Adaptive Group Loading and Weighted Loading for MIMO OFDM Systems

Robin Shrestha and Jae Moung Kim
INHA-WiTLAB, Inha University
253 Younghyun-dong, Nam-gu, Incheon, 402-751 – Korea
[e-mail: robinsth@inha.edu, jaekim@inha.ac.kr]
*Corresponding author: Jae Moung Kim

Received April 21, 2011; revised October 12, 2011; accepted November 3, 2011; published November 29, 2011

Abstract

Adaptive Bit Loading (ABL) in Multiple-Input Multiple-Output Orthogonal Frequency-Division Multiplexing (MIMO-OFDM) is often used to achieve the desired Bit Error Rate (BER) performance in wireless systems. In this paper, we discuss some of the bit loading algorithms, compare them in terms of the BER performance, and present an effective and concise Adaptive Grouped Loading (AGL) algorithm. Furthermore, we propose a "weight factor" for loading algorithm to converge rapidly to the final solution for various data rate with variable Signal to Noise Ratio (SNR) gaps. In particular, we consider the bit loading in near optimal Singular Value Decomposition (SVD) based MIMO-OFDM system. While using SVD based system, the system requires perfect Channel State Information (CSI) of channel transfer function at the transmitter. This scenario of SVD based system is taken as an ideal case for the comparison of loading algorithms and to show the actual enhancement achievable by our AGL algorithm. Irrespective of the CSI requirement imposed by the mode of the system itself, ABL demands high level of feedback. Grouped Loading (GL) would reduce the feedback requirement depending upon the group size. However, this also leads to considerable degradation in BER performance. In our AGL algorithm, groups are formed with a number of consecutive sub-channels belonging to the same transmit antenna, with individual gains satisfying predefined criteria. Simulation results show that the proposed "weight factor" leads a loading algorithm to rapid convergence for various data rates with variable SNR gap values and AGL requires much lesser CSI compared to GL for the same BER performance.

Keywords: MIMO-OFDM, ABL, SVD, adaptive group loading, weight factor, BER

This research was supported by the Ministry of Knowledge Economy (MKE), Korea, under the Information Technology Research Center (ITRC) support program supervised by the Institute for Information Technology Advancement (IIPA), (IIPA-2011-C1090-1011-0007). The primary version of this work was presented in part at the International conference on ICT Convergence, Korea, Jeju, 2010 [12].

DOI: 10.3837/tiis.2011.11.005

1. Introduction

Wireless technology has more or less included Orthogonal Frequency-Division Multiplexing (OFDM) as one of its most applicable base technologies. Its wide application is evident to the fact that reflects its property of high spectral efficiency (by converting the frequency-selective channel into a parallel collection of frequency flat fading sub-channels), and robustness against Inter Symbol Interference (ISI) and multipath fading [1]. Deploying Multiple-Input Multiple-Output (MIMO) to the OFDM system further improves the bandwidth and power efficiency of the system [2]. A MIMO system utilizes the spectral diversity of a dense multipath channel environment by spatially separated antennas, thereby dramatically increasing the spectral efficiency.

The overall Bit Error Rate (BER) performance (performance margin) of the conventional multi-carrier modulation systems are dominated by those sub-channels with the worst performance as it uses same modulation scheme over all sub-channel. Adaptive Bit Loading (ABL), also referred as adaptive modulation, plays a vital role in improving the system-wide error performance or performance margin by utilizing the fading property of the channel. As a result, the data rate enhances by adaptively allocating power and/or bits to each sub-channel depending on the channel condition in a specific sub-channel. Adaptive bit allocation improves the system–wide error performance or performance margin. This in return demands inherent assumption in channel adaption in some form of channel knowledge in both transmitter and receiver. When the Channel State Information (CSI) is available, the transmission power and bits for each sub-channel can be adapted according to CSI to reduce the overall transmission power or increase the total bit rate. The optimal adaptive loading scheme to achieve the Shannon capacity is based on water-pouring distribution [3], but it is difficult to compute. There are different algorithms for adaptive bit and power loading attempting to maximize the bit-rate subject to fixed power budget, or to minimize the transmit power subject to fixed bit-rate respectively called as Rate Adaptive (RA) and Margin Adaptive (MA) paradigms [4][5][6][7]. There are also those MA paradigm based on bit error rate whose main idea is to allocate bits and power in order to minimize the average error probability [8]. In this paper, we analyze and compare some of MA loading algorithms namely, Chow's algorithm [4], Fast Discrete Bit Allocation (FDBA) algorithm [5], and optimum loading algorithm [6] with respect to their BER performance. The optimum loading algorithm presented in [6] is the combination of Chow's algorithm and Campello's algorithms [7]. The motivation for this analysis is backed by the lack of appropriate BER performance analysis of different loading algorithms on loaded MIMO-OFDM.

In this paper, we also show later that the claim of FDBA algorithm to converge rapidly to be somewhat true only for the very low value of Signal to Noise Ratio (SNR) gap. The convergence of the loading algorithm depends on how close the algorithm estimates the total number of bits to the target number of bits, which is found to be very poor in case of FDBA algorithm. It is shown later that the initial estimation of both Chow's and FDBA algorithm is unstable with variable SNR gap. So, we propose a "weight factor" that depends on target rate and SNR gap to improve the convergence of an algorithm. This "weight factor" improves the initial bit estimation of the loading algorithm close to the target rate. Since each algorithm has different methods for estimating the total numbers of bit, each algorithm demands a unique "weight factor". Moreover, such "weight factor" can be designed for various other loading algorithms as well.

