of the minimal numbers of required measurements for recovery in these experiments that all of experiments had near value of the numbers. Besides, three cases of N=250,500 and 1000 were considered to ensure the common expression was valid for various cases. Second, we identify the mathematic expression using some variables of raw data according to the result of previous test. In the end, we took 10000 times of extra experiments using measurements with corresponding number of target bound directly to check that the bound is valid. Hence, the lower bound of required measurements for recovery in our work according to experience and experimental result is approximate as following expression:

$$m_{req} = 3 \cdot S \cdot \log_{10}\left(1.2 + \frac{N}{S}\right) \qquad (2\text{-}5)$$

The required number of measurements can be computed simply by the sparsity and dimensions of raw data and efficiently used for the rest of process. The target bound and experimental result are shown in Figure 2-4 including three cases, and the bounds are greater than and close to the experimental results.

2.4 Significant Characteristic

Unlike conventional transmitted data, the content of transmission carried in the packets is the CS measurements that are the encoded raw data through some process. It results in a flexible transmission that each measurement is replaceable and can be supplemented by

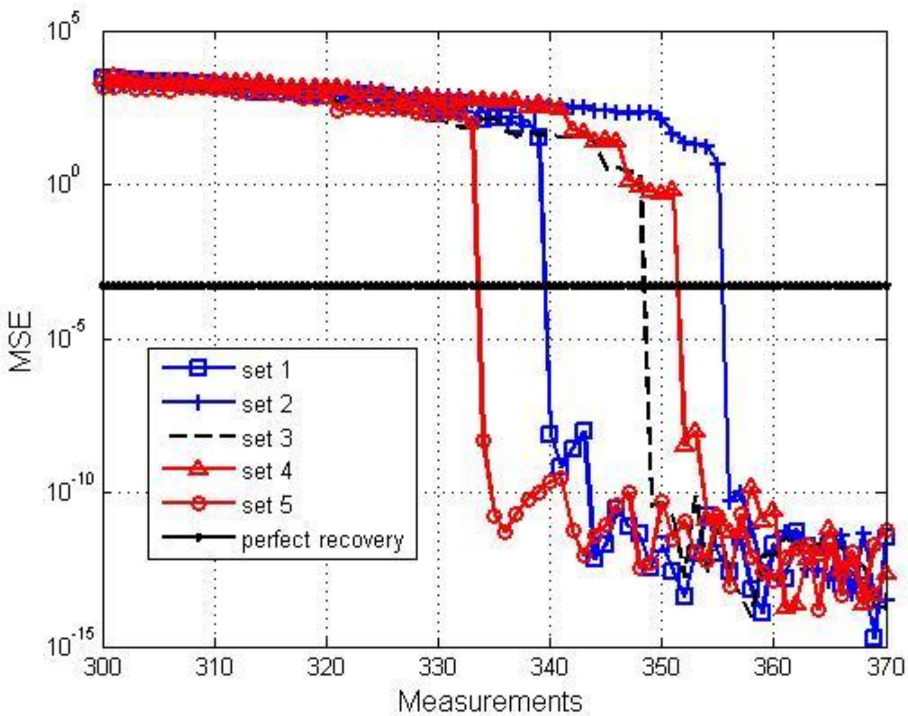

Figure 2-5 Recovery performance versus number of measurements using different parts of measurements. (*N*=500, *L*=8, *s*=0.5)

the others. In other words, we can accomplish the perfect recovery successfully by decoding with a random selecting set of measurements that the number of measurements is greater than or equal to the requirement. An experimental result is shown in Figure 2-5, all of them uses one and the same raw data and encoding matrix but different sets that may have a number of the same measurements with some probability. We can see that all the sets obtain the raw data successfully and have the near turning points of MSE lower than the bound discussed in section 2.3. It is not necessary to reach any specific measurement, but to randomly use some measurements for decoding.

This significant property that measurements are replaceable is applied to our work widely, and it results in a more flexible and efficient adaptive transmission. The loss of the measurements or the invalid measurements can be supplemented by the other measurements, and the detail of application will be talked in chapter 3 and 4. Moreover, it further results in the sooner reliable transmission without retransmission mechanism.

CHAPTER 3
SYSTEM ARCHITECTURE AND FLOWCHART

The overview of the dataflow and the system architecture of the proposed system will be talked in this chapter. We will introduce the working mechanism and flowchart of the design system based on the previous assumption and the CS setting. And the optimization work will be talked in the later chapters.

3.1 Flowchart

We propose a cross-layer design including data process, MAC and PHY layers design which can adjust the system's variables to meet the request of QoS according to the raw data and the channel condition. The signal process and optimization work are concurrent

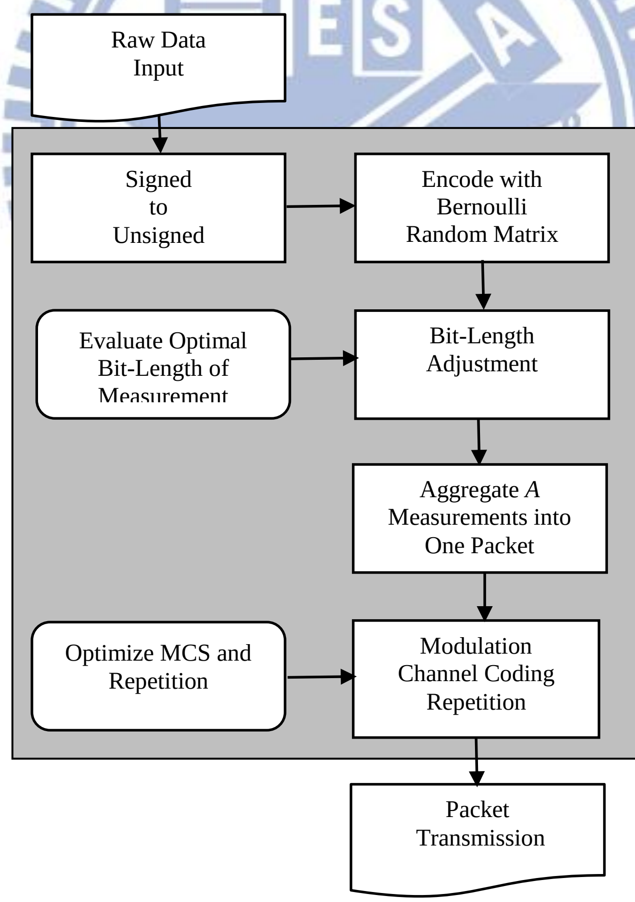

Figure 3-1 The dataflow of designed process at transmitter.

and real time, and the dataflow of designed process at transmitter is simply shown in Figure 3-1. The process executes continuously and start once the segment of raw data is ready. According to the suggestion of CS setting and the experimental result provided in Chapter 2, the flowchart of designed process at transmission side is as following. The first step is to transform the raw data into unsigned format due to that nonnegative data requires fewer measurements discussed in section 2.2. Then, the data is encoded by Bernoulli random matrix that results in fewer bits per measurement comparing with Gaussian random matrix. In order to make the value of the measurements have zero mean and save the hardware, the Bernoulli random variables in the matrix are either 1 or -1 with equal probability. In the third step, the adjustment of bit-length per measurement can further reduce the total transmitted bits and improve bit-utilization efficiently that will be talked in this chapter. The optimization of bit-length only requires the information of the raw data, the format of the encoding matrix and the packet format. Consequently, the optimization of bit-length can work individually, and it is not necessary to wait for the encoding process or collecting the measurements. In the next step, the measurements using the optimal bit-length are collected and packetized every *A* measurements. Finally, the packets are encoded and enhanced based on the results of the optimization of MCS and repetition that result in the reliable adaptive link. The optimization work of adaptive link is to achieve the minimal transmission energy according to not only the channel condition but also the information of the raw data and the optimal bit-length which can further estimate the necessary number of the packets and payload length. In other words, the optimization work can execute before the packetization finishes completely. Hence, the packets are generated and sent continuously without waiting for collecting and buffering all packets. At another side, the strong receiver receives the packets to collect and identify the measurements in the packets passing the error-detect of cyclic redundancy check (CRC). And the receiver would further distinguish the valid measurements from the invalid measurements that is overflow and incorrect value. Then, the receiver tries to reconstruct the raw data by using valid measurements and CS decoding method, such as $\boldsymbol{l_o}$-minimization and $\boldsymbol{l_1}$-minimization case by case. Moreover, it may require to transform the data of decoding result into signed format if necessary.

