Orthogonal Frequency Division Multiple Access with an Aggregated Sub-channel Structure and Statistical Channel Quality Measurement

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Abstract— **In this paper, an orthogonal frequency division multiple access (OFDMA) is considered for mobile air interface. To reduce the reverse link overheads for CQI feedback, we consider an aggregated sub-channel structure, where a set of adjacent sub-carriers are tied up to a sub-channel to be used as a unit of user-multiplexing and the corresponding power/rate allocation. Modeling the SNR distribution over the bandwidth of a sub-channel as Ricean, the channel quality of a sub-channel is summarized with the mean and variance of channel gain envelop divided by noise standard deviation. Then, We develop a generalized two step channel/resource allocation algorithm, which uses the two statistical measurements, and analyze the spectral efficiency of the OFDMA system in terms of average frequency utilization.**

Keywords-OFDMA, Resource Allocation

I. INTRODUCTION

With the successful application to fixed wireless networks, such as WLAN, OFDM is now widely considered for mobile communication systems, where the channel characteristic is assumed to vary (relatively) fast. In the OFDM applied to WLAN, the user multiplexing is more like TDMA (actually CSMA/CD), where only one user occupies the whole bandwidth at a time and adaptive modulation and coding (AMC) is applied in the form of water pouring type solution [1,2]. It was rather recent that the water-pouring algorithm has found practical applications related to discrete multi-tone (DMT) systems, where the so-called bit-loading algorithms have been intensively studied [3-5]. More recently, many researchers have considered joint bit-loading/sub-carrier allocation for improved throughput [7-10]. Comparing to OFDM, it is often called as OFDMA or multiuser OFDM, in the sense that the entire bandwidth is shared by many users.

Implementing these schemes, however, requires the perfect knowledge of the channel condition of each sub-carrier, i.e. CQI for every sub-carriers of every users have to be reported to the base station. This is a plausible scenario for fixed wireless network, where only once, or at least not very often, CQI report is enough to handle the network traffic. Unfortunately, however, in time-varying fading channel, the CQI have to be frequently reported and sometimes the amount of CQI may be prohibitive, especially when intending to support high speed mobiles.

As a way of reducing this prohibitive CQI feedback, we in this paper consider an aggregated sub-channel structure, which consists of a set of adjacent sub-carriers and is used as the unit of CQI measurement, dynamic channel allocation and power/rate assignment. By modeling the channel quality fluctuation over a sub-channel as Ricean distributed random variable, we develop a generalized dynamic resource allocation policy based on 1st and 2nd order statistical measurements of the channel gain and analyze the performance in terms of frequency utilization.

In the next section we briefly overview the system description and in Section III, the channel quality over a sub-channel is modeled as Ricean distributed random vector. Section IV provides a generalized channel/resource allocation algorithm and analyzes the performance of OFDMA with various configurations. Section V provides some numerical results and Section VI gives concluding remarks.

II. SYSTEM DESCRIPTION

A. Preliminaries

Consider a downlink channel in an isolated OFDM system, consisting of a base station (BS) and many mobile stations (MS). Let $\mathbf{x}^{(k)} = [x_1^{(k)}, x_2^{(k)}, \ldots, x_N^{(k)}]$ be the received OFDM symbol vector at k^{th} MS, where N is the number of useful sub-carriers. Each component of the vector can be expressed as

$$x_n^{(k)} = g_n^{(k)} P_n s_n + n_n^{(k)} \tag{1}$$

where $g_n^{(k)}$ is the complex channel gain for the n^{th} sub-carrier, P_n the signal power assigned at the transmitter, s_n the transmitted data symbol, and n_n is the complex Gaussian noise of mean zero and variance N_0. Let us say K users' data are waiting to be served from the base station. Assuming that the base station knows about the each user's channel profile for each sub-carrier, let $\gamma_n^{(k)}$ be the channel quality of the n^{th} sub-carrier of the user k defined as $\gamma_n^{(k)} \equiv |g_n^{(k)}|^2/N_0$.