MIMO-OFDM scheme with ABL has been widely studied assuming different level of CSI. Singular Value Decomposition (SVD) based MIMO-OFDM system requires full CSI at the transmit side, whereas there are those systems which require partial or no CSI at the transmit side. VBLAST, Wrapped Space-Frequency Coding (WSFC), etc. are some of the systems that do not require CSI at the transmitter. These systems with ABL are well investigated in [9]. Regardless of the system type being mentioned, ABL requires the feedback, which occupies considerable channel resources. Group Loading (GL) can dramatically reduce the feedback requirement but on the contrary, it also deteriotes the BER performance as group size increases. Reference [10] presents a simple loading algorithm for OFDM-based systems, mainly to reduce the complexity, based on partitioning the sub-channels into different group based on the channel gain arranged in ascending order and then assigning bits to each group and its corresponding group element. Similar method of bit loading is presented in [11] with reduced computational complexity. However, the associated BER performance of the algorithm, are not studied in both [10] and [11]. In this paper, we also present an effective and concise Adaptive Group Loading (AGL) algorithm based on grouping the consecutive sub-channel falling under the predefined criteria. The fact that there is finite M-ary Quadrature Amplitude Modulation (M-QAM) that can be available (M = 1, 2, 4, 6…), implies that the rate remains fixed where the sub-channel gain does not vary widely enough, which is widely utilized in our AGL algorithm to adaptively size the group. We simulate to test the enhancement that can be achieved by our AGL algorithm in coded and uncoded MIMO-OFDM system.

The remaining portions of this paper are organized as follows. Section II introduces the system model for loaded MIMO-OFDM system. Section III presents the description on ABL and some of the loading algorithms discussed above. The description for the proposed "weight factor" in weighted loading is presented in section IV. Section V introduces our proposed AGL algorithm. Section VI presents the simulation results and discussion, and finally Section VI gives the conclusion.

2. System Model

We consider the structure of OFDM system with N_T transmitting and N_R receiving antennas such that each of N_T transmit antennas transmit N sub-channels. The block diagram of the MIMO-OFDM system with adaptive bit-loading is depicted in **Fig. 1**. At the transmitter, the input bit stream is fed to the modulation block, which modulates the bit stream into an appropriate signal constellation to allocate to each of the N OFDM sub-channels of N_T transmit antennas individually. The number of bits to be allocated to each sub-channel is obtained as a feedback from the ABL unit in the receiver side. Depending on the CSI, the ABL unit calculates the number of bit allocation for different sub-channels. The feedback from the ABL is in the form of a vector of integers specifying the number of bits assigned to each sub-channel of each antenna. It is to be noted that the feedback is different from that for MIMO processing. We assume ideal channel estimation in the system, such that, perfect CSI at the receiver is available. The modulated signal for each transmitter is individually multiplexed using Inverse Fast Fourier Transform (IFFT) operation and Cyclic Prefix (CP) is added on them.

Let us take a simple narrow band MIMO-OFDM channel H for realizing the system. That is, the channel does not change during one OFDM symbol but may vary from one symbol to

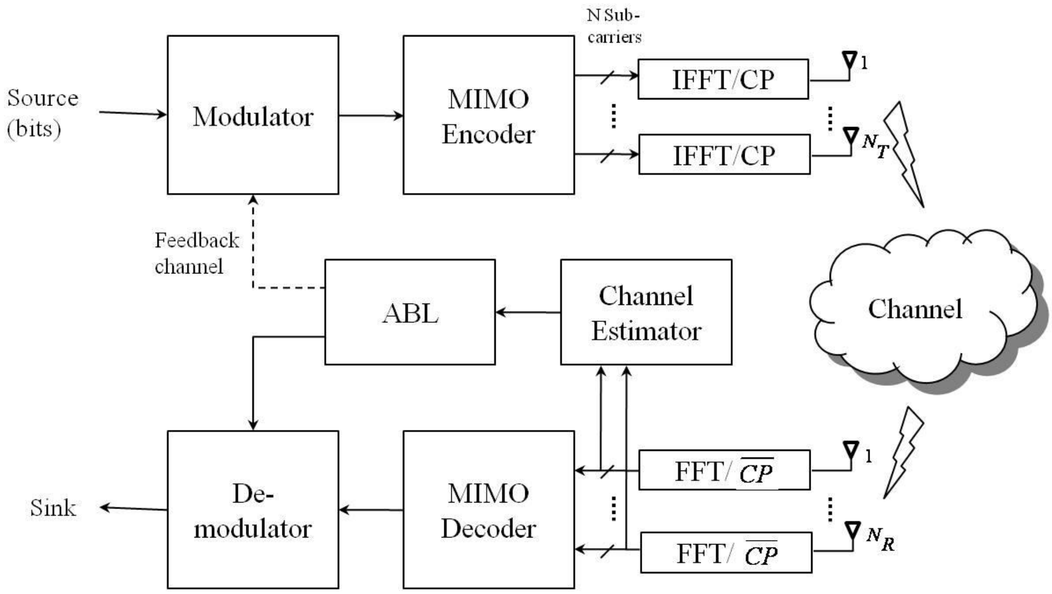

Fig. 1. Block diagram for bit loaded MIMO-OFDM system

another. If $X_k = \left[x_{k,0} \ldots x_{k,N_T-1}\right]^T$ represents k^{th} sub-channel N_T -dimensional vector transmitted over N_T antennas, and assuming standard OFDM transmission and reception, the corresponding N_R -dimensional received vector is given by,

$$y_k = H_k x_k + n_k, \qquad 0 \le k \le N \tag{1}$$

where, H_k is the $N_R \times N_T$ channel matrix for the sub-channel k and n_k is the spatial and spectral Additive White Gaussian Noise (AWGN).

The MIMO processing can be done in various ways with varying CSI requirement. Here, we formulate a near optimal SVD based MIMO-OFDM system. It requires the full CSI at the transmitter, which can be an ideal scenario for comparing the loading algorithms and to present the accurate measure of our proposed AGL algorithm. Performing SVD, the channel matrix H_k can be decomposed as,

$$H_k = U_k \Lambda_k V_k^H \tag{2}$$

where, U_k and V_k^H are unitary matrices, and Λ_k is the diagonal matrix of singular values of H_k whose elements are shorted and non-negative ($\lambda_{k,0} \ge \ldots \ge \lambda_{k,N_T-1} \ge 0$). Now, by applying pre-coding filter of V_k at transmitter and a shaping filter of U_k^H at the receiver, the equivalent

MIMO channel decomposes into N_T parallel channels with gain $\lambda_{k,i}, 0 \le i < N_T$, for each sub-channel *k*. This can be numerically expressed as,

$$\begin{aligned} y_k &= U_k^H H_k V_k x_k + U_k^H n_k \\ &= U_k^H U_k \Lambda_k V_k^H V_k x_k + n_k^1 = \Lambda_k x_k + n_k^1 \end{aligned} \tag{3}$$

Thus, Λ_k along with U_k and V_k^H can perfectly represent H_k. In other word, SVD converts the MIMO channel matrix to simple parallel channels.

