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Machine Learning Assisted Adaptive LDPC Coded System Design and Analysis

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Abstract: In this paper, we propose a novel machine learning (ML) assisted low-latency low density parity check (LDPC) coded adaptive modulation (AM) system, where short block-length LDPC codes are used. Conventional adaptive modulation and coding (AMC) system includes fixed look-up table method, which is also called inner loop link adaptation (ILLA) and outer loop link adaptation (OLLA). For ILLA, the adaptive capability is achieved by switching the modulation and coding modes based on a look-up table using signal-to-noise ratio (SNR) thresholds at the target bit error rate (BER), while OLLA builds upon the ILLA method by dynamically adjusting the SNR thresholds to further optimize the system performance. Although both improve the system overall throughput by switching between different transmission modes, there is still a gap to optimal performance as the BER is comparatively far away from the target BER. Machine learning (ML) is a promising solution in solving various classification problems. In this work, the supervised learning based k-nearest neighbours (KNN) algorithm is invoked for choosing the optimum transmission mode based on the training data and the instantaneous SNR. This work focuses on the low-latency communications scenarios, where short block-length LDPC codes are utilized. On the other hand, given the short block-length constraint, we propose to artificially generate the training data to train our ML assisted AMC scheme. The simulation results show that the proposed ML-LDPC-AMC scheme can achieve a higher throughput than the ILLA system while maintaining the target BER. Compared with OLLA, the proposed scheme can maintain the target BER while the OLLA fails to maintain the target BER when the block length is short. In addition, when considering the channel estimation errors, the performance of the proposed ML-LDPC-AMC maintains the target BER, while the ILLA system's BER performance can be higher than the target BER.

1 Introduction

Wireless communication requires reliable and robust communication techniques that can adapt to the fading channel for maintaining the quality of service [1]. The primary motivation of applying adaptive modulation (AM) in wireless communication is to combat the fading effects of narrowband channel as well as to increase the overall system throughput by adaptively changing the transmission modulation mode [2]. With the development of emerging communication technologies, the required overall bandwidth has increased dramatically, which in turn requires the AM system to utilise the transmission mode more efficiently. Historically, the research of AM began in 1968, when Hayes [3] adapted the signal amplitude based on the channel environment. In 1994, a variable-rate variable-modulation AM scheme was introduced [4]. The AMC problem has been traditionally addressed through two methods: the inner loop link adaptation (ILLA) and the outer loop link adaptation (OLLA) technique[5]. The ILLA approach involves uses a predetermined look-up table to determine the appropriate modulation and coding scheme based on the channel conditions, which is the conventional solutions to the adaptive modulation and coding (AMC) problems[6]. On the other hand, the OLLA technique builds upon the ILLA method by dynamically adjusting the SNR thresholds to further optimize the performance of the system [6]. In the ILLA scheme, the transmission mode is selected based on the thresholds set according to the channel state information (CSI) fed-back from the receiver. However, the switching thresholds in the ILLA system are usually difficult to implement in practice to achieve optimum performance. This is due to the deficiencies introduced at the various stages of the transmission, including time-varying channel, non-linearity of amplifier and transmission frequency instability [7]. In recent years, the AM was further assisted by machine learning (ML), which shows a near-optimal performance with significantly lower complexity [8].

The world becomes more and more connected with advanced wireless communication technologies. From 1st generation (1G) to the 5th generation (5G) and beyond 5G telecommunication systems, the internet of thing (IoT) requires huge amounts of data transmission between smart devices, such as Radio-Frequency IDentification (RFID) tags, sensors, actuators, mobile phones, etc. to interact with each other and cooperate with their neighbours [9–11]. In the near future, autonomous driving, remote medical surgery and virtual reality (VR) experiences will further interact with the human in daily life [12–14]. In addition, lots of new technologies will emerge benefiting from the higher capacity, higher transmission rate and ultra-low latency of the next-generation wireless network[15]. The 5G new radio (5G NR) cellular system is characterized by three main usage scenarios, namely the enhanced mobile broadband (eMBB), the ultra-reliable and low latency communications (URLLC), and the massive machine type communications, which also requires improved throughput, latency, and reliability [16].

Low density parity check (LDPC) code is a powerful capacity-approaching channel coding technique, which has been selected as a candidate in the 5G NR standard [17]. As a powerful channel coding scheme, LDPC codes are designed to support high throughput and variable code rate in addition to their powerful error correcting capability [16]. Many IoT applications including industrial automation, haptic feedback in virtual/augmented reality and the tactile internet require URLLC[18]. Given the low latency requirements of such IoT applications, in this paper we consider the use of short block length LDPC coded system.

