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Cross-Layer Approach using k-NN Based Adaptive Modulation Coding (AMC) and Incremental Redundancy Hybrid Automatic Repeat Request (IR-HARQ) for MIMO

J. Sofia Priya Dharshini, Dr. M. V. Subramanyam, Dr. K. Soundararajan

Abstract – **In MIMO Technology, a cross layer design enhances the spectral efficiency, reliability and throughput of the network. In this paper, a cross-layer approach using k-NN based Adaptive Modulation Coding (AMC) and Incremental Redundancy Hybrid Automatic Repeat Request (IR-HARQ) is proposed for MIMO Systems. The proposed cross layer approach connects physical layer and data link layer to enhance the performance of MIMO network. By means of MIMO fading channels, the coded symbols are forwarded in the physical layer on a frame by frame fashion subsequently using Space Time Block Coding (STBC). The receiver computes the signal to noise ratio (SNR) and forwards back to the AMC controller. The controller selects a suitable MCS for the next transmission through k-NN classifier supervised learning algorithm. IR-HARQ is utilized at the data link layer to regulate packet retransmissions. The obtained results prove that the proposed technique has better performance in terms of throughput, BER and spectral efficiency.**

Keywords – **Adaptive Modulation and Coding, Algorithm, Incremental Redundancy-Hybrid Automatic Repeat Request, Technique-Nearest Neighbor Classifier.**

I. Introduction

The most important technique in the rear of Multiple Input Multiple Output (MIMO) technology is space-time signal processing. It processes both the time and spatial dimensions by exploiting multiple spatially distributed antennas. Using spatial multiplexing, the MIMO technology enhances data transmission rate and using space-time coding techniques, it improves reliability. When Adaptive Modulation and Coding (AMC) scheme is used along with MIMO technology, it increases spectral efficiency by amending transmission parameters to the channel condition but still satisfying the target error performance [1].

A designing mechanism that brings together the layers in order to enhance the system spectral efficiency and throughput while still maintaining delay and performance constraints is referred as cross layer architecture. Literatures on cross layer design incorporate AMC at the physical layer with automatic repeat request (ARQ) protocol at the data link layer. The cross layer design permits the interaction of data link layer with the network layer and higher layers. Achieving high spectral efficiency is the main motive behind integration of the adaptation ability of the AMC and the error-correcting capability of ARQ. At the data link layer, the ARQ protocol appropriates the infrequent packet errors and at the physical layer, the error control necessity is lessened for AMC. The AMC transmissions assure the required performance by means of the error-correcting capability of the truncated ARQ that relies on the highest permitable number of retransmission [2][3]. The grouping of AMC with the truncated ARQ protocol enhances throughput, reduces packet loss, and satisfies delay requirements for delay-sensitive traffic and buffer sizes [4].

To improve the transmission reliability and robustness of the network at the physical layer, it is essential to amplify the transmit power that drains out the battery life or reduce the transmission rate by choosing a smaller constellation size or declining the code rate of forward error correction coding. Above and beyond, implementing spatial or polarization diversity solutions at the physical layer may not be a possible solution in practical on minute sized sensor nodes. The lack of ARQ protocol permits retransmissions of redundant packets and diminishes the reliability and system throughput when put side by side with using forward error correction (FEC) codes at the physical layer only [5][6].

Yuling Zhang et al. [7] have proposed a cross-layer design framework. Their framework incorporates adaptive modulation and coding (AMC) with hybrid automatic repeat request (HARQ). Cross layer design has been operated on Rate-Compatible Low-Density Parity-Check codes (RC-LDPC) in MIMO fading channels with estimation errors. They have introduced a new puncturing pattern for RC-LDPC codes. RC-LDPC codes are applied with the new puncturing pattern to the cross-layer design combing AMC with ARQ over MIMO fading channels. The effect of channel estimation errors on the system throughput is also investigated. Considerable spectral efficiency gain was achieved. Xin Wang et al. [8] have proposed a new design that in cooperation makes use of the error-correcting capability of the truncated ARQ protocol at the data link layer and the adaptation ability of the AMC scheme at the physical layer. The main objective of cross layer design is to enhance system performance for QoS guaranteed traffic. The queuing behavior induced by both the truncated ARQ protocol and the AMC scheme is analyzed with an embedded Markov chain. The advantage of this approach is that the overall system throughput is maximized under the specified QoS constraints. Jalil S. Harsini et al. [9] have proposed a cross layer design approaches for hybrid ARQ (HARQ) protocol in wireless networks. Their protocol has employed AMC at the physical layer and is subject to time-correlated fading channels. They have derived throughput and the packet loss probability based on a rate compatible punctured convolution (RCPC) code family by means of a Markov channel model that is applicable for the temporal correlation in successive parity transmissions by the adaptive rate HARQ protocol .Further, the authors have presented a cross-layer AMC design that has considered the performance gain of the HARQ protocol at the link layer. The advantage of this approach is that throughput of the network is increased and the packet loss is controlled. Robert C. Daniels et al., [10] have proposed a new machine learning framework. Their proposed algorithm used past observations of error rate and the associated channel state information to predict the best modulation order and coding rate for new realizations of channel state without modeling the input-output relationship of the wireless transceiver. Their approach has been operated through the new error rate expression. It is parameterized only by post-processing signal-to-noise ratios (SNR), ordered over subcarriers and spatial streams. Using ordered SNR the authors have proposed a low-dimension feature set that enables machine learning to increase the accuracy of link adaptation. The advantage of this approach is that it improves the performance of the network. Morteza Mardani et al. [11] have put forward a cross-layer approach. Their approach has jointly incorporated AMC at the physical layer and cooperative truncated ARQ protocol at the data link layer. They have derived a closed form expression for the spectral efficiency of their joint AMC-cooperative ARQ scheme. The performance of the system is maximized by optimizing AMC scheme. Tania Villa et al. [12] proposed a scheduling and resource allocation mechanism for latency-constrained operation. Their solution considerably improves the spectral efficiency of delay-constrained networks by exploiting a joint hybrid- ARQ and AMC policy that modifies the number of dimensions (physical resources) used in every round.