With this signal model, consider two-step resource allocation algorithm, as in [9], which first allocate sub-channels to the user whose SNR is the best in that sub-channel and, then distribute the total power over the sub-channels using water-pouring algorithm. Although the primary purpose of dividing the algorithm into two steps is for analytical simplicity, it does not necessarily mean that the two-step approach is sub-optimal. In fact, the two-step approach was proven in [10] to be optimum in maximizing total throughput of all the users. Let κ_m be the user index chosen for the m^{th} sub-channel and P_m the power allocation. The two-step resource allocation algorithm can be expressed as, for given set of channel quality profile $\{\gamma_n^{(k)}; k = 1,2,..,K\}$,

Step 1: $\kappa_m = \arg\max_{1 \le k \le K} \gamma_m^{(k)}$ for $m = 0,\ldots,M\text{-}1$ (2)

Then, for given set of $\{\gamma_n^{(k)}; k = \kappa_1, \kappa_2,.., \kappa_M\}$

Step 2: $\{P_m\}_{m=0}^{M-1} = \arg\max_{P_0, P_1,..,P_{M-1}} \left(\sum_{m=0}^{M-1} \log(1 + \gamma_1^{(\kappa_1)} P_m) \right)$ (3)

subject to $\sum_{m=0}^{M-1} P_m = MP$ (constant). The solution of (3) results in the well-known water-pouring algorithm.

B. Distributed vs. Aggregated Sub-channel structure

As mentioned before, however, implementing this scheme requires the perfect knowledge of the channel condition of each sub-carrier and a way of reducing this prohibitive CQI feedback in the uplink would be chunking a set of sub-carriers. Two possible scenarios can be considered according to how a sub-channel is defined; i.e. 1) distributed sub-channel structure and 2) aggregated structure. In the former, the sub-carriers belonging to a sub-channel is distributed over the entire bandwidth, where a primary purpose is to obtain frequency diversity so that a minimal link quality can be maintained almost all the time. On the other hand, in the aggregated structure, a sub-channel consists of a set of adjacent sub-carriers to facilitate aggressive dynamic channel allocation and adaptive modulation/coding.

In fact, constructing a sub-channel by tying up adjacent sub-carriers is virtually equivalent to widening the bandwidth of sub-channel. Although it may cause the effective throughput improvement with multiuser diversity and/or the water-pouring algorithm reduced, they are still effective if the sub-channel bandwidth is smaller than the coherence bandwidth. At least, it would show the same performance as that of the distributed sub-channel; i.e. in the opposite case where the sub-channel is wider than the coherence bandwidth, enough frequency diversity still can be obtained.

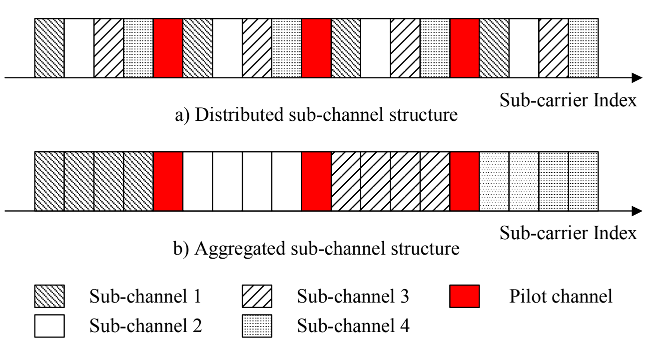

Fig.1 Simplified block diagram of Sub-channel structure, Distributed (a) vs. Aggregated (b)

III. CHANNEL MODELING

In the previous sub-section, we defined the sub-channel as a set of sub-carriers, either aggregated or distributed. Generally speaking, even in aggregated structure, the channel quality fluctuates within a sub-channel bandwidth unless the coherence bandwidth is much larger than the sub-channel bandwidth. In this sub-section, assuming aggregated structure, we model the statistical characteristic of the channel quality fluctuation over a sub-channel. As will be discussed later, however, SNR fluctuation over a distributed sub-channel can be regarded as a special case.