The utilization of high coding rate channel codes is crucial to improve the coded throughput performance [2]. The general motivation of applying channel coding in AM system is to utilize its error correcting and detection capability to improve the bit error rate (BER) and throughput performance compared with the uncoded AM system [2]. Lots of research have been done on combining channel coding with AM, which forms AMC system. For example, a convolutional coded AM system was investigated in fading environments in [19], while turbo coding has also been investigated in [20, 21]. LDPC coded AM system was also investigated with irregular modulation that applies different coding rate in different sub-blocks of a codeword [22].

Table 1 Comparison of the State-of-the-art AMC systems

	Adaptive Modulation	Coding	Channel Estimation Error	Short Block Length	Machine Learning
Liu et al. (2020) [7]	x				x
Zhou et al. (2005) [27]	x		x		
Yang et al. (2019) [8]	x				x
Kojima et al. (2019) [28]	x	x			x
Ha et al. (2006) [29]		x		x	
Paris et al.(2004) [30]	x		x		
Daniels et al. (2010) [31]	x	x			x
Ha et al. (2019) [32]	x				x
Mota et al. (2020) [33]	x	x			x
This work	x	x	x	x	x

More specifically, fixed mode transmission with fixed modulation scheme cannot satisfy the increasing need of the data throughput. Traditional communication system requires fixed modulation order while the AM system takes the channel condition into consideration. AM technique has been used to change the modulation scheme at the transmitter based on the CSI from the receiver. The aim is to increase the throughput by switching to higher modulation order when the channel quality is improved. By contrast, a lower modulation order is used when the channel quality degrades. Prior research has been done in the conventional AM system including ILLA and OLLA [23]. The AM estimates the CSI and feed them to the transmitter to decide the suitable modulation scheme [24, 25]. Same method has also been applied in global navigation satellite system where six modulation and coding schemes (MCS) have been applied [26].

However, the thresholds in the ILLA scheme are often not optimum due to the uncertainty from the hardware and the channel [7]. The common issue with existing AMC systems is either inaccuracy due to model-based approximations or unmanageability due to large-scale lookup tables [34, 35]. By contrast, ML is capable of jointly optimizing the AMC-aided system by using a unified non-linear framework [36]. During the past few decades, ML has been widely applied in many fields of study, such as natural language processing (NLP), predictive analytics and computer vision [37, 38]. It is also commonly applied in wireless communication systems to improve the system performance and reduce the complexity [39].

On one hand, long block-length codes tend to give very sharp edge in the BER curves, where the AMC switching boundaries are not overlapping and hence ML is not needed for classifying these boundaries. On the other hand, short block-length codes would not be able to provide training data at low BER although their AMC switching boundaries overlapped and ML based classification is beneficial.

The foundation of AM can be simplified as a classification problem, which can be solved by different ML techniques. In recent years, researchers have applied different ML techniques to the AM problem, as in [7, 39]. KNN algorithm has been widely applied in uncoded AM system design. In [40], the KNN aided MIMO-OFDM-AM framework was regarded as a classification problem using channel quality information (CQI), transmitted signal energy and receiver noise power. Recently, KNN algorithm was applied in OFDM-aided system supported by the compressed sensing assisted index modulation (OFDM-CSIM), where the KNN algorithm was used to maximize the system's throughput [7]. A so-called E_{COST} KNN method was proposed in [41] to improve the performance of link adaptation (LA) of MIMO systems. The CQI of the MIMO system is used to get the corresponding modulation coding scheme (MCS). By minimizing the E_{COST}, the parameters of the learning method are adjusted to improve the spectral efficiency. Similar method has also been utilized for AMC in underwater acoustic communications [42].

Support Vector Machine (SVM), also known as maximum margin classifier, has also been applied in adaptive transmission for classification problem [31, 43, 44], where [43] and [44] used the training dataset offline, while [31] applied the online training data, which updates the channel environment simultaneously for higher accuracy.

Reinforcement learning (RL) is also a popular ML technique applied in wireless communication [45]. The agent automatically determine the optimal behaviour to achieve a specific goal based on the feedback it receives from the environment in which it operates after taking an action from a known set of appropriate actions [46]. The RL assisted AMC selection system has been exploited, where the proposed RL-AMC framework was used to overcome the mismatch between the present channel state and the feedback CQI caused by time delay, known as CQI ageing [47]. Specifically, the proposed RL-AMC framework determines the best MCS based on the previous AMC decisions by comparing the correction factors, which significantly reduce the impact of channel estimation errors on link adaptation.