From the above literature review, it is evident that there is no work which considers IR-HARQ protocol in conjunction with AMC that uses machine learning techniques. In this paper, a supervised learning technique is considered in which mappings between the SNR and the optimal AMC parameters are contained in the example data. It further captures the SNR through low-dimensional mappings onto a feature space. This paper presents a cross layer design approach for hybrid ARQ (HARQ) protocol in MIMO systems which employ AMC at the physical layer applying k-NN supervised learning with convolution coding and Viterbi decoding.

The organization of the paper is as follows. In the first section the introduction of the proposed system is presented. The proposed model is presented in second section. The main module of the proposed system, k-NN supervised learning is presented in third section. SNR evaluation is given in forth section. Simulation results and conclusions are presented in fifth and sixth sections respectively.

II. Proposed System

In this paper, a cross-layer approach using k-NN based Adaptive Modulation Coding (AMC) and Hybrid Automatic Repeat Request (HARQ) is proposed for MIMO. The proposed cross layer approach connects physical layer and data link layer to enhance the performance of MIMO network. Initially, the coded symbols are forwarded in the physical layer on a frame by frame fashion subsequently space time block coding and then through MIMO fading channels. For every input symbol, the receiver calculates the signal to noise ratio (SNR) and forwards back to the Adaptive Modulation and Coding (AMC) controller. The controller selects a suitable MCS for the next transmission through k-NN classifier supervised learning algorithm. It chooses a set of nearest neighbors of a class considering distance as an essential metric.

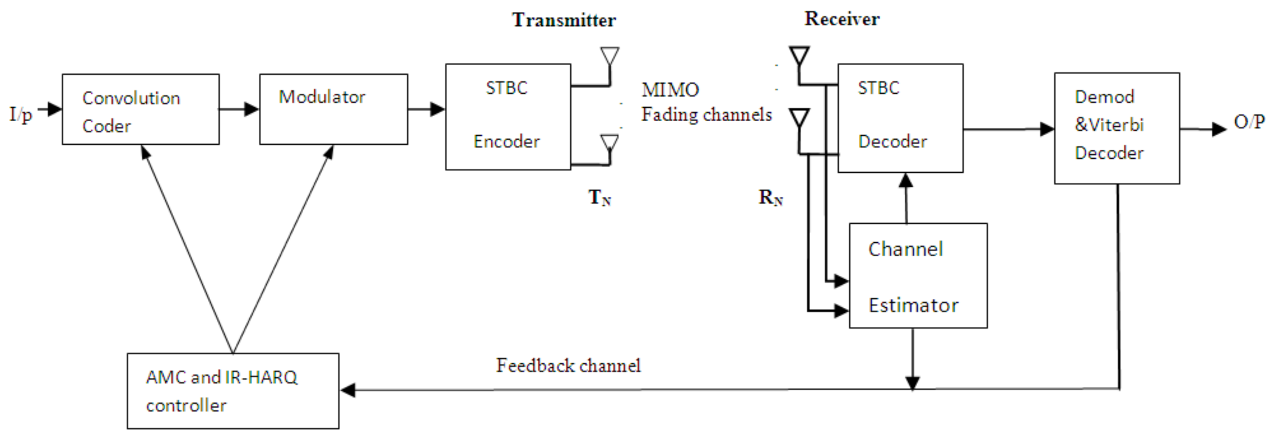

Fig.1. Proposed Network Architecture

When two classes yield a similar number of neighbors, then the class is selected pondering data rate and low index of spatial stream. Hybrid automatic repeat and request (hybrid-ARQ or HARQ) is utilized at the data link layer to regulate packet retransmissions.