Let L be the number of sub-carriers belonging to a sub-channel and $\mathbf{g}^{(k)}_m$ the complex channel gain vector of the m^{th} sub-channel seen by the k^{th} user defined as

$$\mathbf{g}^{(k)}_m \equiv [g^{(k)}_{m,1}, g^{(k)}_{m,2},.., g^{(k)}_{m,L}] \;\; \forall m \tag{4}$$

such that $g^{(k)}_{m,l} \equiv g^{(k)}_{mL+l}$ with L the number of sub-carriers in a sub-channel and $M = N/L$ the total number of the available sub-channels. Without loss of generality, we consider only integer value of N/L. The corresponding channel quality vector is given by $\gamma^{(k)}_m \equiv [\gamma^{(k)}_{m,1}, \gamma^{(k)}_{m,2},\ldots, \gamma^{(k)}_{m,L}]$ with $\gamma^{(k)}_{m,l} \equiv |g^{(k)}_{m,l}|^2/N_0$. Note that the channel quality has different meaning from SNR which is given by $\beta^{(k)}_{m,L} = P_m \cdot \gamma^{(k)}_{m,L}$. Our objective here is to statistically characterize the complex channel gains and the channel quality profile in a sub-channel.

Now, consider multipath fading channel with normalized exponential delay profile expressed as

$$v_d = \exp(-d/2D_{rms}) \cdot w_d / V \quad \text{for } d\text{=0, 1,.., } D_{max} \tag{5}$$

where D_{rms} is the rms delay in sample unit, D_{max} the maximum delay spread, v_d the sampled complex delay profile, w_d a zero-mean complex Gaussian noise process with variance 1. V is the normalization factor such that $\Sigma_d|v_d|^2$=1. The N-point Fourier transformation of v_d is the complex channel gain

$$g_n = FT_N[v_d] \equiv (N)^{-1/2} \sum_{d=0}^{N-1} v_d \cdot \exp(-2\pi dn/N) \tag{6}$$

which is a filtered complex Gaussian noise sequence defined as a circular convolution of $\eta_n \equiv \mathrm{FT}_N[w_d]$ and

$$\varepsilon_n \equiv \mathrm{FT}_N[\exp(-d/D_{rms})/D_{rms}] \quad \text{for } d\text{=0,1,..,}D_{max} \tag{7}$$

Note that $E[g_n] = 0$ and $Var[g_n] = 1$. For large signal bandwidth, we can safely assume that the empirical distribution of g_n, as well as η_n, converge to complex Gaussian. Let ψ_n be the autocorrelation function of g_n and l_{cbw} the coherence bandwidth of the channel in sample unit, at which point $\mathrm{Re}[\psi_{l_{cbw}}]/\psi_0 \approx \rho$. Usually, 0.5 would be one of the typical values of ρ. We define the normalized coherence bandwidth $f_{cbw} \equiv l_{cbw}/N$.

Let us define the average of $g^{(k)}_{m,l}$ over the m^{th} sub-channel of the k^{th} user as

$$G_m^{(k)} \equiv L^{-1} \sum_{l=0}^{L-1} g_{m,l}^{(l)} \tag{8}$$

and the fluctuating component

$$h^{(k)}_{m,l} \equiv g^{(k)}_{m,l} - G^{(l)} \quad \text{for } l = 0,1,\ldots,L\text{-}1 \tag{9}$$

Note that $G^{(k)}_m$ is a fixed value for a given sub-channel, while it is assumed to be a complex Gaussian random variable in the scope of the entire bandwidth. With these definitions, we first consider two extreme cases; i.e. $f_{cbw} >> f_{sub\text{-}ch}$ and $f_{cbw} << f_{sub\text{-}ch}$.