3. Adaptive Bit Loading

OFDM based system has an advantage over relatively narrowband sub-channel that is assumed to be flat-fading. The sub-channels have a variation in the fading statists that allow more bits and/or less power allocation to those sub-channels with high channel power gain, and vice versa for weak sub-channels. The ABL algorithm assigns a certain number of bits to each sub-channel, such that $\sum_{i=1}^{N} b_i = b_{tot}$ (b_{tot} is total number of bits). The optimal adaptive transmission scheme, water-pouring solution [3], suggests that the sub-channel having a higher Channel gain to Noise Ratio (CNR) can be assigned with more bits. The number of bits allocated to the ith sub-channel under CNR constrains can be formulated as,

$$b_i = \log_2\left(1 + \frac{E_i \cdot CNR_i}{\Gamma}\right) = \log_2\left(1 + \frac{E_i \cdot |H_i|^2}{\Gamma \cdot N_0}\right) \tag{4}$$

where, E_i denotes the sub-channel i transmitted energy, CNR_i is the i^{th} sub-channel gain-to-noise ratio, $|H_i|^2$ is the absolute square of channel frequency response and $N_0 = \sigma_i^2$ is the noise power spectral density for the sub-channel *i*, and Γ is the SNR gap that represents how far the system is from Shannon channel capacity. SNR gap is obtained from the gap-approximation analysis based on target BER.

In many practical scenarios with OFDM-based systems, data rate is preferred to be in a stable state. This can be viewed as a MA paradigm, since any other paradigm would require more energy to reach the target rate. The MA optimization paradigm, i.e., minimizing the energy subject to a fixed bit-rate constrain, can be stated by the following equations.

$$\begin{aligned} &min\ E = \sum_{i=1}^{N} E_i \\ &subject\ to: \sum_{i=1}^{N} b_i = B_{target} \\ &\qquad 0 \le b_i \le b_{max},\ for\ 1 \le i \le N \end{aligned} \tag{5}$$

where, B_{target} is the target bit rate and b_{max} is the maximum number of bits that can be assigned to each sub-channel. The final power allocation regarding MA paradigm is computed as follows,

$$E_i = \left(2^{b_i} - 1\right) \cdot \frac{\Gamma}{CNR_i} \tag{6}$$

Next, we deal with some of the bit loading algorithms namely Chow's algorithm [4], the FDBA algorithm [5], and the optimum loading algorithm [6].

While the optimal water-pouring energy allocation is complex and practically non-realizable [3], Chow has presented a practical and efficient iterative loading algorithm. The algorithm consists of three major sections, namely; performance margin (γ_{margin}) estimation (approximately), guaranteing convergence with sub-optimal loop, and energy distribution adjustment. A detail description of the algorithm is given in [4].

Modulation dynamics, referring to CSI, is the main factor for ABL. Considering the computational complexity of various algorithms, the authors in [5] has proposed optimal algorithms, which claims to converge rapidly to the final solution with significantly reduced computational complexity while satisfying the target bit rate.

The optimal loading algorithm [6] uses Chow's algorithm and Campello's algorithm. Chow's algorithm is used to estimate the initial number of bits to be transmitted via each sub-channel of the multi-channel transmission system and Campello's algorithm is used to increase the additional bit(s) on the sub-channel that would require the least incremental energy for its transport. After the initial number of bits estimation by Chow's algorithm, Campello's algorithm iteratively translates any bit distribution into an efficient bit distribution, such that the movement of a bit from one sub-channel to another reducing the symbol energy. Given the initial bit allocation, the B-tightness in Campello's algorithm, simply states that the correct number of bits is being transmitted and optimizes the bit allocation.

4. Weighted Loading

In this section, we analyze how fast the algorithm converges to the final solution. The claim of rapid convergence in [5] is based on the initial bit estimation of the algorithm, which the authors claim to be faster. The initial bit estimation determines the number of loops required for the total bit to converge to a target bit rate. We discuss on the issue of the rapid convergence of Chow's and FDBA algorithm. The initial bit estimation for each sub-channel respectively for Chow's and FDBA algorithm are given by,

$$b_i = \begin{cases} \log_2\left(1 + CNR_i / (\Gamma + \gamma_{margin})\right) : chow's \\ \log_2\left(K \cdot CNR_i / \Gamma\right) : FDBA \end{cases} \tag{7}$$

The factor γ_{margin} and K are the parameters of Chow's and FDBA algorithms respectively, which are well formulated in [4] and [5] respectively. Clearly from (7), it can be seen that the bit estimation decreases as Γ increases. However, in Chow's algorithm the optimal margin tends to correct it with increasing iterations but in case of FDBA algorithm the estimation is very poor. This is later shown in **Fig. 5** in section V. We address this problem by introducing a "weight factor" depending on the target rate and the SNR gap. Since the energy for every sub-channel is calculated as in (6), the "weight factor" to stabilize the bit estimation would not have any negative implication on the performance of the system itself. The bit estimation for each algorithm has different mechanism requiring different "weight factor". We demonstrate the derivation of "weight factor" for FDBA algorithm next.

Following the derivation of the factor K in [5] used in (7), we assume CNR to be constant and SNR gap a variable, i.e., Γ_i in equation (6). Now, using Lagrange multiplier λ and (6), we can reformulate optimization problem in (5) as a constraint optimization problem.

$$\min J(\lambda) = -\sum_{i=1}^{N} (2^{b_i - 1}) \cdot \frac{\Gamma_i}{CNR} + \lambda \left(\sum_{i=1}^{N} b_i - B_{target} \right) \tag{8}$$

By differentiating (8) with respect to b_i and solving thus obtained equations, we can get the optimal solution for the problem in (5) as,

$$w_c = \lambda = 2^{\left(\frac{R}{\alpha} + \log_2(\Gamma_i)\right)} \tag{9}$$

where, R represents the target rate, Γ_i represents the varying SNR gap and α accounts for the constant CNR assumed for derivation. The MA paradigm for varying SNR gap is achieved by allocating $b_i^{\bullet} = \log_2\left(w_c \cdot CNR / \Gamma_i\right)$ into sub-channel i. Finally, using (7) and (9), the "weight factor" for FDBA algorithm is implemented as,

$$b_i^* = \log_2\left(w_c \cdot K \cdot CNR_i / \Gamma_i\right) \tag{10}$$

Similarly the "weight factor" for Chow's algorithm can also be derived by following the derivation in [4]. Here we only demonstrate the derivation for FDBA algorithm.