3.2 System Architecture

Figure 3-2 shows the designed system architecture which is a cross-layer design relative to application layer, MAC layer and physical layer. The raw data segment is the unsigned N-by-1 vector, of which the sparsity is S and each element is L-bits long. The control unit in MAC layer is responsible for the work of control and optimization that operate with the information of raw data and channel quality. And the most important optimization work of bit-length optimization and link adaptation are included in the control unit. The work of compression unit, bit-length adjustment and packetization is a continuous real time process all controlled by the control unit. The compressive unit is responsible for encoding or transforming the raw data and generate the full-precision measurements one by one continuously, and it may be put in the application layer sometimes if we directly process the input of compressed raw data (measurement). Then, the measurements are cut off redundant bits by the bit-length adjustment unit according to the output of bit-length optimization in control unit. The bit-length optimization unit would estimate a best bit-length by considering

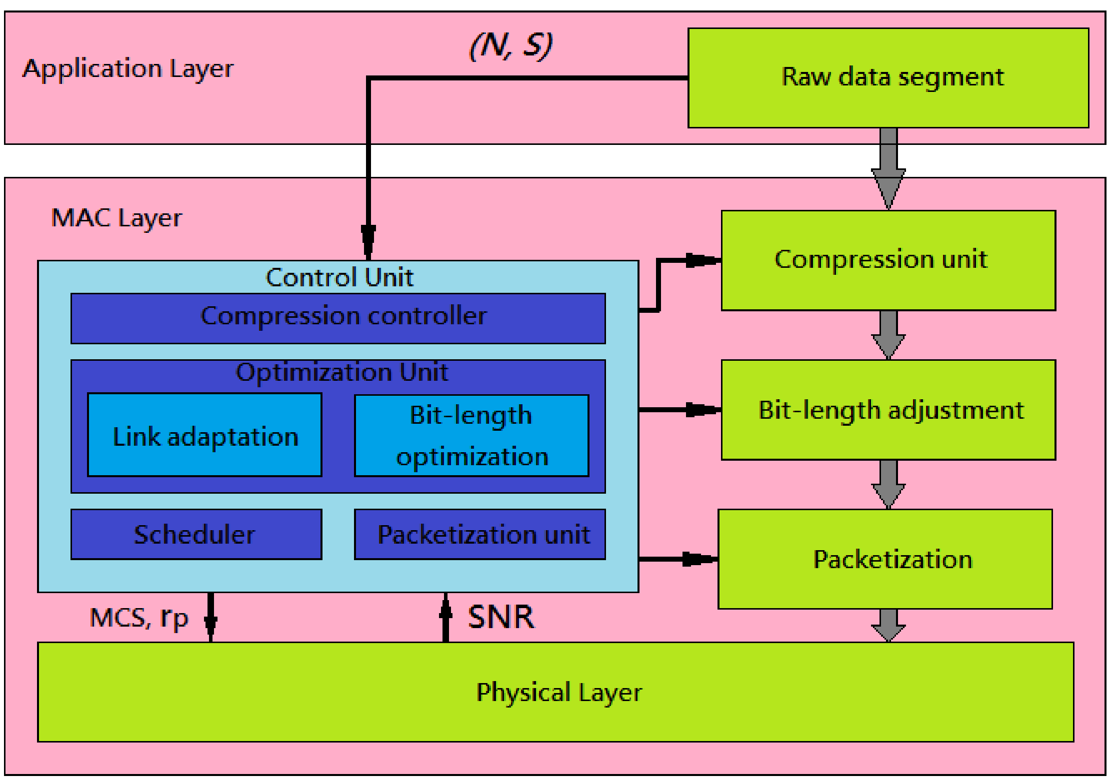

Figure 3-2 The system architecture at transmitter

the distribution of the measurements, the overflow probability, aggregating number A and overhead of CRC, MAC and PHY header. Next, the packetization unit aggregates a number of measurements into one packet and adds the overhead of MAC header and CRC once it collects the last A measurements generated from the bit-length adjustment unit. The packet in physical layer will be added PHY header and be sent immediately once the packet finishes the modulation and channel coding using the result of optimization executing in link adaptation unit. The link adaptation is responsible for optimizing the MCS and repetition according to the SNR of varying channel to reduce the transmission energy.

Chapter 4
Optimal Bit-Length of Measurements

To efficiently achieve higher bit-utilization, the optimal bit-length of measurements is proposed in this chapter that is able to be transmitted in fewer bits than full-precision measurements before modulation and channel coding. Besides, the aggregation mechanism and fixed format for packing are applied to further reduce the overhead.

4.1 Packet Format

It is impractical and extravagant to send each measurement separately due to that it spends too much resource on redundant overhead of packets. Obviously, to prevent this situation, the aggregation of measurements is the efficient and simple solution. We consider a fixed number of measurements in each packet in our investigation so far. Hence, the measurements are divided into many sets in order for the corresponding packets.

It is important to realize that each measurement is encoded by corresponding row of encoding matrix that must be known for the receiver. Actually, it is needlessly to record the encoding matrix if both sender and receiver make use of the same random hardware. All we should do is to let the receiver know which measurement it is. For the purpose of avoiding redundant overhead of the indices of measurements, we not only aggregate A measurements into a packet, but also transmit the useless overflow value resulted from the adjustment of bit-length that is presented in next section in the format of negative maximal value (2's complement 1000…000) depending on the precision of measurements. The reason is that the components of each packet are fixed now. Consequently, the packet does not require to include the information of all indices of corresponding measurements but the

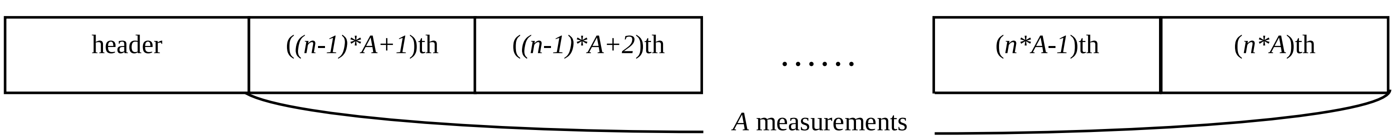

Figure 4-1 The aggregation packet format, in which the number in block is the index of the measurement. (n: nth sets of measurements, A: number of measurements in a packet)

information of which set it is in this packet. By the way, the measurements is invalid and useless if its value is negative maximal value. The format of packet is shown in Figure 4-1, and each measurement adopts the optimal bit-length discussed in the following section.