In [48], the AMC mode selection is based on the real-time signal to interference-plus-noise ratio (SINR) value by interacting with the radio channel. More specifically, the mean SINR value was used to identify the channel environment states. Then, based on MCS, the interactions with the environment and optimal policy, the optimal MCS can be chosen. RL based AMC technique was also investigated in 5G NR networks in [6], where the proposed framework trains the agent at specific time instants using the Q-learning algorithm. Compared to [48], the agent finds its best policy by considering the values of a predefined action-value Q-function $Q^{\pi}(s_t, a_t)$, which represents the overall expected reward for taking an action a_t in a state s_t and then following a policy π. However, the applications of ML for AMC in [6, 47, 48] are all related to channel estimation mismatches rather than related to improving the throughput.

Deep learning (DL) is part of a broader family of ML methods based on artificial neural networks (ANN) [28]. The application of deep neural network (DNN) in wireless communication has attracted a lot of research interest in recent years [49, 50]. Examples include CSI prediction [51, 52], MIMO system design [53] and sparse code multiple access (SCMA) application[54]. The modern wireless communication networks become increasingly complicated because of various channel coding techniques and MIMO applications, which requires high-load computing capacity and large data sets. DL has the advantage of providing high prediction accuracy over channel variation, interference, etc. by utilizing the hidden layers to abstract the in-depth patterns of the input parameters [55]. In [28], a similar work has been done by introducing convolutional code in AM design using ML. ANN was applied to estimate the received SNR by extracting the features from the power spectrum density (PSD) at the receiver. The ANN algorithm showed very high accuracy in SNR estimation. Although the proposed framework is similar with this work, the main target in [28] is to increase the accuracy of SNR estimation while this work is to optimise the AM system design in order to increase the throughput while maintaining a low BER. In [39], DNN was applied in uncoded adaptive index modulation system for mmWave communications, where the DNN improves the throughput compared to the ILLA system.

The large amounts of data available can be redundant and highly correlated, which can reduce the efficiency of ML algorithm. The principal component analysis (PCA) technique can be applied to reduce the complexity of raw data, which shows significant performance improvement when preprocessing high dimensional data [56–60]. In [32], the proposed hybrid DNN-PCA assisted AM framework shows the advantage on the throughput performance. The PCA block implements unsupervised learning to improve the performance of classification performance of supervised learning, therefore the PCA can transform the raw data features into a more easily interpreted format for the DNN to work more efficiently.

In summary, ML assisted AMC schemes have not been properly investigated in the literature. In this paper, we invoke the k-Nearest Neighbour (KNN) supervised learning technique, which is based on majority voting rules of the nearest K neighbours. The basic idea of KNN assisted AMC system is to classify the instantaneous target signal-to-noise ratio (SNR) value based on the artificially generated training dataset. The decision is used to choose the modulation type and the coding rate for the next transmission frame.

Compared with other ML techniques, the advantage of applying KNN algorithm to solve the classification problem is that it does not require the information of the functional mapping between the classifier and the feature sets, and it does not require any knowledge or assumption of the collected data distribution in practical scenarios [61].

Against this background, we propose a ML assisted short block-length LDPC coded AMC (ML-LDPC-AMC) system. We commence with a single objective aimed at improving the throughput while maintaining the target BER. We use KNN as an example to show the advantages of ML applied in AMC systems. The contributions of this paper are summarized as follows:

1. We propose a short-delay ML-LDPC-AMC scheme by applying short block-length LDPC code. In the proposed system, the modulation order and coding rate are adaptively chosen according to the ML decision, which was trained based on the varying channel condition, with the objective of maximizing the overall throughput at a target BER. Our proposed system is beneficial to the low latency scenario.
2. For a short block-length LDPC code, the simulation uses the frame length of less than 1000 bits, which results in the instantaneous BER being consistently higher than the target BER of 10^{-3}. In other words, collecting the training data for the ML model becomes infea-sible. Therefore, we propose a method to generate the training data artificially. The ML algorithm considered was KNN, where the near-est K neighbours were considered to make the decision. We use KNN as an example to show the advantages of ML applied in AMC systems.
3. We also consider the effect of channel estimation error on the performance of the considered system. The simulation results show that our ML-LDPC-AMC system can maintain the target BER while the conventional ILLA system does not meet the target BER when the channel estimation error is considered.
4. The novel low-latency ML-LDPC-AMC system is capable of choosing better transmission modes than the ILLA and OLLA methods while always maintaining the required BER performance. The throughput is improved at a given SNR compared to the ILLA method.

In Table 1, we explicitly contrast this work to the most relevant adaptive system design. The rest of the paper is organised as follows, Section 2 discusses the design of the proposed ML-LDPC-AM system and then Section 3 discusses the simulation result by comparing to the ILLA system. Finally, Section 4 concludes the paper.