Multiple Input Multiple Output (MIMO) system: MIMO system with T_N number of transmitting antennas and R_N number of receiving antennas is considered as shown in Fig.1. The proposed technique uses Convolution Turbo coding (CTC) scheme to achieve diversity. In CTC

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long sequences of message bits are encoded using a finite state machine implemented with shift registers. The memory of the encoder (specified by the number of shift registers) determines the complexity of the code. If for each set of *k* information bits input to the encoder, there are *n* output bits produced, then the code rate is *k/n*. Optimal decoding of a convolution ally coded sequence (in AWGN) is achieved using the Viterbi algorithm. The diversity order is described as:

$$D \overset{\Delta}{=} T_N R_N \quad \text{..... (1)}$$

Where, Y is the received symbols matrix of order $R_N \times nS$ and X is the transmitted symbols matrix of order $T_N \times nS$ and N is the noise matrix of order $R_N \times nS$, the matrix elements are designed as i.i.d. complex circular Gaussian random variables having zero mean and unit variance. *nS* stands for number of symbols per antenna. By means of MIMO fading channels, the coded symbols are forwarded in the physical layer on a frame by frame fashion subsequently with space time block coding. There are many modulation and coding schemes (MCSs) available in the physical layer. The receiver computes the SNR and sends back to the AMC controller. The controller selects a suitable MCS for the next transmission. If ds is the data sequence, it is encoded into z_i code words where i = 0,1,…,Z-1.Therefore more than one code words z_i may contain the part of information in ds. The technique makes use of CTC for encoding *ds* through a rate-1/3 mother code, which is punctured to generate the z_i. Diverse z_i may enclose common systematic or parity bits of the mother code. The length of code words (Le_i) may not be equal.

For the codeword z_i forwarded at every transmission, the received signal is specified as, [13]

$$Y_{i,j} = h_{i,j} x_{i,j} + N_{i,j} \quad \text{....... (2)}$$

Here, Block flat fading is considered for the channel remains constant during the transmission of one symbol. If the channel is known only at the receiver, the receiver tries to decode the received data. If no error detected or the decoder corrects the errors then the successful reception is indicated to the transmitter. Then, the system progresses on transmitting a new data sequence ds. Upon a failure, a retransmission is invoked. Previously transmitted data are tracked at the receiver in order to associate the decoding, since the channel is known only at the receiver.

IR-HARQ: Incremental Redundancy Hybrid Automatic Repeat Request (IR-HARQ) is used in the data link layer to reduce the number of retransmissions and meet the delay constraints. A Maximal Ratio symbol Combining (MRC) approach is used to bring into being a symbol sequence $\tilde{Y}_0$, which will be transmitted to a Maximum-Likelihood (ML) receiver. When Maximum Ratio symbol Combining (MRC) is used along with a block-fading channel, the received symbols are collaborated as [14],

$$\tilde{Y}_0 = \sum_{i=0}^{n-1} h_i^* Y_i = \tilde{h}_0 x_0 + \sum_{i=0}^{n-1} h_i^* n_i = \tilde{h}_0 x_0 + \tilde{z}_0 \quad \text{..... (3)}$$

Where, $\tilde{h}_0 = \sum_{i=0}^{n-1} h_i^* h_i$ and n stands for the number of transmissions. To measure the Log-Likelihood Ratios (LLRs), the ML receiver uses $Y_0' = \frac{1}{\sqrt{\tilde{h}}}\tilde{Y}_0$ and $\sqrt{\tilde{h}}$, which will be transmitted to the decoder so as to estimate the information sequence *ds*. At each retransmission, different code words z_i are forwarded in IR-HARQ.

III. Supervised Learning

Machine Learning is a technique using which the performance of the system is enhanced through a series of data observation.

In this paper, it is intended to use the machine learning for classification process. Data observation is done through a supervised learning technique for AMC. Supervised learning requires a training set that includes channel realization information such as ideal coding rate, modulation order and the number of spatial streams. The training set is obtained from system measurements of physical layer. In this paper, SNR is taken as a measurement from the physical layer. SNR estimation procedure is given in section-4. Supervised classification scheme is shown in Fig.2 In MIMO system model, the AMC scheme is utilized to choose the Quadrature Amplitude Modulation (QAM), Modulation order (M_O), Convolution Coding Rate (C-C_R) and the number of spatial streams (*nS*). In exact, AMC scheme is exploited to select appropriate Modulation and Coding Scheme (MCS). It is assumed that MCS list is finite and the list is indexed with $i \in I_L \subset L$. Here, the cardinality of I_L symbolizes the number of on hand M_O, C-C_R and *nS*. In this paper, index is termed as the class, it maps the channel information M_O, C-C_R and *nS* and then characterizes MCS_i. Considering the triplets namely M_O, C-C_R and *nS,* every class is mapped to a single data rate (DR_i). The classification process of AMC chooses a class i according to MCS_i.

This process ensures the enhancement in data rate DR_i even in the different conditions of the channel state. A class is selected by AMC considering SNR value of MCS_i for a specific channel. The class '*i'* is preferred only when the associated SNR of MCS_i of channel $\{\overline{H}[n]\}_{n=0}^{L-1}$ that has transmission power *AvgP* and receiver noise variance σ^2 i.e. $\left|SNR_i\left(\{\overline{H}[n]\}_{n=0}^{L-1}, AvgP, \sigma^2\right)\right|$ is lesser than or equal to *tP*.

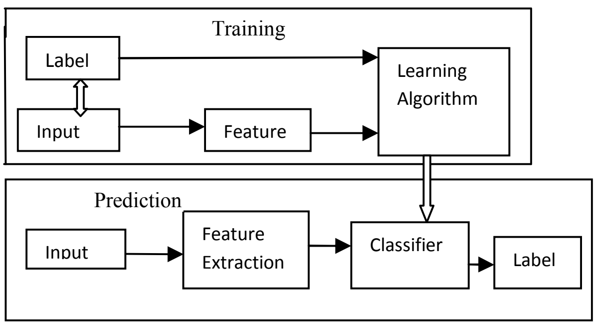

Fig.2. Supervised Classification Scheme.