4.2 Proposed Optimal Bit-Length

Each compressive sensing measurement can be seen as a sum of *n* (equal to sparsity *S*) uniform random variables written by:

$$m_i = \sum_{i=0}^{n} b_i x_i \qquad (4\text{-}1)$$

where x_i are the unsigned data within bit-length L resulting in nonnegative numbers ranging from 0 to $2^L - 1$, and b_i are Bernoulli random variables which are either -1 or 1 with $p = 0.5$. The Bernoulli random variables work as the operation of addition and subtraction from the hardware's point of view. It results in that each term of summation distributes on the interval $[-2^L + 1, 2^L - 1\,]$ uniformly. Moreover, the value of measurements distributes like Gaussian distribution with zero mean that the more significant bits are less used (see Figure 4-2), and that it mainly locates around the zero is the reason for why we choose Bernoulli random variables like this. To efficiently achieve higher bit-utilization, the optimal bit-length of measurements is proposed that is able to be transmitted in fewer bits than full-precision measurements. We will cut off a proper number of bits to express the measurements that will cause some overflow measurements.

Conventionally, the bit-length of transmitted data must be sufficient longer than or equal to the required precision for expressing the data. Firstly, we can quickly evaluate the maximum bits of each measurement:

$$b_{max} = \lceil \log_2 n(2^{L+1} - 2) \rceil \qquad (4\text{-}2)$$

where $\lceil\ \rceil$ denotes the operation of selecting the nearest integer greater than or equal to the inside value. Thus the minimal sufficient bit-length of each full-precision measurement without overflow is shown as Eq. (4-2) and can be simplified as:

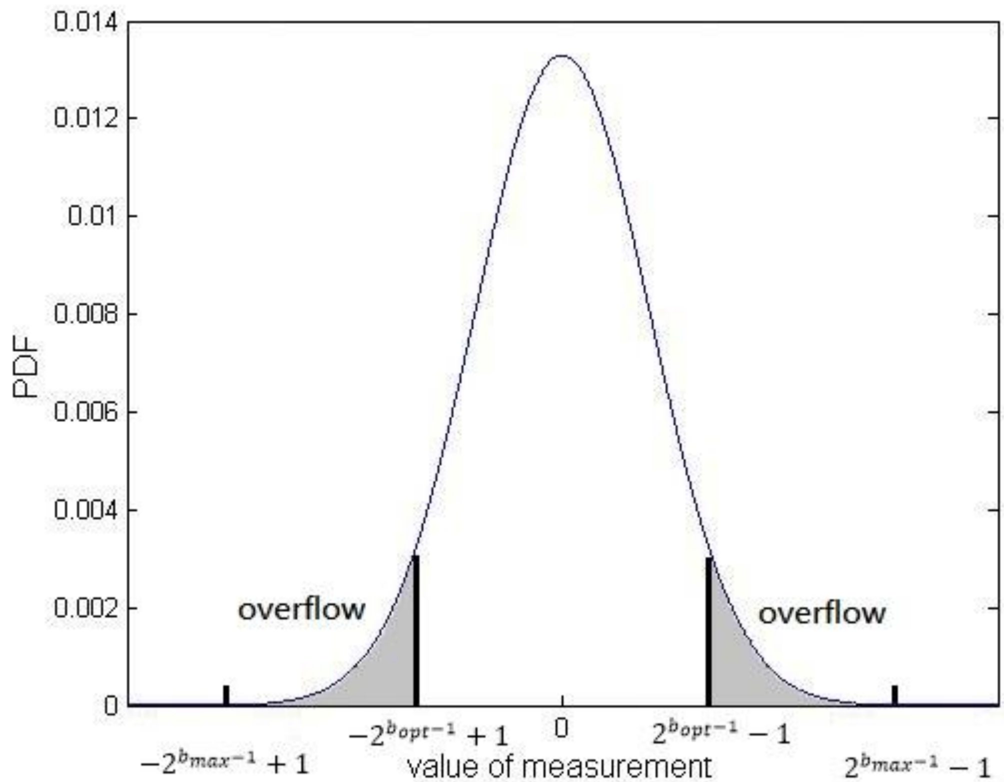

Figure 4-2 The distribution of the value of the measurements

$$b_{max} = \lceil \log_2 n \rceil + L + 1 \tag{4-3}$$

And the full-precision bit-length depend on the sparsity and the bit-length used for the raw data.

To reduce the total transmitted bits, the optimal bit-length which is l-bits less than b_{max} is adopted that there is a probability of overflow. Now the optimal bit-length for use is expressed as following:

$$b_{max} - l^* \tag{4-4}$$

where $l^*$is the redundant bits which would be cut and found in our optimization work. In order to minimize total transmitted bits, let we consider the expectation of bits per measurement that must be generate successfully till a non-overflow measurement is produced.

The overflow measurements would also be transmitted in a special format (2's complement 1000…000) due to the consideration of the packet format. As a result, the expectation of bits of *l*-bits less can be review as a summation below:

$$\sum_{i=0}^{\infty}(H/A + b_{max} - l)\,(P_{err}^{l})^{i} \tag{4-5}$$

where P_{err}^{l} is the probability of overflow corresponding to the *l*-bits less bit-length. H is the overhead in a packet without modulation and channel coding, and A is the aggregation number of measurements per packet. This expectation includes the overhead estimation and the bit-evaluation of measurements that is the result of sum of infinite geometric series according to the employed content of packet format. The summation of infinite geometric series can be calculated because the overflow probability is smaller than 1 which makes the series convergent. Hence, the optimization problem becomes to minimize the expectation of bits per measurement:

$$\begin{aligned} &\min_{l} \quad (H/A + b_{max} - l)/(1 - P_{err}^{l}) \\ &s.t. \quad 0 \le l < b_{max}\,, l \in Z \end{aligned} \tag{4-6}$$

And the overflow probability of l-bits less can be expressed as:

$$P_{err}^{l} = 2P(x > 2^{b_{max}-l-1} - 1) \tag{4-7}$$

To further calculate the value of probability, consider the accumulation of *n* signal uniformly distributing on the interval [0, a]. The cumulative density function (CDF) of cumulative value can be computed below [17]:

$$F_n^a(x) = \frac{1}{n!a^n}\sum_{j=0}^{n}(-1)^j\binom{n}{j}[(x-aj)^+]^n \tag{4-8}$$

where $(x - aj)^+$ denotes $\max(0, x - aj)$. To compute the probability of overflow, the above CDF can be shifted to match our case with zero mean. Therefore, the overflow probability of l-bits less can be bounded by:

$$P_{err}^{l} = 2 \cdot (1 - F_n^a(x + n(2^L - 1)))|_{x=2^{b_{max}-l-1}-1} \qquad (4\text{-}9)$$

where $a = 2^{L+1} - 2$ resulted from that Bernoulli weighting can double L-bits precision of data. And Eq. (4-9) can be also written as:

$$P_{err}^{l} = 2 \cdot (1 - F_n^a(x))|_{x=n(2^L-1)+2^{b_{max}-l-1}-1} \qquad (4\text{-}10)$$

Combine a and Eq. (4-3), x in Eq. (4-10) can be rewritten as:

$$x = n\frac{a}{2} + 2^{\lceil log_2 n \rceil}\frac{a+2}{2^{l+1}} - 1 \qquad (4\text{-}11)$$

Because a is large comparing with the constants, we can simplify Eq. (4-11), and substitute it and Eq. (4-8) into Eq. (4-10):

$$x \approx a(\frac{n}{2} + 2^{\lceil \log_2 n \rceil - l - 1}) \qquad (4\text{-}12)$$

$$P_{err}^{l} = 2(1 - \frac{1}{n!a^n}\sum_{j=0}^{n}(-1)^j\binom{n}{j}[(x - aj)^+]^n)|_{x=a(\frac{n}{2}+2^{\lceil \log_2 n \rceil - l - 1})} \qquad (4\text{-}13)$$

Since the numerator and numerator in Eq. (4-13) both have the term of a^n, the equation of probability of overflow can be further simplified by eliminating a :

$$P_{err}^{l} = 2(1 - \frac{1}{n!}\sum_{j=0}^{n}(-1)^j\binom{n}{j}[(x - j)^+]^n)|_{x=\frac{n}{2}+2^{\lceil \log_2 n \rceil - l - 1}} \qquad (4\text{-}14)$$

Hence, the optimal bit-length $b_{max} - l$ with corresponding probability of overflow evaluated by Eq. (4-14) can be solve by Eq. (4-6) now.