2 Proposed ML-LDPC-AMC System

2.1 LDPC coded System Model

In this section, we discuss the short block-length LDPC coded system, as shown in Fig. 1. We first describe the transmitter and receiver processing without the 'Adaptive Algorithm' block in Fig. 1. The input binary information bits are encoded by an LDPC encoder, where the LDPC encoder introduces parity bits into the input bit stream. Due to the latency requirement, short block-length LDPC code was considered with the maximum output bits length less than 1000 bits [62]. After the encoding process, M-ary modulator would map the coded bits onto M-ary symbols, where the modulation scheme used are M-ary phase shift keying (M-PSK) and M-ary quadrature amplitude modulation (M-QAM). We consider a Rayleigh fast and slow fading channel, where there is no line of sight (LoS) from the transmitting antenna to the receiving antenna. The received signals are first soft demodulated by the M-ary demodulator, then decoded by the LDPC decoder.

Adding parity bits into a bit stream can ensure that information bits are correctly decoded at the receiver. In this process, actual throughput is decreased as parity bits are considered as redundant bits, which has no information. Therefore, the number of parity bits must be considered to balance between detection performance and throughput. For the subject of block code, code rate R is given by

$$R = \frac{k}{n}, \tag{1}$$

where k is the number of input bits into the encoder and n is the number of output bits from the encoder, which is called block length. The number of parity bits added is $n-k$, while the n output bits will be modulated by M-ary PSK/QAM after the encoding process. In order to maximize the throughput of a LDPC coded system and to operate near Shannon capacity, only one parity bit is added to each modulated symbol. Based on the multilevel coding principle [63], the code rate of LDPC code in this case is given by

$$R_{LDPC} = \frac{\log_2(M) - 1}{\log_2(M)}, \tag{2}$$

or close to it. In other words, each M-ary modulation symbol consist of one LDPC parity bit and $log_2(M) - 1$ information bits.

In addition, the latency of the transmission should also be considered. Specifically, short block-length code has been applied in URLLC system, which is designed as a part of the recent 5G NR standard that aims to improve the transmission accuracy and reduce delay[17]. The challenge of implementing a short block-length LDPC code is to maintain a BER at the acceptable level.

2.2 Achievable Rate

The number of information bit transmitted per modulated symbol is given by [64]:

$$\eta = \log_2(M) R_c \ , \tag{3}$$

where M is the number of modulation levels and R_c is the code rate of the channel encoder. Finally, the average received SNR of a symbol experiencing Rayleigh fading channel can be represented by [64]:

$$\gamma_r = \frac{E_b}{N_0} |h|^2 \eta \ , \tag{4}$$

where the channel gain is $|h|^2$ and $\frac{E_b}{N_0}$ is the SNR per information bit. The received signal y can be modeled as

$$y = hx + z \ , \tag{5}$$

where h represents the complex Gaussian channel fading, x represents the transmitted signal and z represents the additive noise. The closed-form channel capacity of Rayleigh fading channel for Continuous-Input Continuous-Output Memoryless Channels (CCMC) is expressed in [65] as

$$C_{Ray,CCMC} = \mathbb{E}\left[\log_2(1 + \gamma_r)\right] \ \text{[bit/s/Hz]}, \tag{6}$$

where $\mathbb{E}(\cdot)$ denotes the expected value of $(\cdot)$, which is averaged over h and z. As for the Discrete-Input Continuous-Output Memoryless Channel (DCMC), its capacity is further limited by the modulation

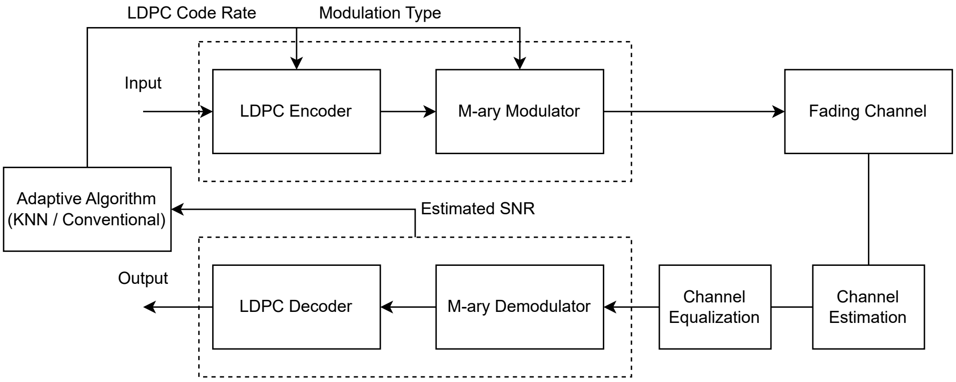

Fig. 1: System block diagram.