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In exact, $SNR(\cdot) \le tP$ .... (4)

The set of classes that has assured SNR constraint are selected. Among these, class i is chosen associated to MCS_i with highest data rate DR_i. Thus, the classification criteria is defined as,

$$\arg\max_i \{DR_i : SNR_i(\cdot) \le tP\} \quad \text{......... (5)}$$

In cases such as, when no MCS assures the above criteria then highly reliable MCS will be chosen by the algorithm. On the other hand, when two various classes assure the SNR condition and produces the similar data rate then *k*-Nearest Neighbor algorithm (*k*-NN algorithm) selects the most appropriate MCS.

k- Nearest Neighbor Classification Algorithm:

The classifier in AMC exploits *k*-Nearest Neighbor (*k*-NN) classification algorithm as it accurately determines the type of class without necessitating the knowledge of a functional mapping among feature sets and the class.

The k-NN classification algorithm is trained with unique realizations of feature set U and corresponding training set. For every feature set in the training set, the realization index is defined as,

$$u \in \{0,1,2,\cdots,U-1\} \quad \text{........... (6)}$$

In the training set $(S_u \in \Re)$, the feature set related to index u is allocated to class $i \in I_L$ that satisfies the criteria given in (12) by means of realization of channel state evaluated from S_u. The mapping of MCS for every element in the training set is as given below,

$$\{S_u\}_{u=0}^{U-1} \mapsto \{i(u)\}_{u=0}^{U-1} \quad \text{......... (7)}$$

Here, corresponding to classification criteria given in [12], the value $i(u) \in I_L$ denotes the ideal AMC classification.

For every spatial stream, X distinct SNR values are obtained with respect to every subcarrier. $2X$ specific SNR values for two spatial streams related to every subcarrier and spatial stream are obtained. As a result, it is a challenging task to compare statistics collected from post processing SNR with mixed spatial stream dimensions. Therefore, X_s different classification procedures are applied over X_s different training sets. MCS with same number of spatial streams are pondered by every training set. The supervised learning technique of k-NN classifier algorithm is portrayed in figure-3. The classes related to MCS with spatial streams *sp* are considered as $I_{sp.}$ Assuming $\{S_{u,sp}\}_{u=0}^{U_{sp}-1}$ and $\{i(U,sp)\}_{u=0}^{U_{sp}-1}$ as the feature set realizations and related classes for the training set that contain *sp* spatial streams. Let $Q \in \Re$ be the query that represents the feature set for the channel realization.

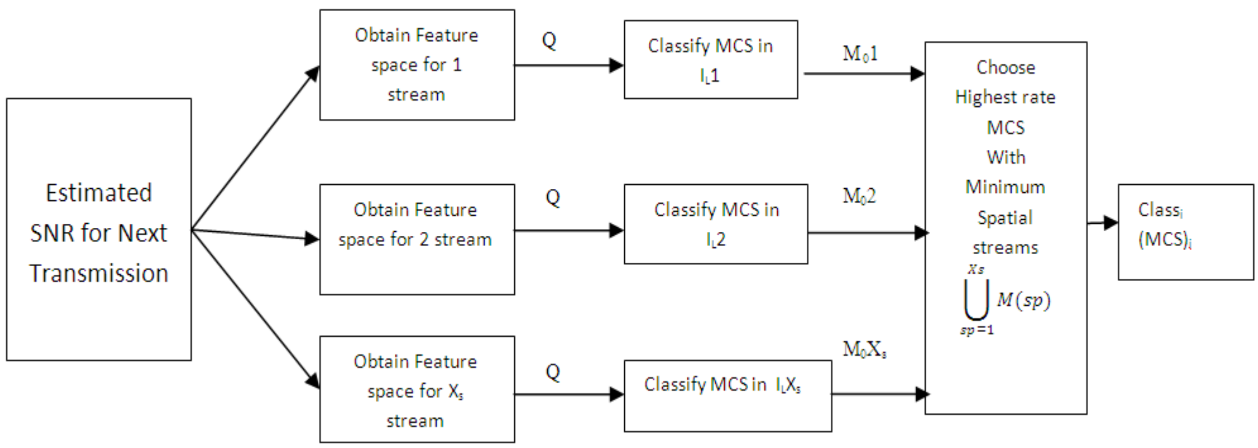

Fig.3.Supervised Learning Technique in AMC.

The *k*-NN classifier algorithm predicts the class for every new realization of the channel state information. The variable such as the depth of the search (*k*) and the distance (*di*(·,·)) endures randomly.

The classifier algorithm takes advantage of distance as a metric to discover the 'neighbors' in the training set. While receiving a query Q_i from a channel observation phase, the classifier examines throughout the training set in order to discover the *k*-nearest neighbors. The nearest neighbors are sorted out in terms of their distance metric (*di*). The class that occurs most frequently among k-nearest neighbors in the training set is chosen as the class and assigned to the requested query. The proposed technique considers Euclidean distance as a distance metric. The *k*-NN classifier algorithm is depicted below.