With the increase of the sparsity (S or n), the computational complexity becomes higher and higher. As a result, it would take too much time to calculate the optimal bit-length if we still use Eq. (4-14) to approach the overflow propability. Fortunately, when the sparsity is large, the distribution of the value of measurements is approximate to Gaussian distribution. So the CDF above in Eq. (4-14) can be replace by Gaussian distribution with mean $\frac{n}{2}$ and standard deviation $\sqrt{n/12}$:

$$P_{err}^{l} = 2(1 - cdf('normal',\ x,\ \frac{n}{2},\ \sqrt{n/12}\,))|_{x=\frac{n}{2}+2^{\lceil \log_2 n \rceil - l - 1}} \tag{4-15}$$

Through this approach, it results in a fast algorithm and makes it possible to construct a real time system even when sparsity is large.

4.3 Simulation Result I

We compare the total bits of required received measurements using optimal bit-length with the measurements using full-precision, and the result is shown in Figure 4-3. The total bits of required received measurements means how many bits of measurements should be

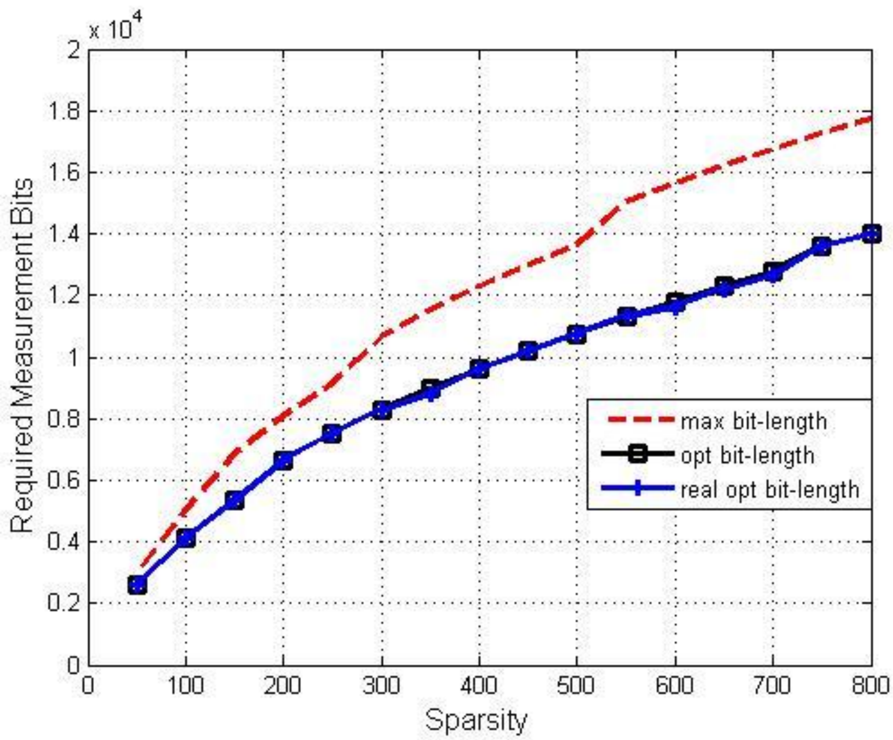

Figure 4-3 Bits of required received data of maximum bits, optimal bits and opt-bit-simulation for recovery. (*N*=1000, *L*=8, *H*=224, *A*=20, 10000 samples)

generated to reach the goal of collecting m_{req} (see section 2.3) valid measurements which are not overflow. In the simulation, we considered aggregating 20 measurements into a packet and 28 bytes overhead due to that it is the length of header of MAC and PHY. It is apparent that the adjustment of bit-length of measurements can produce fewer necessary transmitted data. It saves about total 20% bits, and the cutting off bit-length can improve bit-utilization efficiently. Except the theoretic simulation, we also took the 10000 times of real experiments to generate the sufficient valid random measurements using the optimal bit-length. The average result of real test is very close to our proposed as good as expected.

CHAPTER 5
ADAPTIVE LINK FOR MINIMAL ENERGY

The present wireless network supports multiple modulation and channel coding schemes (MCSs). And repetition is an effective way to enhance the strength of signal when the channel condition is bad. The adaptive link is proposed to minimize the transmission energy and time through using optimal modulation, channel coding scheme and repetition of symbol according to channel's signal-to-noise ratio (SNR) in this chapter, and corresponding simulation will be shown, too.

5.1 Considered MCSs and Channel

To accomplish flexible and efficient transmission, the various modulation and channel coding schemes can be chosen in the present wireless communication system. The hardware provides different MCSs which have different throughputs and power consumptions for the users according to their request of QoS and the channel quality. In order to save the transmission energy and time in the situation of varying channel and different error constraints, we use the optimal modulation and channel coding scheme which are supported

TABLE 5-2 Throughput of Raw Data

PHY mode index (m)	Throughput (bits per symbol duration)
1	2/3
2	1
3	5/4
4	2
5	5/2
6	3
7	4
8	6

in our system. We consider the modulation including QPSK, 16-QAM and 64-QAM which are available in LTE. Although the common channel coding schemes include block code, convolution code and turbo code, we only use convolution code in this thesis due to that all of them have the similar analytical method. The MCSs used in this experiment which have different throughputs and bit error rate are shown in Table 5-1, and additive white Gaussian noise (AWGN) and single-input-single-output (SISO) channel is considered here.

TABLE 5-1 Available MCSs (convolution code)

PHY mode index (m)	Code rate	Modulation
1	1/3	QPSK
2	1/22qazaaz	QPSK
3	5/8	QPSK
4	1/2	16-QAM
5	5/8	16-QAM
6	3/4	16-QAM
7	1	16-QAM
8	1	64-QAM

5.2 Resource Block Allocation

To achieve the goal of shorter time duration of transmission is also an important issue in our research. Due to the property of CS that the losing measurements can be replaced by the others, we consider sending packets consecutively without retransmission mechanism that can avoid spending time on waiting for the ACK/NACK and hardware's idle. For timing analysis, we adopt LTE resource block and uplink channel due to that it is proper to do complicate CS decoding at powerful computational base station.