scheme used. The DCMC is presented in [65] as

$$C_{Ray,DCMC} = \log_2(M) - \frac{1}{M}\sum_{m=1}^{M}\mathbb{E}\left[\log_2\sum_{n=1}^{M} e^{\Phi_{m,n}} x_m\right], \tag{7}$$

where M is the number of modulation levels of PSK/QAM scheme and $\Phi_{m,n}$ is given by

$$\Phi_{m,n} = \frac{-|h(x_m - x_n) + z|^2 + |z|^2}{N_0}. \tag{8}$$

2.3 Link Adaptation

The purpose of LA is to adjust the various parameters of the communication link to optimize its performance based on the current channel conditions and the requirements of the data being transmitted. Traditional LA schemes include ILLA and OLLA, where the ILLA is used to determine the optimal MCS based on the predefined fixed look-up table, given the estimated SNR values. The OLLA method is proved to increase the throughput further by adjusting the estimated SNR value with an offset (Δ_{OLLA}) value, which is updated online based on a feedback representing the accuracy of the transmitted information [33]. To be more specific, the OLLA updates the esti-mated SNR value up and down (*i.e.*, Δ_{up} and Δ_{Down} respectively) based on the Hybrid Automatic Repeat Request (HARQ) acknowl-edgments (ACKs) and negative acknowledgments NACKS, received from the User Equipment (UE) [33].

Let us denote the index of a transmission time interval as k. The evolution of the discrete time OLLA offset is given by [33]:

$$\Delta_k^{OLLA} = \Delta_{k-1}^{OLLA} + \Delta_{up}\cdot e_k - \Delta_{down}\cdot(1-e_k), \tag{9}$$

where $e_k = 0$ for ACK, and $e_k = 1$ for NACK. In this paper, we consider four OLLA schemes, denoted as OLLA 1, 2, 3 and 4, which consider Δ_{up} 0.001dB, 0.01dB, 0.1dB and 1dB, respectively, as suggested in [33, 66].

2.4 Adaptive System Design

In this section, we discuss the proposed the ML assisted short block-length LDPC coded AMC system, as shown in Fig. 1. Based on the single loop of the LDPC coded system, we add the adaptation to the existing system by considering the 'Adaptive Algorithm' which implements the feedback information (the estimated SNR) from the receiver side. Having the CSI information at the transmitter, the modulation and coding modes can be adapted to achieve the optimum throughput for the given channel fading [40, 47]. The ILLA system uses a pre-defined lookup table of MCS based on the estimated CSI [47, 67]. The details the proposed ML-LDPC-AMC system are described below.

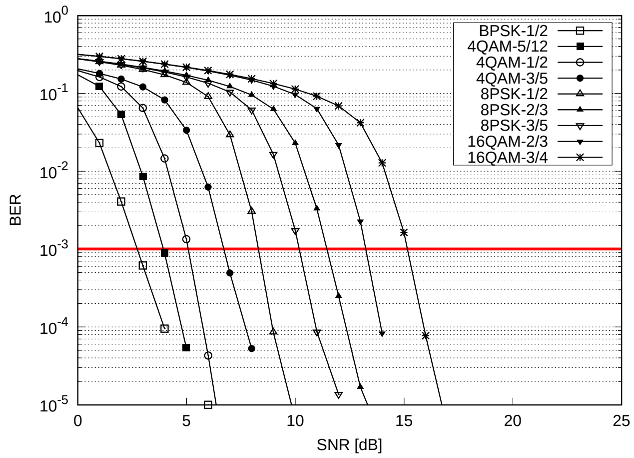

Fig. 2: Average fixed mode simulation result to obtain the thresholds.

Table 2 Switching Thresholds for Conventional Scheme at a target BER of 10^{-3}.

Mod	Rate	Tp	SNR Thresholds(dB)	
			Perfect Channel	$\theta_{Noise} = 1\%$
BPSK	1/2	1/2	0.991	1.158
4QAM	5/12	5/6	2.521	2.695
4QAM	1/2	1	3.825	4.040
4QAM	3/5	6/5	5.495	5.745
8PSK	1/2	3/2	7.228	7.575
8PSK	3/5	9/5	9.030	9.509
8PSK	2/3	2	10.333	10.960
16QAM	2/3	8/3	12.273	13.137
16QAM	3/4	3	14.120	15.544

The 'Adaptive Algorithm' as shown in Fig. 1 can work as either conventional based or ML-aided. Both of the algorithms are used to make a decision concerning the transmitter parameters for the next transmission frame. Specifically, index i is referred to as a class, and the corresponding mode, namely, $MODE_i$ corresponds to a given coding rate and modulation type. In the ILLA system, a fixed lookup table consist of pre-defined SNR thresholds at the target BER. Fig. 2 illustrates an example of the curves of average BER against SNR over a flat Rayleigh fading channel of the 9 modes mentioned in Table 2. The SNR thresholds at BER = 10^{-3} for look-up table based AM system are shown in Table 2. The SNR switching threshold values of the ILLA system are the crossover point between the average BER curve and the target BER level of 10^{-3}. In Table 2, 'Mod' represents the modulation scheme and 'Tp' represents the throughput with the unit of bits per symbol (BPS).