The former corresponds to the case that the rms delay is small enough for the received signal power at each sub-carrier to be almost the same within a sub-channel and the latter to that the rms delay is large. For analytical purpose, we assume that, even when the rms delay is small, enough frequency selectivity still exists through the entire signal bandwidth such that the empirical distribution of the channel gain of each sub-channel follows complex Gaussian PDF. With this assumption, the received signal statistics for the two extreme cases can be summarized as follows. When $f_{cbw} >> f_{sub\text{-}ch}$, $g^{(k)}_{m,l}$ is almost constant for given m, while $G^{(k)}_m$ is zero-mean complex Gaussian random variable in the scope of the entire bandwidth. This is the ideal case for frequency selective multiplexing. In another extreme, when $f_{cbw} << f_{sub\text{-}ch}$, $g^{(k)}_{m,l}$ is (almost) zero-mean complex Gaussian even for given m, while the fluctuation of $G^{(k)}_m$ over the entire bandwidth is (almost) zero. Assuming all the users have the same statistical channel characteristics, no multiplexing gain can be obtained in this extreme. Frequency diversity would be the only way to maintain link quality.

Now, we consider more general case, i.e. in between of the two extreme cases. Note that $G^{(k)}_m$ is a zero-mean complex Gaussian random variable since it is just a block average of the complex channel gain $g^{(k)}_n$, which is a zero-mean complex Gaussian in the scope of entire bandwidth even though it is likely to be non-zero-mean in local sense. The variance of $G^{(k)}_m$, however, would be smaller than that of $g^{(k)}_n$ depending on the bandwidth of a sub-channel comparing with the coherence bandwidth. In general, for given m, $g^{(k)}_{m,l}$ can be approximated to be a non-zero mean complex Gaussian noise process, which means that $G^{(k)}_m$ is non-zero, over which a zero-mean complex Gaussian noise ($h^{(k)}_{m,l}$) is superimposed. Since a sum of independent Gaussian random variables is a Gaussian random variable with the mean equal to the sum of respective means and the variance to the sum of respective variance, it is easily shown that for any k $E[G^{(k)}_m]=0$, $Var[G^{(k)}_m]=\Omega(L)$, $E[\sum_{l=0}^{L-1} h^{(k)}_{m,l}]=0$ and $E[\sum_{l=0}^{L-1}|h^{(k)}_{m,l}|^2]=1-\Omega(L)$. Noticing that $g^{(k)}_n$ is a circular convolution of a Gaussian noise process η_n and ε_n defined in (7), $\Omega(L)$ is given by

$$\Omega(L)=\sum_n |\varepsilon_n \otimes u_n^{(L)}|^2 \tag{10}$$

where $\otimes$ is the circular convolution operator and

$$u_n^{(L)} \equiv \begin{cases} 1/L & \text{for } n = 0,1,\ldots,L-1 \\ 0 & \text{otherwise} \end{cases}$$

Although the actual empirical density function may not look like Gaussian, we will use the following approximation.

$$G^{(k)}_m \sim \mathcal{CN}(0,\Omega(L)) \quad \text{in global scope} \tag{11}$$

$$h^{(k)}_{m,l} \sim \mathcal{CN}(0,1-\Omega(L)) \quad \text{in local scope} \tag{12}$$

where $\mathcal{CN}(a,b)$ is the PDF of complex Gaussian noise of mean a and variance b. With the normalization in (5), $\Omega(L) \le 1$. In summary, we assume the following

1) $G^{(k)}_0, G^{(k)}_1,\ldots, G^{(k)}_{M-1}$ is a sequence of i.i.d. Gaussian random variables with mean zero and variance $\Omega(L)$.
2) For all m (within a sub-channel), $h^{(k)}_{m,l}$ for $l = 1,2,3,\ldots,L$, is a complex Gaussian noise process with mean-zero and variance $1-\Omega(L)$
3) In the scope of the entire bandwidth, however, $g^{(k)}_{m,l}$ is a zero-mean Gaussian noise with variance 1. While, for given m, $g^{(k)}_{m,l}$ for $l = 1,2,3,\ldots,L$, is a complex Gaussian noise with mean $G^{(k)}_m$ and variance $1-\Omega(L)$.