For the LTE uplink transmission [15], SC-FDMA with a CP is adopted. An uplink radio frame consists of 10 sub-frames, and each sub-frame consists of 2 slots of 0.5 ms each shown as Figure 5-1. For normal CP, there are 7 symbols for each subcarrier in a slot. And

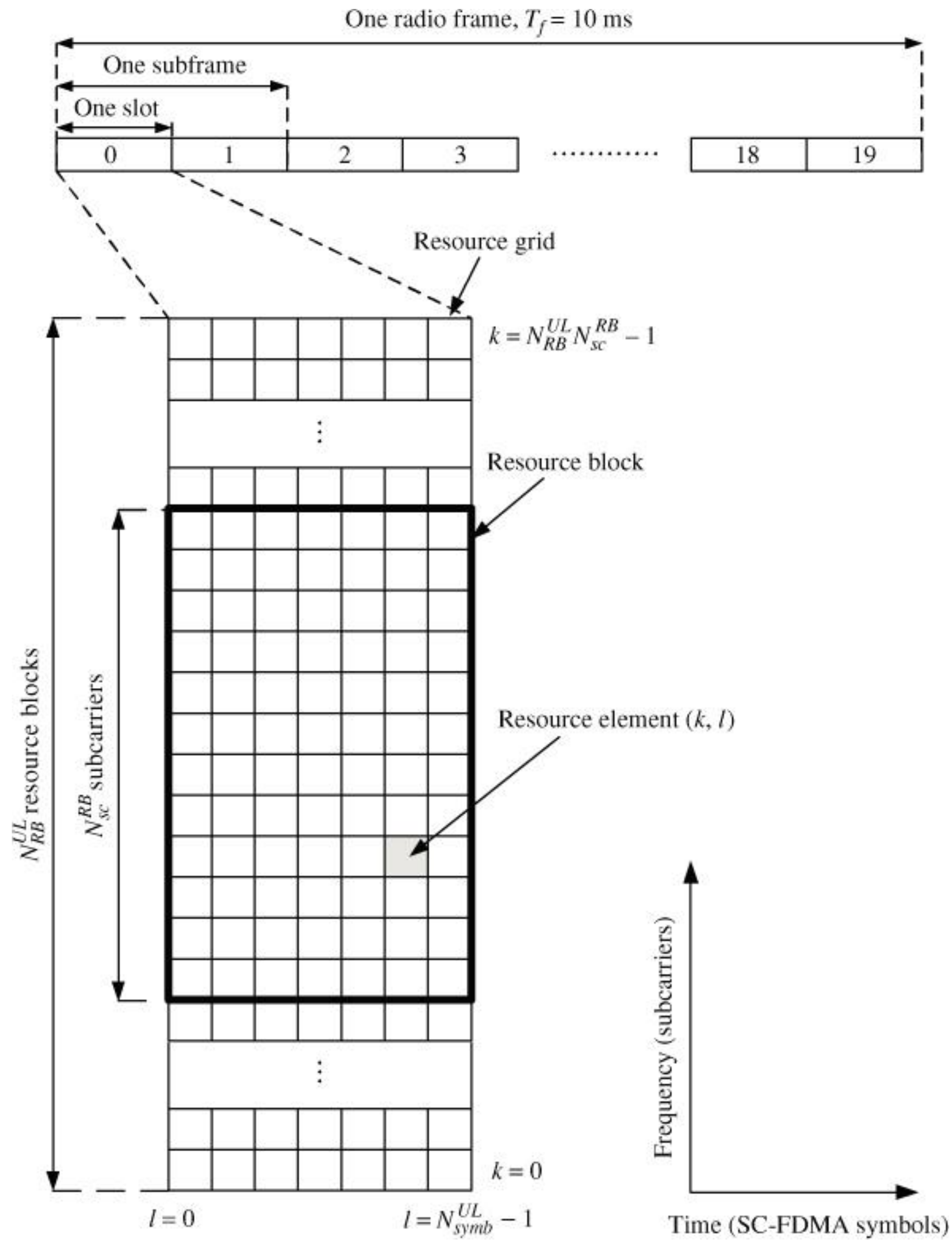

Figure 5-1 The structure of the uplink resource grid.

there are 12 subcarriers that each subcarrier spaces over 15 kHz in frequency domain in one resource block. The number of resource blocks in each resource grid depends on the uplink transmission bandwidth which is configured in the cell and should satisfy:

$$N_{RB}^{min,UL} \leq N_{RB}^{UL} \leq N_{RB}^{max,UL} \qquad (5\text{-}1)$$

where $N_{RB}^{min,UL} = 6$ and $N_{RB}^{max,UL} = 110$ correspond to the smallest and largest uplink supported bandwidth, respectively.

To take a simplified simulation of transmission, we transmit data by using one resource block corresponding to one slot in time domain and 180 kHz in frequency domain once based on the specification of LTE. Moreover, the fourth symbol is used to be reference signal in each slot. The latency of waiting for ACK/NACK back has been defined in LTE that is at least 4 ms including about 3 ms for hardware's decoding. In our simulation, we consider the minimal waiting time and wait-and-stop ARQ mechanism that requires lower complexity of controller and fewer buffer.

5.3 Bit Error Rate Analysis

The different MCSs result in different bit error rates and lengths of packet that would influence the packet error rate and required energy to meet the target of outage rate. We use the theoretical mathematical error bound to find out the suitable MCS and predict the transmission energy. Moreover, we adopt the repetition of symbols to enhance the signal's strength that can decrease the error rate efficiently especially at low signal-to-noise ratio. The average probability of bit error with modulation and channel coding corresponding to PHY mode *j* and channel quality γ_s (SNR per symbol) can be bounded by first event error rate given as following [16]:

$$ber_{j,r_p}(\gamma_s) \leq \sum_{d=d_{free}}^{\infty} a_{d,j} \cdot P_{d,j,r_p}(\gamma_s) \qquad (5\text{-}2)$$

with d_{free} being the free distance of the convolutional code used in PHY mode *j* and $a_{d,j}$ being the total number of error events of weight *d* that both can be obtained in Table 5-3.

TABLE 5-3 Weight a_d and Free Distance d_{free} for Corresponding Convolution Codes

Convolution code rate	d_{free}	a_d
1/3	15	3 3 6 9 4 18 35 45 77 153 263 436 764 1209 2046 3550 5899 10002 16870 28701
1/2	10	11 0 38 0 193 0 1331 0 7275 0 40406 0 234969 0 1337714 0 7594819 0 43375588
5/8	6	1 19 71 168 546 2004 6391 21431 71709 235868
3/4	5	4 36 175 882 4486 23156 120602 622937 3216664 16628990

For hard decision decoding with corresponding probability of bit error ρ caused only by modulation, $P_{d,j,r_p}(\gamma_s)$ is given by:

$$P_{d,j,r_p}(\gamma_s) = \begin{cases} \sum_{k=(d+1)/2}^{d} \binom{d}{k} \cdot \rho^k \cdot (1-\rho)^{d-k} & \text{if d is odd} \\ \frac{1}{2} \cdot \binom{d}{d/2} \cdot \rho^{d/2} \cdot (1-\rho)^{d/2} & \\ \quad + \sum_{k=d/2+1}^{d} \binom{d}{k} \cdot \rho^k \cdot (1-\rho)^{d-k} & \text{if d is even} \end{cases} \tag{5-3}$$

where ρ is the bit error rate for uncoded AWGN channels associating with modulation type, signal-to-noise ratio per symbol and repetition which is equal to the multiplying factor of signal's enhancement, and it is given by:

$$\rho = \begin{cases} Q\left(\sqrt{2 \cdot \frac{E_b}{N_o}}\right) & \text{if QPSK} \\ \frac{3}{4} \cdot Q\left(\sqrt{\frac{4}{5} \cdot \frac{E_b}{N_o}}\right) + \frac{1}{2} \cdot Q\left(3 \cdot \sqrt{\frac{4}{5} \cdot \frac{E_b}{N_o}}\right) + \frac{1}{4} \cdot Q\left(5 \cdot \sqrt{\frac{4}{5} \cdot \frac{E_b}{N_o}}\right) & \text{if 16} - \text{QAM} \\ \frac{7}{12} \cdot Q\left(\sqrt{\frac{2}{7} \cdot \frac{E_b}{N_o}}\right) - \frac{1}{2} \cdot Q\left(3 \cdot \sqrt{\frac{2}{7} \cdot \frac{E_b}{N_o}}\right) + \frac{1}{12} \cdot Q\left(5 \cdot \sqrt{\frac{2}{7} \cdot \frac{E_b}{N_o}}\right) & \\ \quad - \frac{1}{12} \cdot Q\left(9 \cdot \sqrt{\frac{2}{7} \cdot \frac{E_b}{N_o}}\right) + \frac{1}{12} \cdot Q\left(13 \cdot \sqrt{\frac{2}{7} \cdot \frac{E_b}{N_o}}\right) & \text{if 64} - \text{QAM} \end{cases} \tag{5-4}$$

where $\frac{E_b}{N_o}$ is the signal-to-noise ratio per bit in linear scale which can be obtain from γ_s