5. Adaptive Group Loading

In this section, we present our proposed AGL algorithm. So far, there are two basic versions of bit loading with different feedback requirements and computational complexity, which are full/individual loading and grouped loading. In individual loading the bits are allocated to all $N_T N$ equivalent sub-channels individually. Group loading is deployed by forming fixed groups of adjacent sub-channels of the same transmit antenna. The loading algorithm considers all the sub-channels within a group as identical. Grouping of G (group size) adjacent sub-channel corresponding to the same transmit antenna is proposed in [9]. The authors in [9] presented two methods to obtain the group representative for loading algorithm. Those are center sub-channel method and equivalent SNR method, nevertheless, the result in [9] indicates the superiority of center sub-channel method.

While GL reduces the feedback requirement by a factor of G, it also degrades the BER performance considerably. To address this problem, we present AGL algorithm. We formulate a simple and effective idea of grouping the sub-channels corresponding to the same transmit antenna. The grouping is done with those consecutive sub-channels falling under the criteria

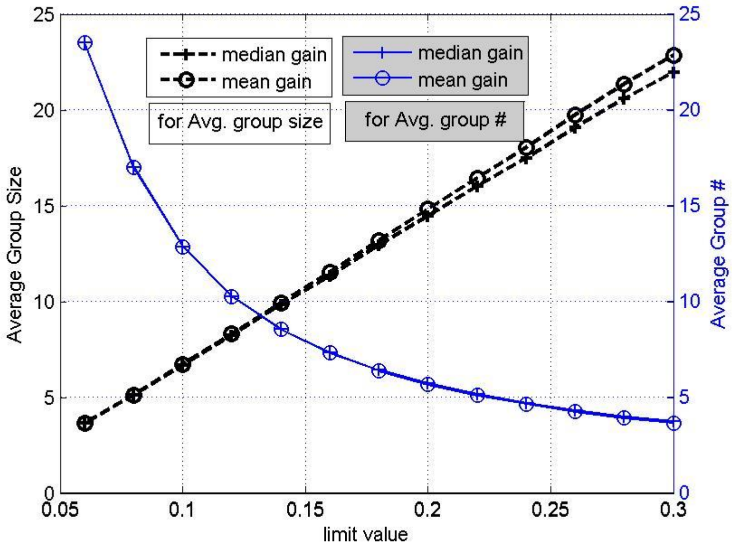

Fig. 2. Average group size and average number of groups for different limit value (Δ) in AGL for ('ITU pedestrian A' channel model

determined by the difference between their gains. The group is formed constructively adding one sub-channel at a time, such that, the very next consecutive sub-channel is allowed into the group only if the group gain and the sub-channel gain have the difference under pre-specified value. A new group begins to form as the criterion is being void. The procedure can be summarized in an algorithmic form as follows.

Adaptive Group Loading Algorithm:

1. *Arrange the sub-channels for each transmit antenna.*
2. *Initialize a group with the first sub-channel.*
3. *Compute the group gain and the next consecutive sub-channel gain.*
4. *Compare the difference with Δ. If the difference is less than Δ, then add the sub-channel into the group.*

$$if\ \left(abs\left(group\_gain - sub\_gain\right) < \Delta\right)$$

$$then,\quad group = \left[group \quad sub\_channel\right]$$

5. *Else, conclude the group and register the group gain and group size.*

$$virtual\_subchannel = \left[virtual\_subchannel \quad group\_gain\right]$$

$$group\_size = \left[group\_size \quad length\left(group\right)\right]$$

6. *Clear the group and initialize next consecutive sub-channel to the group.*
7. *Repeat step 3 to 7 until the last sub-channel for the antenna.*
8. *Conclude the last group and compute the group gain and group size.*
9. *Compute the bit to be loaded for each virtual sub-channel by using an appropriate loading algorithm.*

Now that the adaptive group has been formed, the issue here is to compute the group gain. The group gain used in the proposed AGL algorithm can be computed in different ways. We demonstrate two methods for group gain calculation, mean group gain and median group gain,