Additionally, we have investigated the effect of channel estimation error in our AMC scheme. Due to the powerful decoding ability

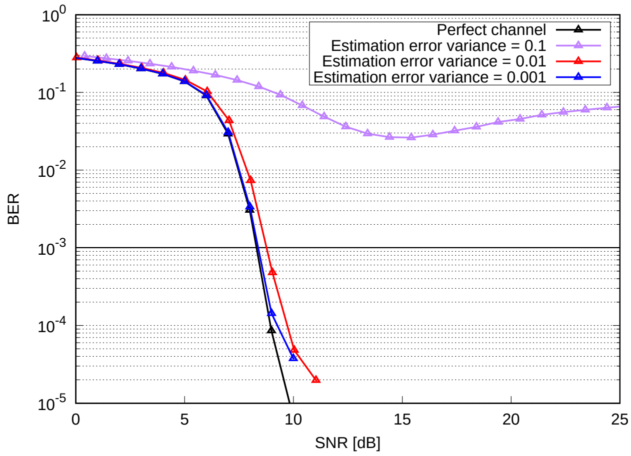

Fig. 3: BER performance of the 8PSK with half rate LDPC coded system with different channel estimation error noise variance.

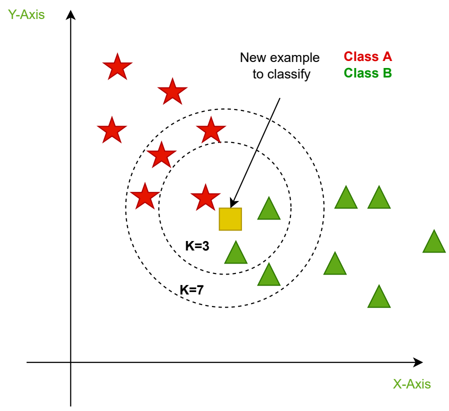

Fig. 4: A simple KNN illustration for cases of K=3 and K=7 [69].

of LDPC code, low estimation error will not affect the performance, where the estimated channel is given by $\hat{h} = h + n$, with n representing the channel estimation error with a specific variance [68]. The corresponding SNR thresholds are given in Table 2, where the channel estimation error noise variance (θ_{Noise}) is chosen as 1%. In Fig. 3, different estimation error variance values are examined. As shown on Fig. 3, the effect of channel estimation error having a variance of 1% has very little effect on the performance.

2.5 *KNN for Adaptive System Design and Training Data Generation*

KNN algorithm has been widely used for solving classification problems [70], where the simple non-parametric procedure decision rule to determine the K-closest neighbours is based on the majority voting principle. Fig. 4 illustrates a simple KNN decision making diagram, where the dash line circle around the example has several red stars and green triangles. The inner dotted line circle represents group of the nearest 3 neighbours (k=3). Inside the circle, there are two green triangles with one red star. According to the majority voting rule, the target star is classified as Class B. In other words, the number of samples inside the circle represents the value of k, which means the nearest neighbour.

In order to determine the transmission parameters such as coding rate and modulation type, the KNN algorithm has to be trained with the training data. Valid training data should train the system to maintain a BER that is lower than 10^{-3}. Hence, the training BER data should also be lower than 10^{-3}.

For a short block-length LDPC code (less than 1000 bits per frame), the BER in a frame cannot be lower than 10^{-3} if there are

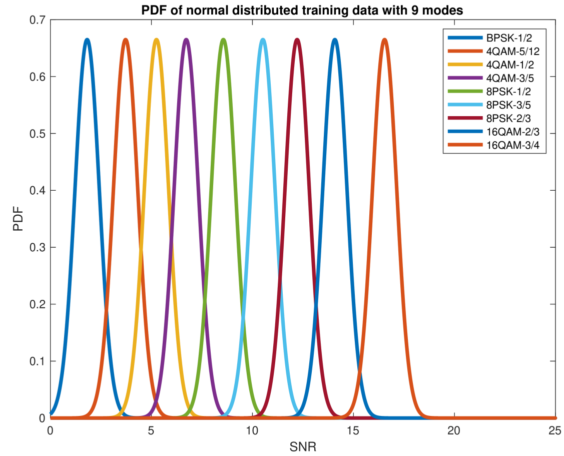

Fig. 5: Plot of PDF vs SNR of the artificially generated training data.

erroneous bits after LDPC decoding. In other words, for any given frame, the BER value of the simulation output are always higher than the target BER level (10^{-3}) except the values at BER=0. Hence, for short block-length, there is no valid training data that can be used as there's no valid training data below the target BER that can be used to train the model.