With this approximation, the empirical density function of the channel gain envelop over an aggregated sub-channel can be approximated to a Ricean distribution, i.e. for any m,

$$\frac{|g^{(k)}_{m,l}|}{\sqrt{N_0}} \sim R_{A^{(k)}_m,B^{(k)}_m}(r) \equiv \frac{r}{B^{(k)}_m} I_0\left(\frac{\sqrt{A^{(k)}_m}\,r}{B^{(k)}_m}\right)\exp\left(-\frac{r^2+A^{(k)}_m}{2B^{(k)}_m}\right), \quad r \ge 0 \tag{13}$$

where $I_0(z)=(2\pi)^{-1}\int_0^{2\pi}\exp(z\cos(u))du$ and the Ricean factor R is defined as $R=A^{(k)}_m/B^{(k)}_m$ for non-negative real value $A^{(k)}_m$ and $B^{(k)}_m$. Comparing (14) with (13), it is identified that, for aggregated sub-channel structure,

$$A^{(k)}_m=\frac{|G^{(k)}_m|^2}{N_0} \sim \frac{1}{\Omega(L)/N_0}\exp\left(\frac{-a}{\Omega(L)/N_0}\right) \tag{14.a}$$

$$B^{(k)}_m = (1-\Omega(L))/2N_0 \text{ (const) for all } m \tag{14.b}$$

The average channel quality and the average SNR are given by $\Gamma^{(k)}_m = A^{(k)}_m + 2B^{(k)}_m$ and $P_m \cdot \Gamma^{(k)}_m$, respectively.

Now, let us consider a distributed structure, where a sub-channel is defined as a set of sub-carriers periodically spaced with a unique offset corresponding to the sub-channel index. In this case, the channel profile over a sub-channel is the sampled sequence of the same channel profile over the entire bandwidth. It means that, assuming signal bandwidth much larger than f_{cbw}, $G^{(k)}_m \approx 0\ \forall m$ and $h^{(k)}_{m,l}$ has the same distribution for any k. Specifically, the same assumptions as in 1) to 3) hold with $\Omega(L) = 0$, equivalently to say that, in (13),

$$A^{(k)}_m = 0 \text{ and } B^{(k)}_m = 1/2N_0 \text{ (const) } \forall m \tag{15}$$

This also means that, for any k, all the sub-channels have the same quality. Note that the situation in (15) is equivalent to (14) with the condition $f_{cbw} << f_{sub\text{-}ch}$.

IV. General Formulation and Performance Analysis

A. Generalized Two-Step Algorithm

Since the channel quality fluctuates within a sub-channel, we first need to summarize the fluctuating channel quality to be feedback to BS. One of the easiest ways is, with the Ricean fading model, to use 1st and 2nd moment of the signal envelop or the corresponding parameters $A^{(k)}_m$ and $B^{(k)}_m$. Fig.2 shows a simplified block diagram of resource allocation in OFDMA downlink where the CQI is given by the Ricean parameters, $A^{(k)}_m$ and $B^{(k)}_m$. To formulate the generalized algorithm that incorporate the parameter pairs reported from mobile stations, we define the frequency utilization of a sub-channel with power assignment P and Ricean channel parameter a and b as

$$U(P,a,b) \equiv \int_0^\infty \log_2\left(1+P\cdot r^2\right)\cdot R_{a,b}(r)\cdot dr \tag{16}$$

Note that (17) is monotonically increasing with P for given a and b. Then, the two-step allocation in (3) and (4) can now be expressed as, for arbitrary constant P

Step 1: $\kappa_m = \arg\max_k U\left(P, A_m^{(k)}, B_m^{(k)}\right)$ $m = 0,..,M$-1 (17)

and for given $\{\kappa_m;\ m = 0,1,..,M\text{-}1\}$

Step 2: $$\{P_m\}_{m=0}^{M-1} = \arg\max_{p_0,p_1,..,p_{M-1}} \sum_{i=0}^{M-1} U(p_i, A_i^{(\kappa_i)}, B_i^{(\kappa_i)}) \quad (18.a)$$

subject to the constraint $$\sum_{m=0}^{M-1} P_m = MP \quad (18.b)$$

B. Theoretical Performance

In this section, we evaluate the theoretical performance of the OFDMA in terms of the expected frequency utilization. Basically, we will focus on the two-step algorithm described in (17) and (18) with either aggregated or distributed sub-channel structure. For comparison, however, we will also consider other options, i.e. random channel allocation and equal power allocation in replacement of (17) and (18), respectively. The random channel allocation resembles round robin scheduling in time domain in the sense that it does not take the channel condition into account. For analytical simplicity, we will consider a homogeneous user set, i.e. all the users have the same channel statistics.