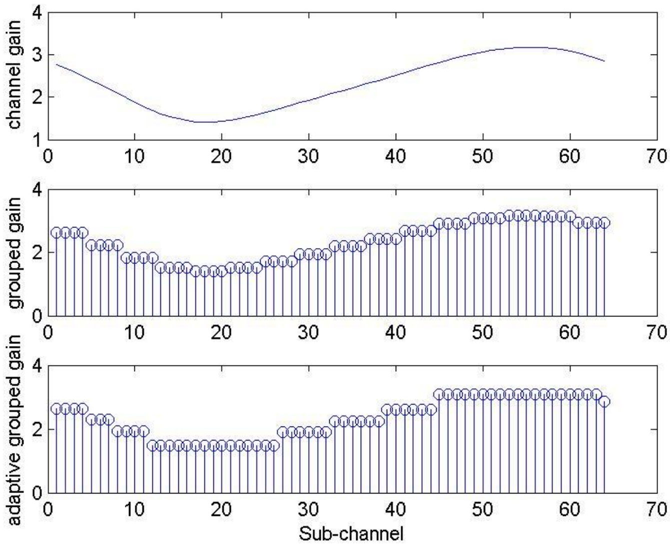

Fig. 3. Example of adaptive grouping of channel gain

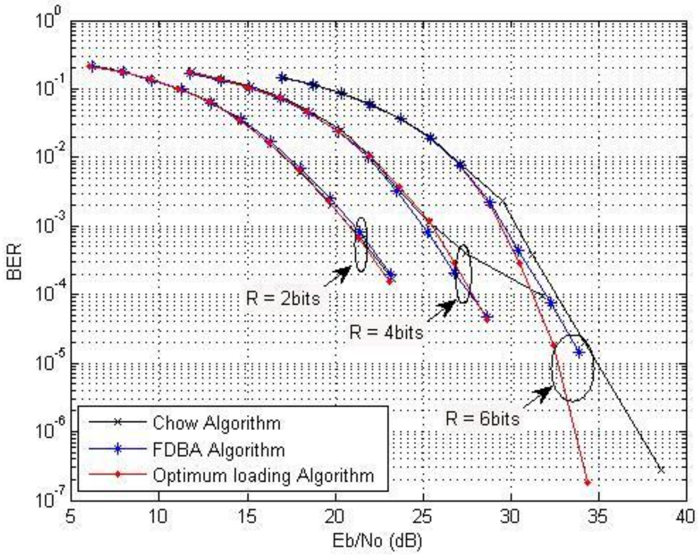

Fig. 4. BER curve for different loading algorithms at variable rates

to represent each group. The median gain approach is equivalent to the center sub-channel method in [9]. The size of different groups in the adaptive group depends on the gain limit (Δ).

We perform a simple Monte Carlo simulation to see the effect of Δ on the average group size and average number of group, for both group gain calculation methods, considering the 'ITU pedestrian A' channel model. The resulting plots are shown in **Fig. 2**. The figure shows that median gain approach has a slightly lower average size compared to that of mean gain approach.

An example of implementing the above algorithm is shown in **Fig. 3**. The figure illustrates a typical channel frequency response which is grouped with fixed grouping method and our

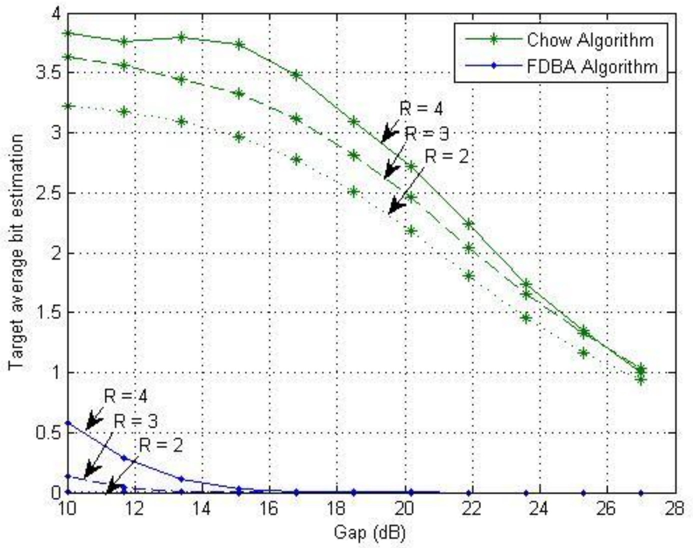

Fig. 5. Comparison of initial bit estimation

proposed adaptive grouping method. The group gain is obtained by using mean gain approach for both cases.

6. Simulation Results and Discussion

In this section, we analyze the simulation results for the SVD based MIMO-OFDM system with ABL. We first compare few chosen bit loading algorithm in terms of BER performance and rapid convergence to the final solution, and then present our proposed AGL simulation results. We adopt OFDM system with 64 sub-channels and cyclic prefix of 16 samples. Rectangular gray coded M-QAM constellations with M = 1, 2, 4, 6, and 8 is used. We further assume 4×4 MIMO system; the 'ITU pedestrian A' and 'ITU Vehicular A' channel models with noise variance of 10^{-3}. We extend our simulation with coded MIMO-OFDM system to demonstrate the performance of AGL algorithm. The underlying principle for BER analysis of different algorithm is that the BER performance of the signal is proportional to the energy of the signal for a predefined SNR gap.

6.1 Comparison of Loading Algorithms

We consider comparing BER performance of well-known Chow's practical and efficient algorithm, recently proposed FDBA algorithm claiming to converge rapidly to the final solution, and the optimum loading algorithm. The maximum iteration for the Chow's algorithm was chosen as "10".

Fig. 4 shows the BER curves for the SVD based MIMO-OFDM system with 'ITU pedestrian A' channel model, deploying the above mentioned algorithm. The curves for each system are simulated for the average data rate per sub-channel of R = 2, 4, and 6 bits. For lower value of R with 2 bits, Chow's algorithm has slightly better BER performance than FDBA algorithm, and the optimal loading algorithm has the best performance. It is surprising to see that besides huge popularity of Chow's practical and efficient algorithm, the BER performance of Chow's algorithm is not stable with respect to the average number of bit per

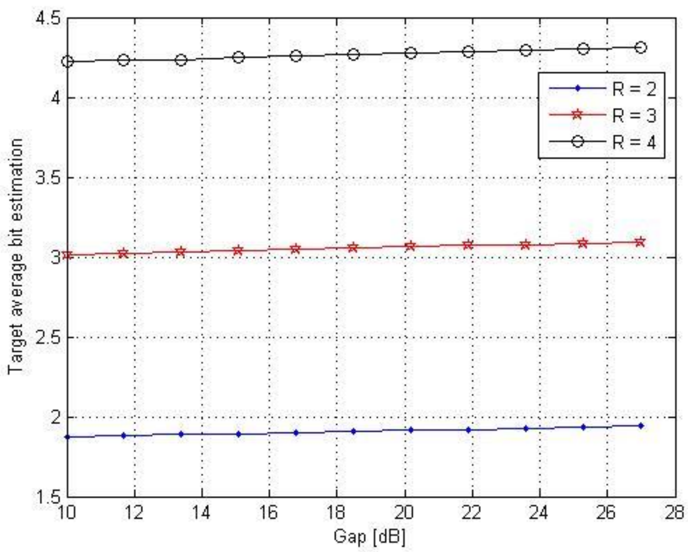

Fig. 6. Initial bit estimation of FDBA with weight factor

sub-channel. The BER performance of Chow's algorithm is highly degraded for R = 4 bits per sub-channel, whereas it is only slightly degraded for the rate of 6 bits per sub-channel. The degradation of BER performance of Chow's algorithm is combat by Campello's algorithm in optimum loading algorithm for all cases of different data rate. FDBA algorithm, on the other hand, is found to be stable to the changing data rate and also consistent with the varying average rate.