In this work, the training data is artificially generated based on a Gaussian distribution with a mean value of μ and a variance of σ. An example probability density function (PDF) of the 9 modes training data plot is shown on Fig. 5.

There are 9 modes in our scheme and each mode has 1000 training data. The mean value μ of the training data is taken from the average value of two SNR thresholds at two different BER level, 10^{-3} and 10^{-4}. In other word, instead of just considering the thresholds value at 10^{-3}, taking the middle SNR values at BER of 10^{-3} and 10^{-4} could provide a higher order modulation, which in turn could improve the throughput. Moreover, both Rayleigh distributed training data and Gaussian distributed training data have been tested. We found that Gaussian distributed training data can maintain the target BER value better than that of the Rayleigh distributed one.

During the model testing, 80% of the training data has been randomly selected to train the model and the rest are used to test the model. The accuracy of the model can achieve 81.2% when K=20. Please note that in wireless communications we use different measure of performance such as throughput and BER, which give a more accurate characterization of the system compared to the accuracy. The 81.3% accuracy is capable of providing an improved performance as will be shown in the following section.

3 Result and Analysis

Table 3 Parameters of fixed mode simulation, where 'NrMS' represents the number of modulated symbols and 'Tp' represents the information throughput.

No.	Mod	M	Rate	L_k	L_n	NrMS	Tp(BPS)
1	BPSK	2	1/2	120	240	240	1/2
2	4QAM	4	5/12	200	480	240	5/6
3	4QAM	4	1/2	240	480	240	1
4	4QAM	4	3/5	288	480	240	6/5
5	8PSK	8	1/2	360	720	240	3/2
6	8PSK	8	3/5	432	720	240	9/5
7	8PSK	8	2/3	480	720	240	2
8	16QAM	16	2/3	640	960	240	8/3
9	16QAM	16	3/4	720	960	240	3

In our simulation, the slow fading channel coefficient is set to $-2 < 10\log_{10}|h_s|^2 < 2$ dB. All other simulation parameters are

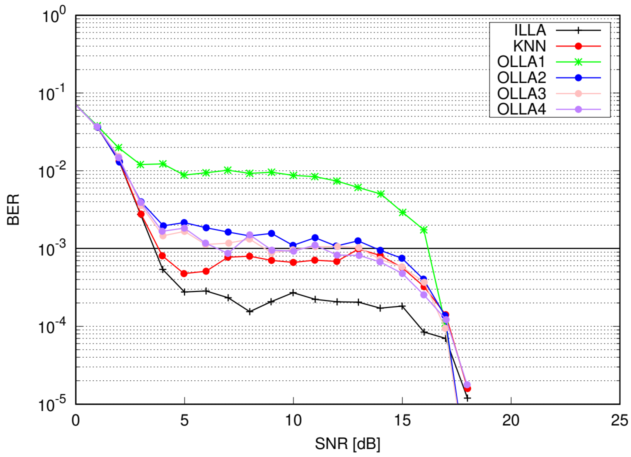

Fig. 6: BER result of adaptive system with perfect channel.

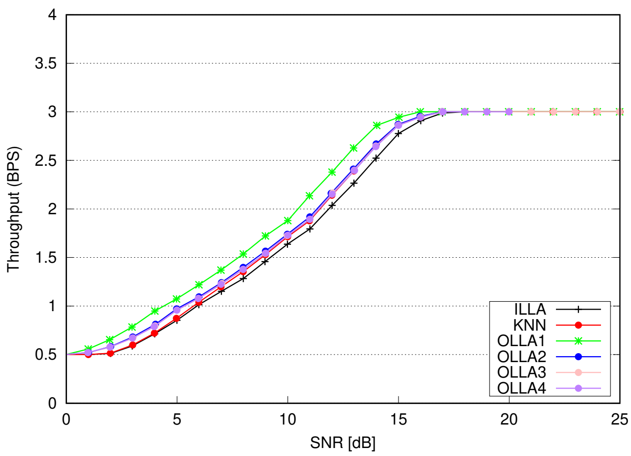

Fig. 7: Throughput performance result of adaptive system with perfect channel.