First, let us define a composite vector $\boldsymbol{\gamma} \equiv [\boldsymbol{\gamma}_0, \boldsymbol{\gamma}_1,\ldots,\boldsymbol{\gamma}_{M\text{-}1}]$ with $\underline{\boldsymbol{\gamma}}_m = \boldsymbol{\gamma}_m^{(\kappa_m)} = [\gamma_{m,0}^{(\kappa_m)}, \gamma_{m,1}^{(\kappa_m)},..,\gamma_{m,L-1}^{(\kappa_m)}]$, which is the channel quality profile over the m^{th} sub-channel, and the frequency utilization conditioned on $\boldsymbol{\gamma}$ as

$$U(\underline{\boldsymbol{\gamma}}) \equiv \frac{1}{M}\sum_{m=0}^{M-1} U_m(\underline{\boldsymbol{\gamma}}_m) = \frac{1}{M}\sum_{m=0}^{M-1}\frac{1}{L}\sum_{l=0}^{L-1}\log_2\left(1 + P_m \cdot \gamma_{m,l}^{(\kappa_m)}\right) \quad (19)$$

where κ_m and P_m be the channel and power assignment according to a certain allocation policy. Assuming the empirical density function of $(\gamma^{(k)}_{m,l})^{1/2}$ converge to its PDF given in (13), (19) can be approximated to

$$U(\underline{\boldsymbol{\gamma}}) \approx \frac{1}{M}\sum_{m=0}^{M-1} U(P_m, A_m^{(\kappa_m)}, B_m^{(\kappa_m)}) \quad (20)$$

Furthermore, assuming M and L are large enough for the empirical density of $A_m^{(\kappa_m)}$ and $B_m^{(\kappa_m)}$ to converge to the respective PDF or the deterministic values in (14) for aggregated structure or in (15) for distributed structure, the expected frequency utilization can be in general expressed as

$$E[U(\underline{\boldsymbol{\gamma}})] = \int_0^\infty U\left(\lambda(a), a, B\right) \cdot p_\kappa(a) \cdot dr \cdot da \quad (21)$$

where $p_\kappa(a)$ is the PDF of $A_m^{(\kappa_m)}$ for given channel allocation policy, $\kappa(\cdot)$.

Note that in general $B^{(\kappa m)}_m$ is not constant and a larger $\Gamma^{(k)}_m$, does not necessarily mean better frequency utilization, making the analysis complicated. Fortunately, however, with the assumption 1) to 3) in Section III and homogenous user set, $B^{(\kappa m)}_m$ is constant $\forall m$, and the same $\forall k$, making the selection of the best user in (17) equivalent to select the user with the largest $A^{(k)}_m$. Hence, using (14), we obtain

$$p_\kappa(a) = \frac{d}{da}\Pr\left\{\max_m A_m^{\kappa_m} \le a\right\} = \frac{KN_0}{\Omega(L)}\exp\left(\frac{-aN_0}{\Omega(L)}\right)\cdot\left[1 - \exp\left(\frac{-aN_0}{\Omega(L)}\right)\right]^{K-1} \quad (22)$$

for the optimal channel allocation in (18). Note that the random channel allocation (i.e. Round robin scheduling) is equivalent to the case with $K = 1$ in (22). On the other hand, for distributed sub-channel structure, we have from (15)

$$p_\kappa(a) = \delta(a), \quad (23)$$

for both the optimal and random channel allocation.