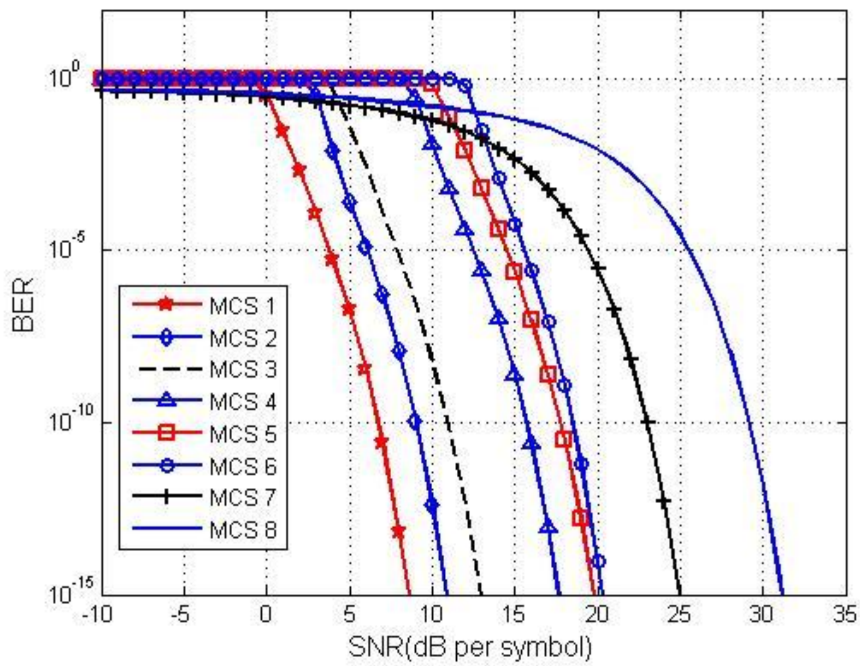

Figure 5-2 BER versus SNR with 8 MCSs.

and the repetition r_p will be discussed in section 5.4:

$$\frac{E_b}{N_o} = \begin{cases} \frac{r_p \cdot 10^{(\gamma_s/10)}}{2} & \text{if QPSK} \\ \frac{r_p \cdot 10^{(\gamma_s/10)}}{4} & \text{if } 16-\text{QAM} \\ \frac{r_p \cdot 10^{(\gamma_s/10)}}{6} & \text{if } 64-\text{QAM} \end{cases} \tag{5-5}$$

Figure 5-2 shows the above mathematical result of average probability of bit error for coded AWGN channels with varying channel quality and MCSs. The lower bit error rate is, the longer payload length of the packet is. Hence, there exists a trade-off between bit error rate and payload length resulting from the uncertain packet error rate. Consequently, it becomes an optimization problem to select proper coding scheme according to the channel quality information and the target of outage rate in order to achieve minimal resource cost and transmission time.

5.4 Proposed Adaptive Mechanism

Because the loss of measurements resulting from transmission-error can be supplemented by other measurements in different packets or sets that each set includes A measurements, it is not necessary to adopt the retransmission mechanism to ensure receiving all packets that results in a shorter time of transmission.

To minimize the transmission energy, we consider the total required transmission energy first, that can be written as:

$$E_{total} = (M * L_{ori} * \frac{r_p}{r_c}) / (\log_2 m) * Es \qquad (5\text{-}6)$$

where M denotes the number of total transmission packets, and Es is the energy per symbol. L_{ori} is the bit-length of data in a packet including overhead before modulation and channel coding which is given by:

$$L_{ori} = H + (b_{max} - l) * A \qquad (5\text{-}7)$$

It makes no difference to eliminate L_{ori} and Es that both have constant value for the optimization finding the suitable MCS (m, r_c) and the number of repetition r_p. Hence, with the target of outage rate P_{out} and the number of necessary correct packets M_{req}, the optimization problem becomes as following:

$$\begin{aligned} &\min_{M,j,r_p} \ \frac{M * r_p}{r_{c_j} * \log_2 m_j} \\ &s.t. \ \ \sum_{i=0}^{M_{req}-1} \binom{M}{i} P_{j,r_p}{}^{i} \left(1 - P_{j,r_p}\right)^{M-i} \le P_{out}, \\ &\qquad M \ge M_{req} \end{aligned} \qquad (5\text{-}8)$$

where j is the index of PHY mode. P_{j,r_p} is the probability of packet received successfully corresponding to mode j and repetition r_p, and is given by:

$$P_{j,r_p} = (1 - ber_{j,r_p})^{L_{ori}/r_c} \qquad (5\text{-}9)$$

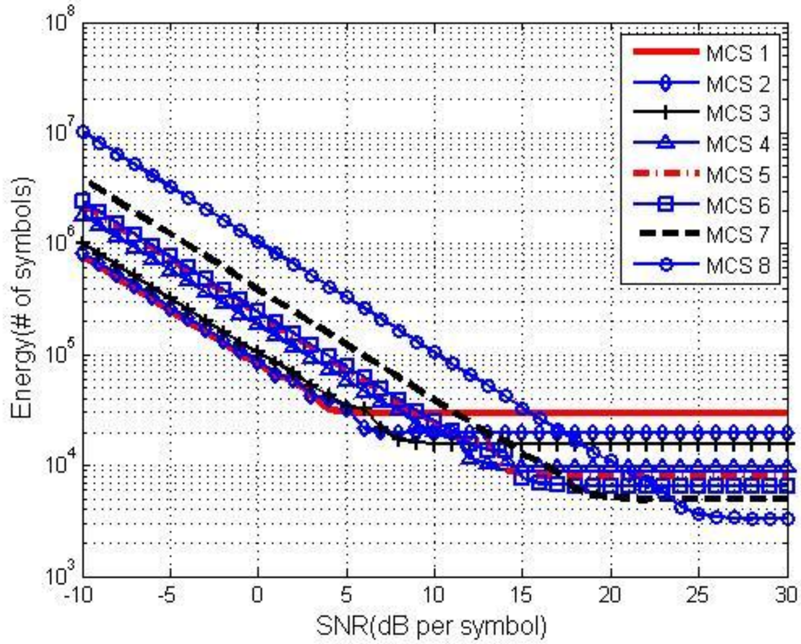

Figure 5-3 The result of optimization with 8 MCSs, respectively.
(P_{out}=10^-3, N=1000, s=0.5, L=8, H=224, A=20)

where ber_{j,r_p} (see section 5.3) is the average probability of bit error bounded by first event error rate which is the function of (j, r_p, γ_s). By the way, M_{req} in Eq. (5-8) which is the number of expected necessary received packets can be evaluated by combination of Eq. (2-4) (4-6) (4-11):

$$M_{req} = \left\lceil \frac{m_{req}}{A \cdot (1 - P_{err}^{l})} \right\rceil \qquad (5\text{-}9)$$

Figure 5-3 shows the results of optimization with different MCSs that we optimize the variables of (M,r_p) based on the channel quality through the similar optimal function like Eq. (5-8), respectively. The intersections of power consumption mainly locate on the interval of [5, 25] (dB per symbol) that is a common practical transmission environment in real world. It means the selection between different MCSs is a reasonable way to save the power and increase the throughput.