The k-NN classifier algorithm

1. *Assume* $\{S_{u,sp}\}_{u=0}^{U_{sp}-1}$ *and* $\{i(U,sp)\}_{u=0}^{U_{sp}-1}$ *as the feature set realizations*
2. *Assume* Q_i *as query, where i= 1, 2…*X_s
3. *Let di be the Euclidean distance metric*
4. *For sp = 1 to* X_s
5. $n_i = 0 \forall i \in I_L sp$
6. $le = 1$ *to k*
7. $u_{le} = \arg\min\{di(S_{u,sp}, Q) : u \notin \{u_1, u_2, \cdots, u_{le-1}\}\}$
8. $n_i(u_{le}) = n_i(u_{le}) + 1$
9. $M_O sp = \min\{\arg\max_i \{n_i : i \in I_{sp}\}\}$
10. *return* $\min\{\arg\max_i \{DR_i : i \in \bigcup_{sp=1}^{X_s} M_{sp}\}\}$

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When two different classes namely $Class_i$ and $Class_{i+1}$ that are in $I_L sp$ yields the same number of neighbors to a query for *sp* spatial streams. Then, this tie is wrecked by comparing its data rates. During this equal finish (tie) broken scheme is used. If $Class_i$ is chosen as a result of classification in $I_L Class_i$ and $Class_{i+1}$ is chosen as a result of classification in $I_L Class_{i+1}$ $(Class_i \neq Class_{i+1})$ and if $DR_i = DR_{i+1}$, then the class with lower index is elected.

The tie-breaking procedure is illustrated below

Tie-Breaking Procedure:

1. *Consider $Class_i$ and $Class_{i+1}$ as the two different classes in $I_L sp$*
2. *$Class_i$ and $Class_{i+1}$ produce same number of nearest neighbors for Q_i*
3. *The tie is broken considering DR of classes*
4. *If ($DR_i < DR_{i+1}$) then*
4.1 *$Class_i$ is selected*
5. *Else*
5.1 *$Class_{i+1}$ is selected*
6. *Else If ($DR_i = DR_{i+1}$) then*
6.1 *The algorithm looks for the index of the classes*
7. *If (sp_i ($Class_i$) < sp_{i+1} ($Class_{i+1}$)) Then*
7.1 *$Class_i$ is selected*
8. *Else*
8.1 *$Class_{i+1}$ is selected*
9. *End if*

Considering a lower data rate and a lower number of spatial streams assures higher communication reliability

IV. Performance Evaluation

The receiver computes the signal to noise ratio (SNR). The complex modulated symbols (R) are mapped by STBC encoder into T_N orthogonal complex symbol sequences of length *nS*. These mapped symbol sequences are forwarded concurrently by T_N. As a result, the coding rate (C_R) of a STBC can be given as,

$$C_R = \frac{R}{nS} \quad \text{…………………(8)}$$

If *AvgP* is the average transmit power for every stream or antenna. Before the computation of maximum likelihood (ML), the received symbol *Y* can be described as per the effective SISO channel model for STBC as,

$$Y = \|H\|_F^2 \, s + N \quad \text{…………(9)}$$

Where, the real and imaginary part of the transmitted complex symbol is represented as *s*, $\|\cdot\|_F^2$ is the squared matrix of Frobenius norm and the channel coefficient $\|H\|_F^2$ is given as,

$$\|H\|_F^2 = \sum_{i,j} h_{ij}^2 \quad \text{……(10)}$$

At the receiver, SNR can be calculated as follows,

$$\gamma = \frac{AvgP}{\sigma^2}\|H\|_F^2 = \frac{tP}{\sigma^2 T_N C_R}\|H\|_F^2 = \frac{\bar{\gamma}}{T_N C_R}\|H\|_F^2 \quad \text{…(11)}$$

Here, *tP* is the total transmission power transmitted at antennas of T_N for every symbol duration. The average pseudo SNR ($\bar{\gamma}$) is given as,

$$\bar{\gamma} = \frac{tP}{\sigma^2} \quad \text{…….(12)}$$

The probability density function (PDF) of γ can be described with the consideration that $\|H\|_F^2$ is the sum of 2D i.i.d χ^2 random variables. Thus, γ is described as,

$$P_\gamma(\gamma) = \frac{\gamma^{D-1}}{\Gamma(D)}\left(\frac{T_N C_R}{\bar{\gamma}}\right)^D \exp\left(-\frac{T_N C_R}{\bar{\gamma}}\gamma\right), \gamma \geq 0 \quad \text{….(13)}$$

Here, $\Gamma(\cdot)$ symbolizes the Gamma function.