To complete the calculation of (20), we need $\lambda(a)$ too. For the optimal power allocation defined in (18.a) and (18.b), it is given by

$$\Lambda(a) = \arg\max_{\lambda(a)} \int_0^\infty\int_0^\infty \log_2\left(1 + \lambda(a)\cdot r^2\right) R_{a,B}(r)\, p_\kappa(a)\, dr\, da \quad (24.a)$$

subject to $$\int_0^\infty \lambda(a)\cdot p_\kappa(a)\cdot da = P \quad (24.b)$$

For aggregated structure, the solution is not mathematically tractable in general, while we can easily obtain the solution for the two special cases mentioned before. That is, when $f_{sub\text{-}ch}/f_{cbw} << 1$, $B = 0$ and $R_{a,B}(\gamma) = \delta(\gamma - a^{1/2})$, so that $\Lambda(a)$ in (24.a) is simplified to

$$\Lambda(a) = \arg\max_{\lambda(a)} \int_0^\infty \log_2\left(1 + \lambda(a)\cdot a\right)\cdot p_\kappa(a)\cdot da \quad (25)$$

which gives the well-known water-pouring solution, i.e.

$$\Lambda(a) = \begin{cases} 1/a_0 - 1/a & \text{for } a \ge a_0 \\ 0 & \text{for } a < a_0 \end{cases}$$

where a_0 is given by solving the constraint (24.b) with $\Lambda(a)$. Using the same conditions, (20) is reduced to

$$E[U(\underline{\boldsymbol{\gamma}})] = \int_0^\infty \log_2(1 + \Lambda(a)\cdot a)\cdot p_\kappa(a)\cdot da \quad (26)$$

with the water-pouring solution above. On the other hand, when $f_{sub\text{-}ch}/f_{cbw} >> 1$, $A = 0$, $B = 1/2N_0$, which are the same conditions for distributed structure in (16). In this case, the channel characteristics are the same for all the sub-channels, so that the transmission power is allocated equally even with water-pouring type power allocation policy, i.e. $\Lambda(a) = P$ (const). Hence, with the conditions in (15) and (23), (20) simply becomes

$$E[U(\underline{\boldsymbol{\gamma}})] = \int_0^\infty \log_2(1 + P\cdot\gamma^2)\cdot R_{0,1/2N_0}(\gamma)\cdot d\gamma \quad (27)$$

For distributed sub-channel structure, with the condition in (15), the solution of (24.a) and (24.b) is trivially $\Lambda(a) = P$ (const) and the performance is given by the same as in (31), regardless of the channel/power allocation policy. As mentioned before, the reason is that with distributed structure all the sub-channels have (almost) equal quality. Note also that with $\Lambda(a) = P$ and $K = 1$, (26) is equivalent to (27), which means that the performance of distributed structure is the same as the worst performance of the aggregated structure with equal power and random channel allocation.

V. NUMERICAL RESULTS

In the numerical results that follow, we assume that every user in the system have the same statistical channel frequency characteristics. Fig.3 shows a comparison of frequency utilization of ideal case for diversity order of 2, 4, 8, 16, 32, 64 and 128, respectively. The term 'ideal' stands for $f_{cbw} >> f_{sub\text{-}ch}$ for the aggregated sub-channel structure. Diversity order of 1 corresponds to distributed sub-channel structure or to random sub-channel assignment with aggregated sub-channel structure. The dashed lines are the performance with water-pouring type power allocation, showing that compared with user-multiplexing gain the water pouring power allocation has little contribution to the performance improvement. Only in the low average SNR region, it improves the frequency utilization with just noticeable difference. For large diversity order, no improvement has been found. We note that the results are consistent with the simulation results reported in [10]. For the aggregated sub-channel structure where SNR fluctuates, Fig.4 show the frequency utilization as a function of coherence bandwidth normalized to the bandwidth of a sub-channel. The figure shows for aggregated sub-channel how the frequency utilization is affected by bandwidth of a sub-channel. It also shows that dynamic channel allocation gives its nominal gain for f_{cbw}>4*$f_{sub\text{-}ch}$, while we lose the gain as f_{cbw} gets narrower and completely lose when f_{cbw}<$f_{sub\text{-}ch}$/16.