5.5 Corresponding Conventional Algorithm

We compare our proposed with the corresponding conventional algorithm optimizing the same variables (M, j, r_p) according to the same error constraint. The difference is that the conventional transmission must ensure receiving all the M_{req} specific packets by re-transmitting the packet once the packet is failed to be transmitted. The total required transmission energy has been shown in Eq. (5-6), and the conventional optimization has the similar form with $M = M_{req} * N_{ave}$, in which N_{ave} is the average expected number of transmission packets including the retransmission packets for successfully receiving a packet. Hence, the optimization problem becomes as:

$$\begin{aligned} &\min_{N_{ave}, j, r_p} \frac{N_{ave} * r_p}{r_{c_j} * log_2 m_j} \\ &s.t. \quad 1 - \left[\sum_{i=0}^{N_t-1} P_{j,r_p} * \left(1 - P_{j,r_p}\right)^i\right]^{M_{req}} \leq P_{out}\,, \\ &\qquad N_t \geq 1 \end{aligned} \tag{5-10}$$

where P_{j,r_p} is the packet success rate as same as Eq. (5-9). To fulfill the constraint of outage rate, N_t is the minimal required number of transmission packets to receive a packet successfully according to the statistic. With the corresponding N_t and P_{j,r_p}, the expectation of average number of transmission packets including retransmission packets for successfully receiving a packet can be evaluated by:

$$N_{ave} = \sum_{i=0}^{N_t-1} \left(1 - P_{j,r_p}\right)^i \tag{5-11}$$

The content of the summation in Eq. (5-10) (5-11) is the finite geometric series, which can be computed easily and fastly. By the equations above, the optimal parameters can be obtained, and we can further estimate the required transmission energy for receiving the target number of packets.

5.6 Simulation Result II

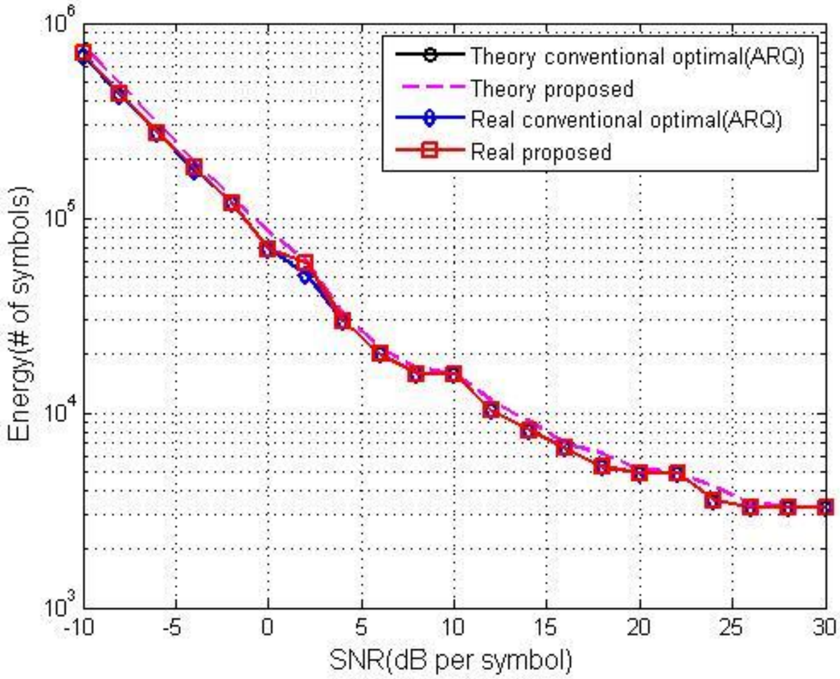

Figure 5-4 Optimal transmission and experimental result with different algorithm.
(P_{out}=10^-3, N=1000, s=0.5, L=8, H=224, A=20, 10000 samples)

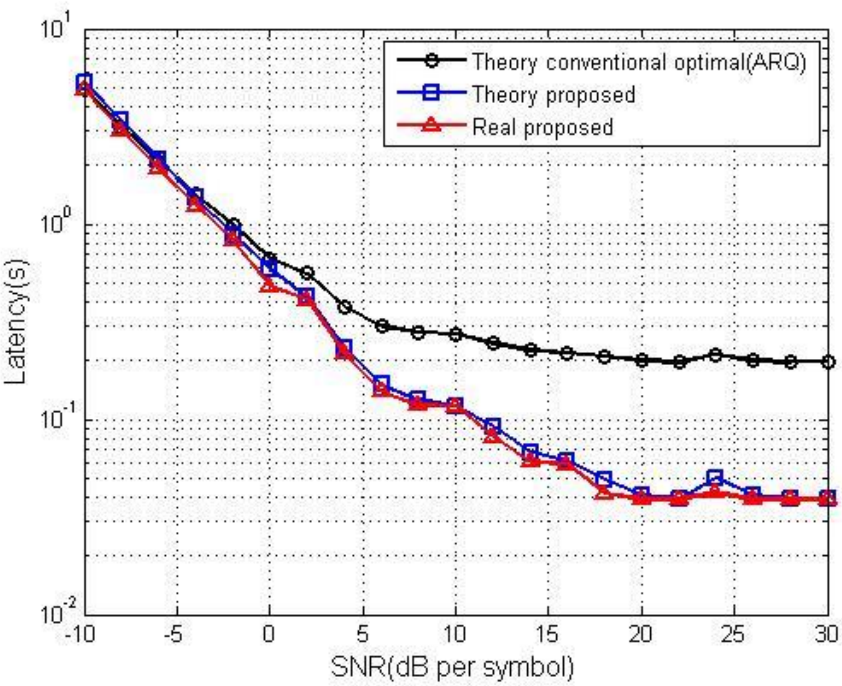

Figure 5-5 Theoretical and experiment latency using LTE-A timing scale.
(P_{out}=10^-3, N=1000, s=0.5, L=8, H=224, A=20, 10000 samples)

In the simulation, we include theoretic and experimental results of the proposed and conventional algorithms with different types of raw data *N*=250, 500 and 1000. For the real test, we randomly generate a set of raw data with the fixed sparsity and an encoding matrix in each experiment, and transmit the packets till receiver receives the target number of packet successfully. All of them achieve the similar results of three cases of *N*, the proposed method's performance of power consumption is close to conventional adaptive link with ARQ. Figure 5-4 shows one of the results with *N*=1000, sparsity ratio=0.5, target of outage rate =0.1% and 10000 samples. It is reasonable that transmission energy decreases when the channel quality becomes better and better resulting in lower packet error rate. The proposed has almost the same transmission energy comparing with the conventional optimization, and the average experimental result has proven the correctness of the algorithm.

Without the necessary of retransmission mechanism, the shorter time of proposed transmission can be achieved based on the significant CS property. For timing analysis, we apply the standard of LTE-A uplink resource (see section 5.2) to our simulation and compare with stop-and-wait ARQ which has the lowest complexity of controller, and the latency simulation is shown as Figure 5-5. The performance is distinctly improved especially at high SNR, the reason is that it spends more ratio of the time on waiting for ACK/NACK back. It means that we can save the working time and prevent redundant hardware idle with low complexity of computation and control at transmission side. Although other types of ARQ mechanism can also save the working time, it needs high complexity of controller and extra buffer for packets at user's device.