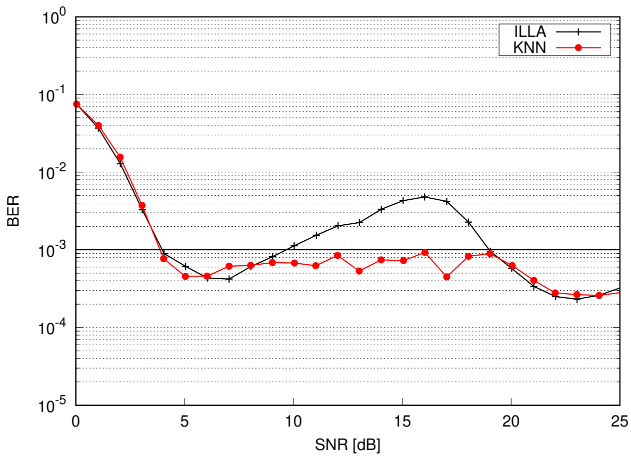

Fig. 8: BER result of adaptive system considering channel estimation error (error variance of 1%).

shown in Table 3, where 'L_k' represents the number of LDPC input bit length and 'L_n' represents the number of LDPC output bit length. The short block-length LDPC code has a maximum block length of 1000 bits per frame.

As shown in Fig. 6, the BER curve of both the KNN assisted and ILLA system can maintain the target BER below 10^{-3}, where the BER curve of the KNN assisted AMC scheme has a BER curve that

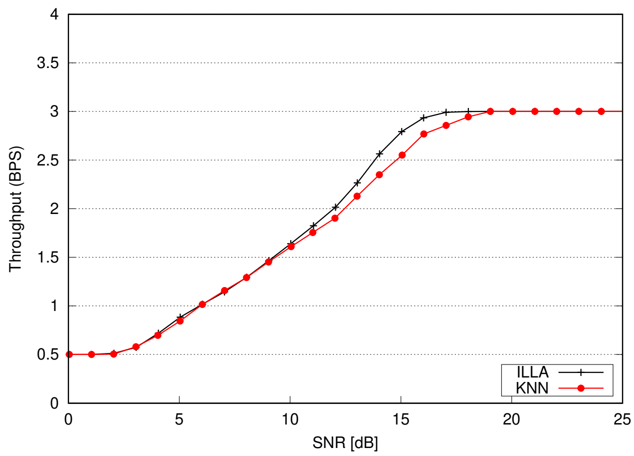

Fig. 9: Throughput performance result of adaptive system considering channel estimation error (error variance of 1%).

is closer to the target BER compared to that of the ILLA system. However, all of the BER curves of the OLLA method are above the target BER of 10^{-3} when considering the short block-length LDPC code. The BER performance of OLLA system becomes better with the smaller Δ_{up} value, but the lowest Δ_{up} value of 0.001 dB still cannot satisfy the BER requirement of 10^{-3}.

As shown in Fig. 7, the KNN assisted AMC system achieves a higher throughput than the ILLA system for all SNR range. In other words, the KNN assisted AMC system can satisfy the target BER requirement while improving its throughput. The throughput curve of both ILLA and KNN assisted AMC system starts from 0.5 BPS when the BPSK half-rate mode was applied prominently. The throughput curve grows steadily based on the 9 modes as seen in Fig. 7, where both KNN and ILLA schemes could achieve the maximum 3 BPS, because the last mode used is the rate-3/4 16QAM mode. However, the KNN assisted AMC system can achieve a higher throughput compared to that of the ILLA method at an SNR range of 4dB to 17dB.

The results shown in Fig. 8 considers the effect of channel estimation error. As discussed before, the estimation error variance is set to 1%. As shown in Fig. 8, the BER curve of both KNN and ILLA system is below the target BER when SNR is smaller than about 10dB. At the SNR range of 10dB to about 18dB, ILLA system fails to maintain the target BER, while the KNN-aided system performance can still maintain the target BER requirement. As shown in Fig. 9, the throughput curve of the ILLA system is higher than that of the KNN assisted AMC from a SNR of 10dB, where its BER performance fails to meet the target.

4 Conclusion

In this contribution, we proposed a novel ML-LDPC-AM system by using the KNN algorithm, where our system is specifically designed for short block-length LDPC code, which has the advantage of short delay and low latency. As our target BER is 10^{-3}, it was not possible to generate valid training data during the fixed mode simulation of each LDPC coded modulation scheme. Hence, we proposed a technique to artificially generate training data to train the KNN assisted AMC system. From our simulation, we found that for given throughput, the SNR performance gain is improved by 0.5 dB compared to the ILLA system, when assuming perfect channel knowledge. Moreover, the proposed system has the advantages compared with the OLLA methods in maintaining the BER below the target.We also investigated the effect of channel estimation error, where we showed that our proposed ML-LDPC-AM system is capable of maintaining a BER below the target BER threshold, while the conventional ILLA based AMC system fails to maintain the required target BER requirement.

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