VI. CONCLUDING REMARKS

An OFDMA system has been considered with an aggregated sub-channel structure. Modeling the SNR distribution over a sub-channel as Ricean fading, it is suggested to feedback both the 1st and 2nd order statistics of the received signal envelop for CQI to be used at the transmitter (BS) for channel/resource allocation. We devised a generalized resource allocation algorithm based on the Ricean distribution model and analyzed the system performance in terms of frequency utilization.

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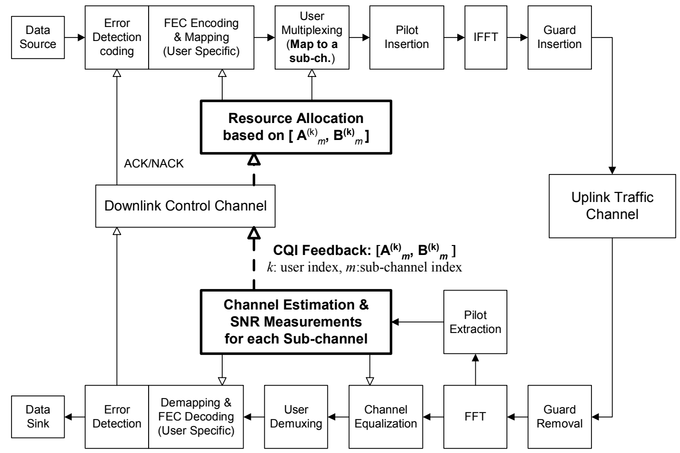

Fig.2. Simplified Block diagram of Resource allocation in OFDMA Downlink

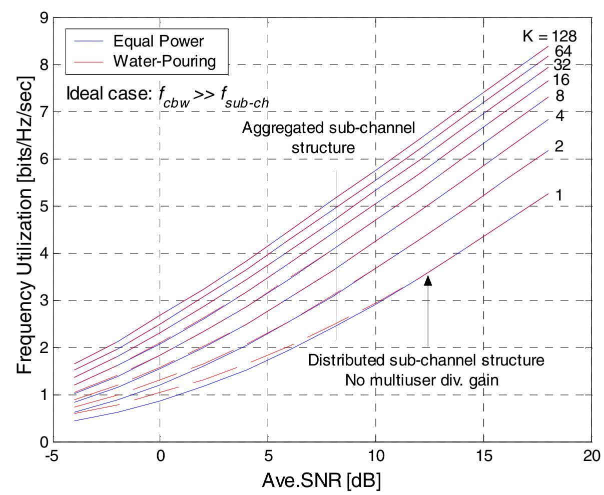

Fig.3 Frequency Utilization as a function of Ave.SNR

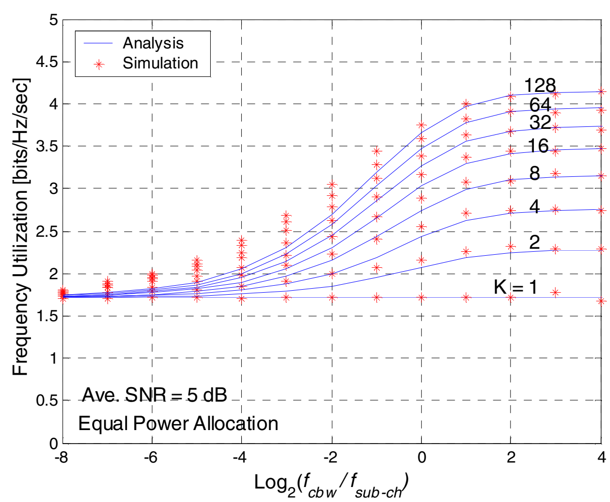

Fig.4 A plot of Frequency utilizations as a function of $\log_2(f_{cbw}/f_{sub\text{-}ch})$, Ave. SNR = 5dB