In addition, Figure 5-6 statistics the probability of the experimental result of the frustrated transmission that receiver doesn't receive more than the target number of measurements m_{req}. We consider the various length of raw data and different error constraint containing 1% and 0.1% two cases in the experiment. It is apparent that the under-reception-rates correspond to the targets of outage rates in rough especially in the case of 0.1% error constraint. As a result, we can adjust the transmission to fulfill the different error constraint according to the requirement of QoS.

Actually, the error rate of CS recovery failure at receiver can be lower than the outage rate because it may decode correctly even with fewer measurements than the target m_{req}. It results from that we applied the numerical lower bound of required number of the

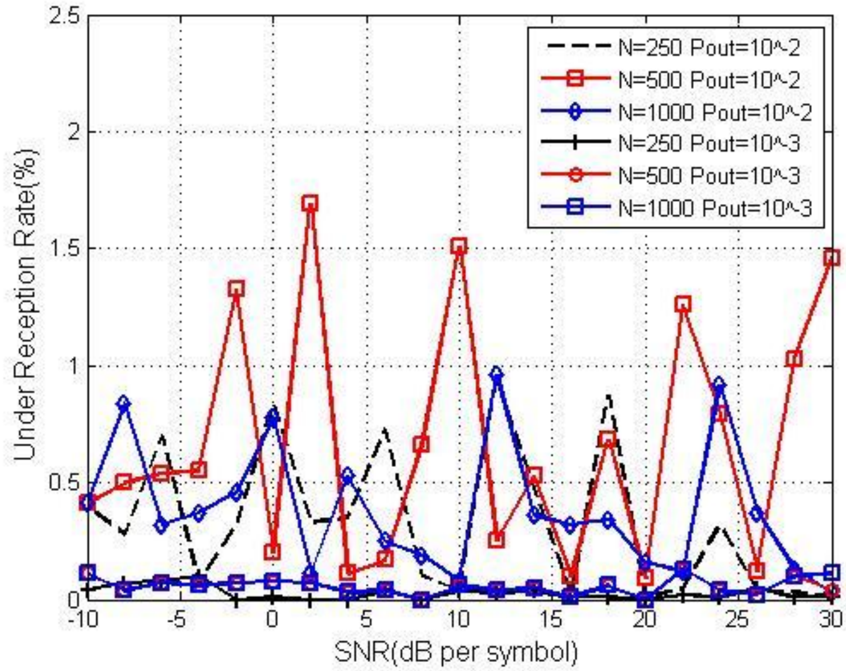

Figure 5-6 The under reception rate resulted from different *N* and outage rate constraint. (*s*=0.5, *L*=8, *H*=224, *A*=20, 10000 samples)

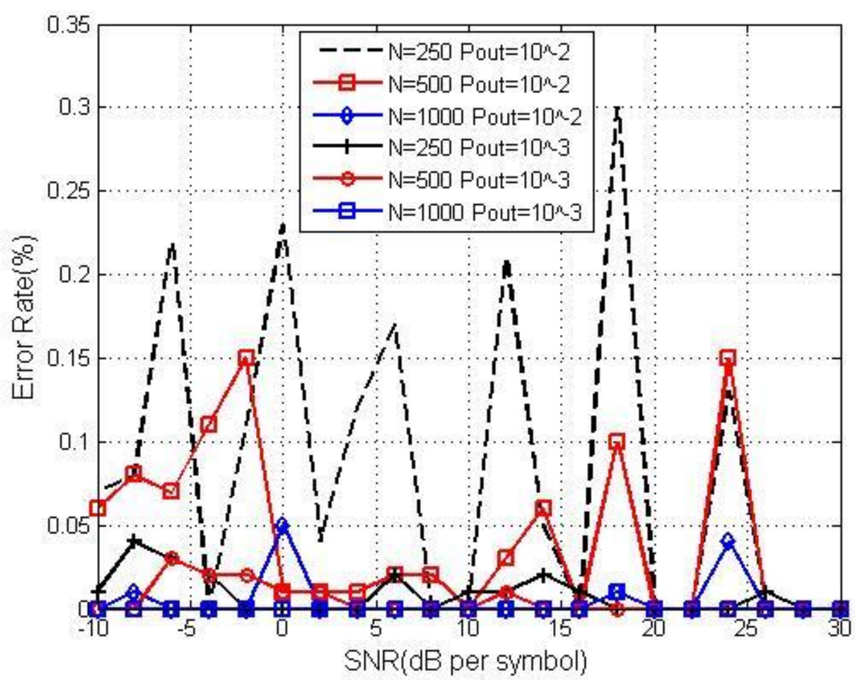

Figure 5-7 The result of CS decoding error rate caused by the lack of measurements. (*s*=0.5, *L*=8, *H*=224, *A*=20, 10000 samples)

measurements to our proposed algorithm to simplify the computation and work at transmission side, and the bound is equal to or higher than the real requirement case by case. Figure 5-7 shows the CS decoding error rate at receiver caused by the lack of measurements. The error rate is directly proportional to the target of outage rate like under-reception-rate, except for that the error rate is lower than the under-reception-rate. Besides, the impact of different N is also shown in the figure, which the larger N has the lower error under the same target of outage rate due to that the given numerical bound is closer to the experimental result with smaller N (see Figure 2-4).

CHAPTER 6
CONCLUSION AND FUTURE WORK

We present a cross-layer design of reliable adaptive transmission for the users applying compressive sensing to wireless communication in this thesis. The proposed system provides an optimal bit-length of measurements and an adaptive link without retransmission policy. The uniform distribution raw data, Bernoulli encoding matrix, and AWGN channel have been considered in this thesis, and the channel coding of convolution code is used to protect the transmitted data away from the noise influence. The proposed optimal bit-length can be evaluated simply by the mathematical calculation in time. The optimal bit-length for a CS measurement efficiently achieves fewer required data saving about 20% bits comparing with the minimal sufficient full-precision bit-length. According to the channel state, SNR γ_s and targeted outage rate, the adaptive link is adopted to minimize the transmission energy which uses the mathematic error bound to select the proper coding scheme for real time system. It accomplishes the goal of lower energy consumption due to the optimal parameter setting. The retransmission is not necessary based on CS's characteristic that the loss of measurements can be supplement by the others, so shorter transmission time is required and the performance improvement is good especially at high SNR. Although there are many techniques to improve the bandwidth-efficiency and avoid redundant hardware ide such as TDD, go-back-to-N ARQ, block ACK and so on, those mechanisms has higher complexity of communication and control and need more buffer to store the uncertain packets. We wish to achieve the reliable transmission with low complexity and hardware cost for the device at transmission side. Besides, it is possible to achieve lower error rate than the target of outage rate.

We hope that each element in the system block model built in this thesis is able to be replaced by the other types of data, coding schemes or channel. It means that the flexible system can be applied to different cases using the similar analysis, the corresponding distribution, corresponding bound and so on. For example, the recovery bound of required measurements can be adjusted according to what kind of CS method is used in the communication system. And the other common channel coding including block code and turbo code can replace the convolution code even jointly use, all we should do is to analyze the corresponding statistic error rate and apply it to the optimization work. In addition, it is possible to further reduce the transmission time if we adopt the real-time decoding given the powerful computational capacity at base station that can stop the transmission early when the decoding result is convergent.

Although the SISO system is considered in this thesis, it can further extend to the MIMO system. Besides, the payload length is our next issue that aggregates different number of measurements into a packet in the future, we think the performance can be further improved. Obviously, the computational complexity must become higher, and it need recursive optimization. It is difficult to obtain the real time transmission. Fortunately, we already has a simplified approach method for adaptive payload length in our previous work if we consider the SNR larger than 5 dB which does not necessarily enhance the signal by repetition. We expect to combine these two works in the future.

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