6.2 Weighted Loading

Through the simulation, the initial estimation of the number of bits for each sub-channel of the FDBA and Chow's algorithm was computed. The estimation of the initial number of bits to each sub-channel determines how fast the algorithm converges.

Fig. 5 depicts estimation of the initial bits for both the algorithms for varying SNR gap values at data rate of R = 2, 3, and 4 bits per sub-channel respectively. Surprisingly, the FDBA algorithm has very low initial bit estimation. The average bit estimation of it hardly reaches to 0.6 per sub-channel for the target rate of 4 bits per sub-channel. The remaining 3.4 bits per sub-channel has to be obtained iteratively adding one or two bit(s) at a time, which in turn causes the algorithm to take longer time to converge. Chow's algorithm has the average bit estimation somewhat closer to the target bit, helping it to converge rapidly. It is also seen that bit estimation for both algorithms decays with increasing SNR gap.

Next, we apply the proposed "weight factor" for FDBA algorithm with the constant $\alpha = 3.5$ and compute the initial bit estimation through the simulation. The result is shown in **Fig. 6**. The figure shows that the "weight factor" results in better initial bit estimation helping the algorithm to rapidly converge to final solution.

6.3 AGL performance

In this section, we present the simulation of our proposed AGL algorithm. We carry out our algorithm with the FDBA algorithm. Both 'ITU pedestrian A' and 'vehicular A' channel models are used for obtaining the BER curves for coded and uncoded MIMO-OFDM system,

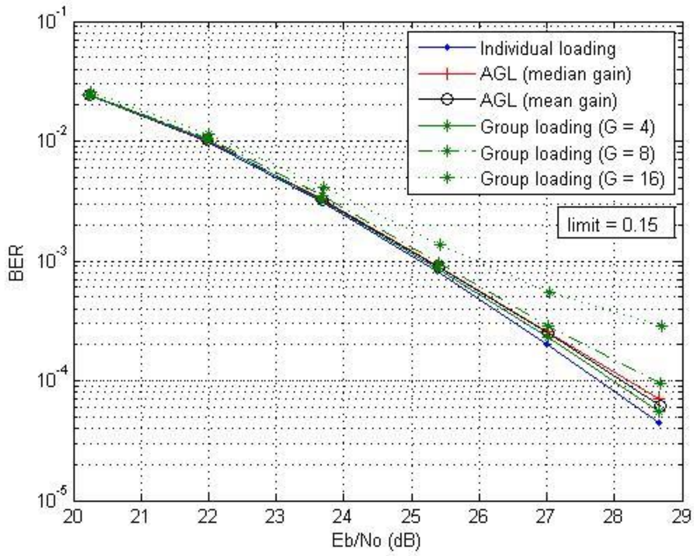

Fig. 7. BER curves ('ITU Pedestrian A' channel model)

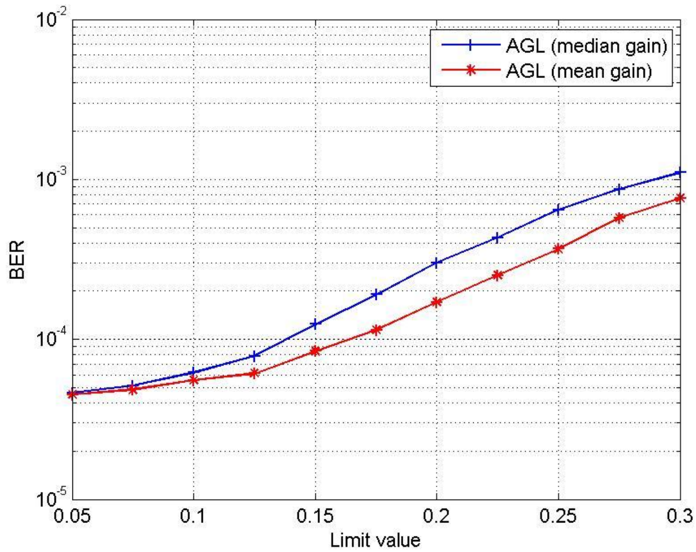

Fig. 8. BER vs. limit value (SNR = 28.5dB Pedestrian A channel model)

deploying individual loading, GL with different group size, and AGL with mean and median group gain respectively. The data rate is set at 4 bits per sub-channel. The coded BER curves are generated only for individual loading and AGL. The rate of the channel coding is obtained using 1/2 (561,753) convolution codes with constrain length of 9, along with Viterbi decoder in the receive side.

Fig. 7 depicts the BER curves for the above mentioned system configurations for 'ITU pedestrian A' channel model for $\Delta = 0.15$. The curve for AGL with mean group gain and median group gain lie close to that of GL with G = 4. However, the curve for AGL with median group gain is more degraded than the curve for AGL with mean gain. From **Fig. 2**, it is found that the average group size for AGL is around 12 sub-channels per group for $\Delta = 0.15$.

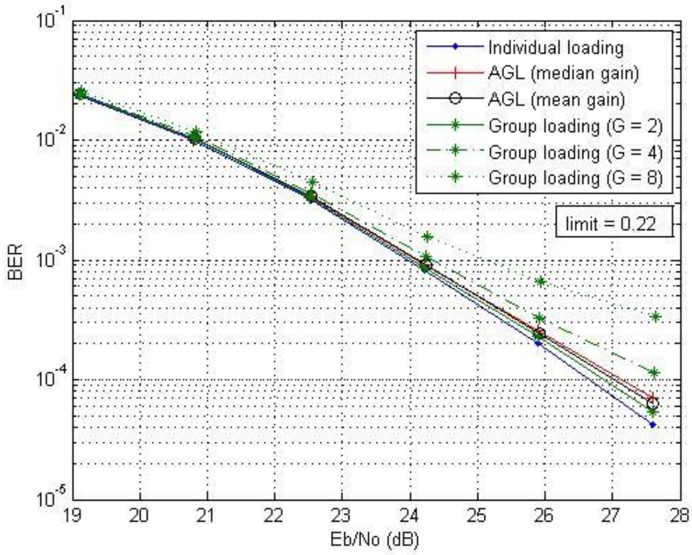

Fig. 9. BER curves ('ITU Vehicular A' channel model)