It is assumed that the computation of the minimum mean square error (MMSE) in the channel is carried out by the receiver. Then, the channel coefficient is,

$$H = \hat{H} + E_{er} \quad \text{……(14)}$$

In equation (14), $\hat{H}$ denotes approximation of channel matrix and E_{er} is the approximation error. The proposed technique presumes that $\hat{H}$ and E_{er} are uncorrelated. Elements in E_{er} are i.i.d, which are the zero mean circulatory symmetric complex Gaussian distributed random variables with variance of σ_{er}^2. The value of variance is computed as,

$$\sigma_{er}^2 = E_{er}\left(h_{ij}^2\right) - E_{er}\left(\hat{h}_{ij}^2\right) \quad \text{…. (15)}$$

The relationship between assessed SNR $\hat{\gamma}$ and instantaneous SNR γ is defined by the equation,

$$\hat{\gamma} = \frac{1-\sigma_{er}^2}{1+\sigma_{er}^2 tP}\gamma \quad \text{…… (16)}$$

Accordingly the PDF of assessed SNR $\hat{\gamma}$ is given as,

$$P_{\hat{\gamma}}(\hat{\gamma}) = \frac{\lambda^D}{\Gamma(D)}\hat{\gamma}^{D-1} e^{-\lambda\hat{\gamma}}, \quad \text{…….. (17)}$$

where $\gamma \geq 0$ .The value of λ is,

$$\lambda = \frac{T_N C_R\left(1+\sigma_{er}^2 tP\right)}{\left(1-\sigma_{er}^2\right)\bar{\gamma}} \quad \text{…… (18)}$$

The correlation involves among h_{ij} and assessed $\hat{h}_{ij}$ is expressed below as,

$$cl = \frac{E_{er}\left(h_{ij}\hat{h}_{ij}\right)}{\sqrt{E_{er}\left(h_{ij}^2\right)E_{er}\left(\hat{h}_{ij}^2\right)}} = \frac{1}{\sqrt{1+\sigma_{er}^2}} \quad \text{…..(19)}$$

Equations given (16) to (19) represent the quality of channel estimation. From equation (17) and (19), it can be clearly concluded that if σ_{er}^2 =0, then $\hat{\gamma} = \gamma$ and cl=1.

Nagakami –m fading environment is considered for simulating MIMO fading channels. The PDF of the Nagakami-m fading channel is proportional to the square of received signal amplitude, has a gamma distribution given by

$$p(\bar{\gamma}) = \left(\frac{m}{\bar{\gamma}}\right)^m \frac{\gamma^{m-1}}{\tau(m)} e^{-\frac{m\gamma}{\gamma}} \quad \text{…….(20)}$$

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Where $\bar{\gamma}$ is the average received SNR.$\tau(m)$ is the gamma function. When m = 1, it corresponds to Rayleigh distribution and the signal does not have a direct line of sight (LOS) component. For m = 2, 3,... it closely approximates the Ricean distribution, which have a LOS component. As m increases, the LOS component becomes gradually stronger.

V. Simulation Results

In this paper, k-NN is chosen as a machine learning technique due to its ability to provide accurate class estimates without knowledge of a functional mapping between the feature sets and the class. The k-nearest neighbor needs three input data namely, sample, group and training sets. The training sets contain the ordered SNR values and are classified into 4 groups. The number of rows in the training sets should be equal to the number of rows in the group. The number of columns in the training should be equal to the number of columns in the sample. So the input to the k-nearest neighbor classifier will be the ordered SNR values, based on which the modulation and coding rate chosen by the classifier. If the class chosen by the classifier is group 1 then the modulation value will be 2 and code rate will be ½. Similarly based on the SNR, the classifier will choose the modulation order and coding rate for the MIMO system. By applying this method better throughput and better reduction in the bit error rate (BER) is obtained at higher SNR.
The parameters used in k-NN classifier for AMC and IR-HARQ MIMO system are given in the Table 1.

Table.1.Simulation Parameters.

No.	Parameters	Values
1	Number of transmitter (Nt)	2,3
2	Number of receiver (Nr)	2,3
3	Modulation	BPSK,QPSK, 16QAM, 64QAM
4	Rate	1/2,1/3,2/3
5	Number of packets	1000
6	Coding technique	Convolution Turbo Codes

The performance of the system is evaluated in terms of average transmission rate, bit error rate, spectral efficiency and convergence time. Rayleigh fading channels were used for simulation. The obtained average transmission rate for the proposed system is shown in Fig.4.From the obtained graph, it is evident that the proposed system has an average rate of 1.27 bps when the channel SNR is 5 dB which is comparatively higher than the conventional system with the same SNR. Similarly when the SNR of the channel is 20dB,the average rate of the proposed system is 1.6 which is better than the conventional system Therefore, the proposed system with k-NN classifier is proved to have better throughput in both the channel conditions i.e. when the channel is poor as well as good.

The performance of the proposed system is evaluated using BER observed with change in SNR of the channel. As SNR increases, the BER is reduced. The comparison graph for AMC and HARQ in MIMO with K-NN classifier and AMC and HARQ in MIMO without K-NN classifier is shown in fig.4. The BER value reduces at 10 db for the K-NN classifier whereas for the existing method the BER value decreases only at 25 db.