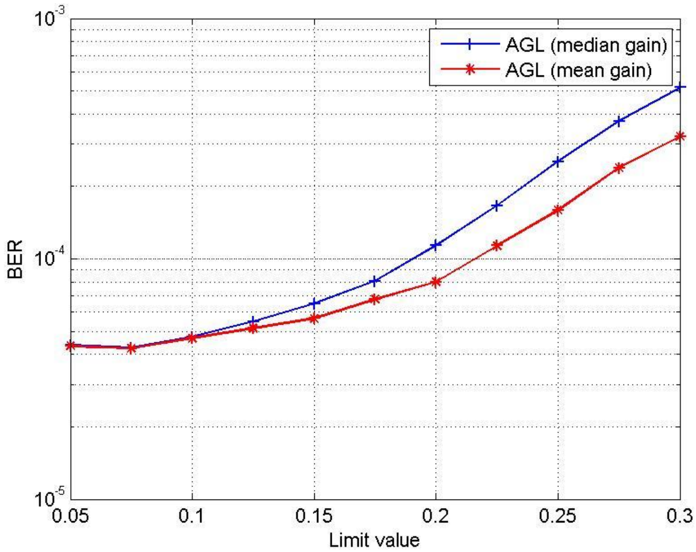

Fig. 10. BER vs. limit value (SNR=27.6dB, Vehicular A channel model)

Fig. 8 shows the BER performance of AGL with mean gain and median gain approach against various limit values. The 'ITU Pedestrian A' channel model is used with SNR = 28.5dB. The mean gain approach is always superior to median gain approach.

Fig. 9 shows the BER curves of the same systems as in Fig. 7 but for 'ITU vehicular A' channel model. For $\Delta = 0.22$, the BER performance of AGL with the mean group gain and the median group gain lies very close to that of GL with G = 2. Furthermore, the curve for the median gain AGL is slightly degraded than that for the mean gain AGL. The average group size for limit value of 0.22 is around 5.1 that can be seen in **Fig. 10**. The figure shows the characteristics of the AGL algorithm, for 'ITU Vehicular A' channel model, with respect to the average group size and the average number of group thus formed.

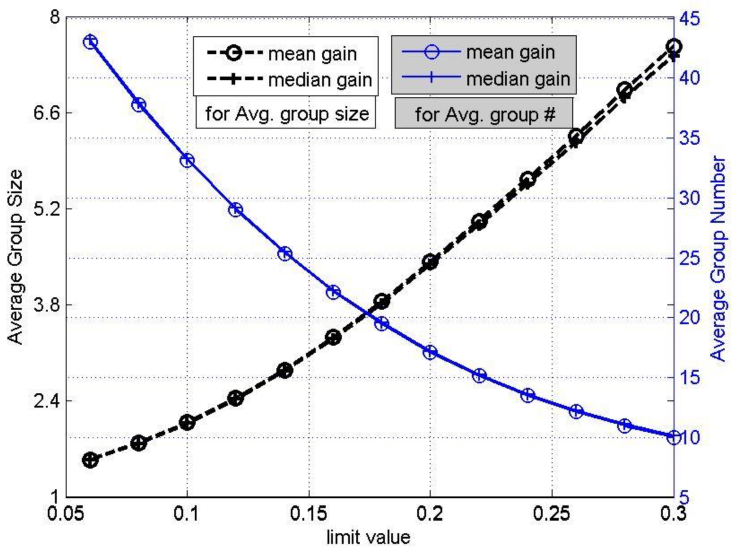

Fig. 11. Average group size and average number of groups for different limit value (Δ) in AGL for 'ITU Vehicular A' channel model

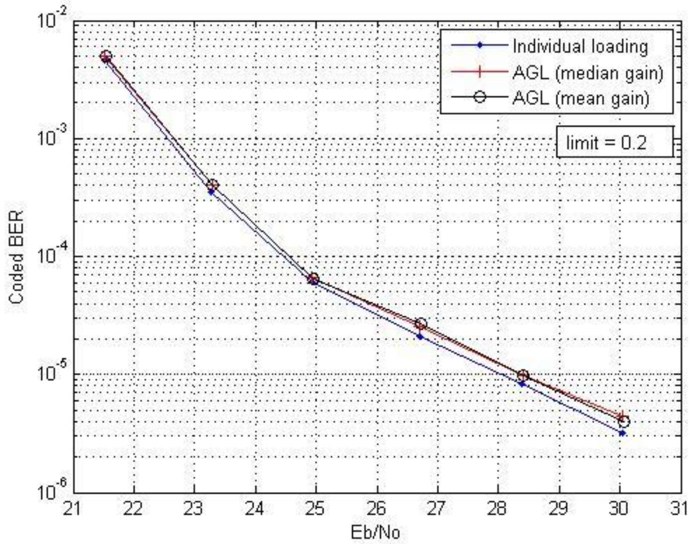

Fig. 12. Coded BER curves ('ITU Pedestrian A' channel model)

Fig. 11 shows the degradation of the BER performance as we increase Δ for SNR of 27.5dB under Vehicular A channel condition. Both **Fig. 9** and **Fig. 11** show that mean gain approach has better BER performance. The gap between the two approaches increases as limit value is increased.

Fig. 12 and **Fig.13** show the coded BER for the aforementioned system comparing AGL with individual loading, respectively for 'ITU pedestrian A' and 'ITU vehicular A' channel models. From both the figures, we can observe that the channel coding enhances the BER performance of our proposed algorithm in both the channel conditions. This is because, channel coding helps to recover the error caused while imperfectly allocating a particular

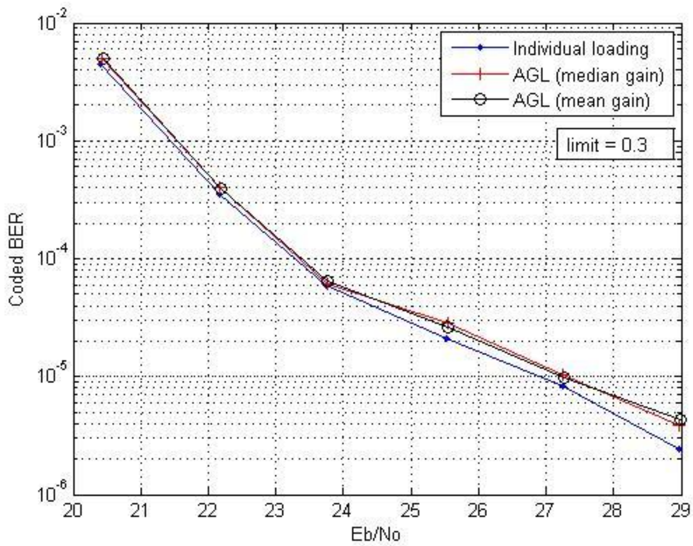

Fig. 13. Coded BER curves ('ITU Pedestrian A' channel model)

sub-channel to group that satisfies the predefined criteria. Every time the group is adaptively formed in AGL, the error caused by grouping is actually limited by Δ. The Δ determines the maximum allowable error, which also includes the error caused by finite M-QAM in practice. Thus, channel coding allows us to increase the limit value, such that, the average group size of the algorithm is increased, which in turn requires less feedback to the transmitter. Mean group gain and median group gain have more or less the same performance when channel coding is deployed.

7. Conclusion

The comparison among the loading algorithm yields that the Chow's algorithm BER performance is unstable to varying data rates. Campello's algorithm, on the other hand, enhances the performance of Chow's algorithm in optimum loading algorithm, whereas, FDBA algorithm is stable to the variable data rate. Furthermore, it is found that it takes longer time to converge to the target bit.

A "weight factor" is derived to enhance the estimation of the number of bit for various data rate with variable SNR gaps. The result confirms that the "weight factor" has contributed to maintain almost perfectly accurate bit estimation with varying SNR gap.

Our proposed AGL algorithm is found effective enough to reduce the CSI required by the factor of around 3 and 2.3 to that of the GL respectively in 'ITU pedestrian A' and 'ITU vehicular A' channel environment. It performs even better when channel coding is deployed allowing the limit value to be increased, which further reduces the feedback requirement imposed by AGL. Moreover, there is always a trade-off between the CSI requirement and the BER performance. The mean group gain approach is found to be slightly superior than the median group gain approach to achieve better BER performance with an optimal group in both channel environments.

References

[1] L.J. Cimini, Jr., "Analysis and Simulation of a Mobile Radio Channel Using Orthogonal Frequency Division Multiplexing," *IEEE Trans. Commu*., vol. 33, no. 7, pp. 665-675, Jul. 1985. Article (CrossRef Link)

[2] C. Oestges, B. Clerckx, "MIMO Wireless Communications, from Real-World Propagation to Space-Time Code Design," *Academic Press*, Jun. 2007.

[3] R.G. Gallager. "Information Theory and Reliable Communication," *Wiley*, New York, NY, 1968.

[4] P.S. Chow, J.M. Cioffi, J.A.C. Bingham, "A Practical Discrete Multitone Transceiver Loading Algorithm for Data Transmission Over Spectrally Shaped Channels," *IEEE Trans. on Commun.*, vol. 43, no. 234, pp. 773-775, 1995. Article (CrossRef Link)

[5] H. Ko, K. Lee, S. Oh, C. Kim, "Fast Optimal Discrete Bit-Loading Algorithms for OFDM-based systems," in *Proc. of International Conference on Computer Commun. and Networks (ICCCN)*, pp. 1-6, San Francisco, CA, Aug. 2009. Article (CrossRef Link)

[6] F. Sarabchi, M.E.K. Kalantari, "On the Use of Adaptive Loading algorithms in MIMO-OFDM Systems," in *Proc. of ICWN*, pp.326-330 , 2006. Article (CrossRef Link)

[7] J. Campello, "Practical Bit Loading for DMT," in *Proc. of IEEE ICC'99*, Vancouver, Canada, vol. 2, pp. 801-805, June 1999. Article (CrossRef Link)

[8] R.F.H. Fisher, J.B. Huber, "A New Loading Algorithm for Discrete Multitone Transmission," in *Proc. of Global Telecommunication Conference*, London, U.K., vol. 1, pp. 724-728, Nov. 1996. Article (CrossRef Link)

[9] H.Z.B. Chen, L. Lampe, R. Schober, "On MIMO-OFDM with Coding and Loading," *EURASIP Journal on Wireless Commun. and Networking*, vol. 2008. Article (CrossRef Link)

[10] S. Nader-Esfahani, M. Afrasiabi, "Simple Bit Loading Algorithm for OFDM-based Systems," *IET Communications*, vol. 1, no.3, pp. 312-316, June 2007. Article (CrossRef Link)

[11] L. Hou, X. Lin, "A Grouping Method of Bit Loading for Real-time OFDM-based Wireless Networks," in *Proc. of WICOM'08*, pp. 1-4, Oct. 2008. Article (CrossRef Link)

[12] R. Shrestha, J.M. Kim, "Adaptive Group Loading for MIMO OFDM Systems," in *Proc. of IEEE ICTC 2010*, Jeju Island, Korea, pp. 63-68, Nov. 2010. Article (CrossRef Link)

Robin Shrestha received a B.E. degree from National College of Engineering, Institute of Engineering, Tribhuvan University, Nepal in 2006 and a M.S. degree in Telecommunication Engineering from Dept. of Information and Telecommunication Engineering, Korea Aerospace University, Korea in 2009. He is currently enrolled in a Ph.D. degree in Graduate School of IT and Telecommunication, Inha University, Korea. His research interests include OFDM, PAPR, Resource Allocation, 3GPP LTE, and LTE-A, and MIMO.

Jae Moung Kim received B.S. degree from Hanyang University, Korea in 1974, a MSEE degree from the University of Southern California, USA in 1981, and Ph.D. degree from Younsei University, Korea in 1987. He was a Vice President of ETRI for Radio & Broadcasting Tech. Lab and Exec. Director of Satellite Comm. System Dept. of ETRI from Sept. 1982 to Mar. 2003. Since then, he has been a professor of School of Information and Communication Engineering, Inha University, Incheon, Korea. He is leading a Director of INHA-WiTLAB on the next generation wireless communications including cognitive radio technologies. Currently he holds a President of Korea Society of Space Technology, a senior member of IEEE, an overseas member of IEICE. His research interests include telecom system modeling and performance analysis of broadband wireless systems, mobile comm., satellite comm., especially cognitive radio and mobile radio transmission tech. for next generation.