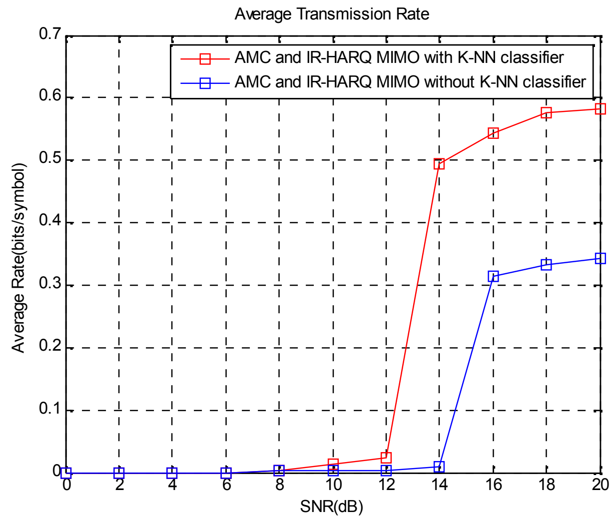

Fig.4. Average Rate for AMC and IR-HARQ MIMO with K-NN classifier & without K-NN classifier over Nagakami fading channels.

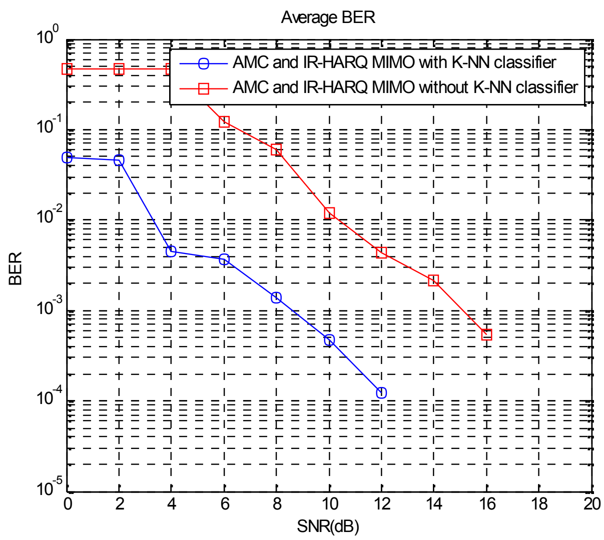

Fig.5. BER performance for AMC and IR-HARQ MIMO with K-NN classifier & without K-NN classifier over Nagakami fading channels

The spectral efficiency for the system with k-NN classifier proved to be higher than the AMC- IR HARQ system without k-NN classifier. As the classifier chooses accurate modulation and date rate classes adaptable to the prevailing channel conditions, the available bandwidth is efficiently utilized in the wireless channel. Spectral efficiency w.r.t the channel condition is shown in fig.6.

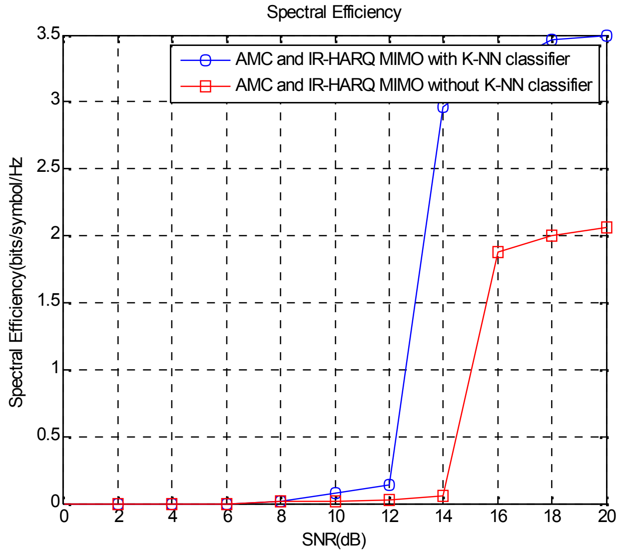

Fig.6. Spectral Efficiency for AMC and IR-HARQ MIMO with K-NN classifier & without K-NN classifier over Nagakami fading channels.

In the proposed system incremental redundancy is implemented in the data link layer. The performance of the system using IR-HARQ at the link layer is compared with that of the MIMO system using ARQ in the link layer. The simulation results are shown in fig.7 and fig.8 in terms of transmission rate and bit error rate.

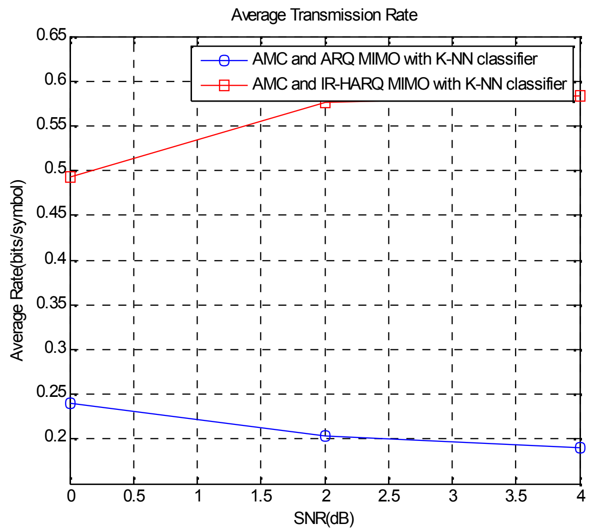

Fig.7. Average Rate for AMC and ARQ MIMO with K-NN classifier & the AMC and IR-HARQ MIMO with K-NN classifier over Nagakami fading channels.

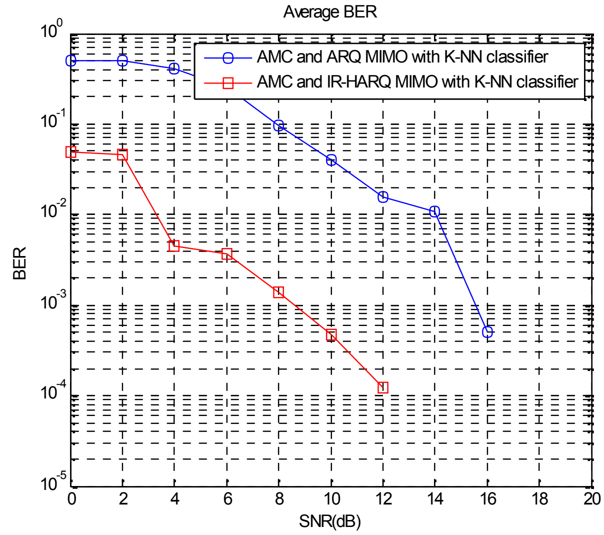

Fig.8. BER performance for AMC and ARQ MIMO with K-NN classifier & the AMC and IR-HARQ MIMO with K-NN classifier over Nagakami fading channels.

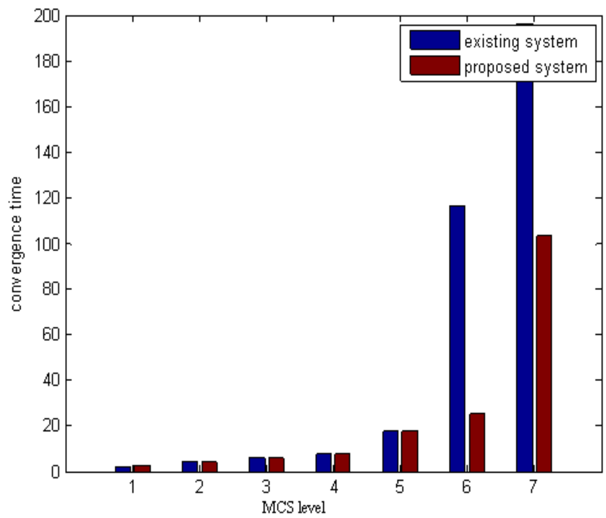

Fig.9. Convergence time for the AMC and HARQ MIMO with K-NN classifier & the AMC and HARQ MIMO without K-NN classifier.

In fig.9, the convergence time taken for AMC-IR-HARQ MIMO system with k-NN classifier is compared with the system without k-NN classifier. It is evident that the simulation time is 105secs for the proposed system where as it is 197secs for the existing system at higher modulation and coding level.

VI. Conclusion and Future Scope

In this paper, a cross-layer approach for k-NN based AMC and IR-HARQ in MIMO has been proposed. The proposed cross layer approach connects physical layer and data link layer to enhance the performance of MIMO network. By means of MIMO fading channels, the coded symbols are forwarded in the physical layer on a frame by frame fashion subsequently using space time block coding. The receiver computes the SNR and forwards back to the

AMC controller. The controller selects a suitable MCS for the next transmission through k-NN classifier supervised learning algorithm. It chooses a set of nearest neighbors of a class considering distance as an essential metric. From the obtained results, it is proved that AMC-IR-HARQ MIMO systems with k-NN classifier has better performance in terms of throughput, bit error rate, spectral efficiency and convergence time. Therefore this system can be chosen as a suitable solution for the present generation wireless systems.

The paper deals with the parameters modulation order, code rate and the number of spatial streams. The transmitted power is maintained constant. Optimal power utilization algorithms can be developed as future scope.

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Author's Profile

J. Sofia Priya Dharshini

has received B.Tech degree (Electronics & Communication Engineering) in the year 2005, M.Tech (Digital Systems and Computer Electronics) in 2009 and also pursuing Ph.D. (Wireless Communications and Networking) from JNTU Anantapur, A.P, India. Presently she is working as Associate Professor in the dept. of ECE, RGMCET, Nandyal. She has published four papers in International Journals and eight papers in National and International Conferences. Her area of interest includes Wireless communications and Networks, Mobile Computing and Video and Image processing.

Dr. M. V. Subramanyam

received B.Tech. degree (Electronics & Communication Engineering) in the year 1989; M.Tech (Digital Systems and Computer Electronics) in 1997 .He obtained his P.hd (Adhoc Networks) from JNTU Hyderabad, A.P, India in 2007.He is a member of IE, ISTE, MIEEE, IEEE and IETE. He has published around 67 papers in various National and International Journals and conferences. He has teaching experience of 23 years. Presently he is working as prof. and Principal in SREC, Nandyal, Kurnool dist. He published four books and is a member of editorial board for two National and 4 International Journals.

Dr. K. Soundararajan

born at Tirupathi and graduated from S.V.U college of Engineering, Tirupathi in the year 1976.He got his post graduation from JNTU College of Kakinada in the year 1979 and obtained his PhD from University of Rcorkee, U.P, India in the year 1992.He produced 130 papers at both International and National journals and conferences. His area of interest is micro computers, Image processing and operating system. He got best teacher award from Andhra Pradesh Govt. in the year 2006 and also got best teacher award from lead India 2020. He worked as professor JNTU college of Anantapur and former rector of JNTUA and also as Special Duty to Vice Chancellor JNTUA.