Paper

Low Complexity Greedy Power Allocation Algorithm for Proportional Resource Allocation in Multi-User OFDM Systems

Najib A. Odhah, Moawad I. Dessouky, Waleed E. Al-Hanafy, and Fathi E. Abd El-Samie

Faculty of Electronic Engineering, Menoufia University, Menouf, Egypt

Abstract—Multi-User Orthogonal Frequency Division Multiplexing (MU-OFDM) is an efficient technique for achieving high downlink capacity in high-speed communication systems. A key issue in MU-OFDM is the allocation of the OFDM subcarriers and power to users sharing the channel. In this paper a proportional rate-adaptive resource allocation algorithm for MU-OFDM is presented. Subcarrier and power allocation are carried out sequentially to reduce the complexity. The low complexity proportional subcarriers allocation is followed by Greedy Power Allocation (GPA) to solve the rate-adaptive resource allocation problem with proportional rate constraints for MU-OFDM systems. It improves the work of Wong *et al.* in this area by introducing an optimal GPA that achieves approximate rate proportionality, while maximizing the total sum-rate capacity of MU-OFDM. It is shown through simulation that the proposed GPA algorithm performs better than the algorithm of Wong *et al.*, by achieving higher total capacities with the same computational complexity, especially, at larger number of users and roughly satisfying user rate proportionality.

Keywords—GPA, MU-OFDM, proportional resource allocation, sum-rate capacity.

1. Introduction

MU-OFDM is a technology that has become increasingly important for wireless systems over the past decade. It is considered as one of the two cornerstone technologies of the next generation wireless networks, with Multiple-Input Multiple-Output (MIMO) systems being the other one. MU-OFDM is an expansion upon the basic principles of the Single-User Orthogonal Frequency Division Multiplexing (SU-OFDM) technology, and is designed to accommodate wideband multi-user systems.

SU-OFDM is one of the promising signal processing techniques to provide a high performance physical layer. It has been widely adopted in standards by wireless industry such as IEEE 802.11a and IEEE 802.11g Wireless Local Area Networks (WLAN), IEEE 802.16 fixed Wireless Metropolitan Area Networks (WMAN) which was later extended in IEEE 802.16e (WiMAX) to satisfy high speed mobility and to support both fixed and mobile user stations [1], [2].

SU-OFDM is based on multicarrier transmission in which the broadband channel is divided into N narrowband subchannels, each with a bandwidth much smaller than the coherence bandwidth of the channel. The high rate data stream is then split into N substreams of lower rate data which are modulated into N OFDM symbols and transmitted simultaneously on N orthogonal subcarriers [3]. The low bandwidth of the subchannels along with the frequency spacing between them are necessary to have flat fading orthogonal subcarriers with approximately constant channel gain during each transmission block.

In SU-OFDM, the user can use the total power to transmit on all N subcarriers. The system is then optimized by exploiting the frequency selectivity of the channel and dynamically adapting the modulation type and power on each subcarrier. These dynamic power allocation schemes [4], [5] have shown significant performance gain in terms of throughput compared to static schemes.

In an MU-OFDM system there is a need for a multiple access scheme to allocate the subcarriers and the power to the users. In static subcarrier allocation schemes, each user is assigned to predetermined time slots or the frequency bands respectively, regardless of the channel status. In other words, in non-adaptive fixed subcarrier allocation schemes, an independent dimension is allocated to each user without considering the channel status. In such systems, the optimization problem of maximizing the total throughput of the system reduces to only power allocation or bit loading on the subcarriers. On the other hand, since the fading parameters for different users are mutually independent, the probability that a subcarrier is in deep fade for all users is very low. Each subcarrier is likely to be in a good condition for some users in the system. This is the principle of MU-OFDM with adaptive power allocation in which subcarrier allocation itself plays a very significant role in maximizing the total throughput by using multiuser diversity. A survey of the adaptive MU-OFDM system design problems including an overview of physical layer, Medium Access Control (MAC), and radio resource allocation design issues are provided in [6], [7].

The problem of allocating the base station resources (subcarriers, rates, and powers) to the different users in an MU-OFDM system has been an area of active research over the past several years. This problem has been studied from two perspectives; schemes that minimize the amount of transmit power (Margin Adaptive (MA) approaches [8]–[11]), and those that maximize the sum-rate capacity of the system (Rate Adaptive (RA) approaches [12]–[19]).

In an MU-OFDM system with adaptive subcarrier and power allocation, since the fading parameters for different users are mutually independent, the probability that a subcarrier is in deep fade for all users is very low, and thereby each subcarrier is likely to be in a good condition for some users in the system. This allocation plays a very significant role in maximizing the total sum-rate capacity by using a multi-user diversity [7].

In [16] the RA problem was investigated, wherein the objective was to maximize the total sum-rate capacity over all users subject to power and Bit Error Rate (BER) constraints. It was shown that in order to maximize the total sum-rate capacity, each subcarrier should be allocated to the user with the best gain on it, and the power should be allocated using the waterfilling algorithm across the subcarriers. However, no fairness among the users was considered in [16]. This problem was partially addressed in [12] by ensuring that each user would be able to transmit at a minimum rate, and also in [13] by incorporating a notion of fairness in the resource allocation through maximizing the minimum user's data rate. In [18] the fairness was extended to incorporate varying priorities. Instead of maximizing the minimum user's capacity, the total sum-rate capacity was maximized subject to user rate proportionality constraints. This is very useful for service level differentiation, which allows flexible billing mechanisms for different classes of users. However, the algorithm proposed in [18] involves solving non-linear equations, and this requires computationally expensive iterative operations and is thus not suitable for a cost-effective real-time implementation. The authors in [19] developed a subcarrier allocation scheme that linearizes the power allocation problem, while achieving approximate rate proportionality. The resulting power allocation problem is thus reduced to a solution of simultaneous linear equations.

This paper uses the subcarrier allocation algorithm proposed in [19] and simplifies the power allocation using the GPA algorithm to optimally allocate the transmit power. In simulation, the proposed algorithm achieves a higher total sum-rate capacity than that achieved by [19] and satisfies the same computational complexity, while achieving an acceptable rate proportionality.

The rest of this paper is organized as follows. In Section 2, the system model of MU-OFDM with adaptive subcarrier and power allocation is presented. The proposed resource allocation algorithm is described in Section 3. Simulation results are given in Section 4. Finally, conclusions are given in Section 5.

2. System Model

The block diagram of the downlink of MU-OFDM system is shown in Fig. 1. At the base station transmitter, the bits for each of the different K users are allocated to the N subcarriers, and each subcarrier n $(1 \leq n \leq N)$ of user k $(1 \leq k \leq K)$ is allocated a power $p_{k,n}$. It is assumed that subcarriers are not shared by different users. Each of the user's bits are then modulated into N M-level Quadrature Amplitude Modulation (QAM) symbols, which are subsequently combined using the Inverse Fast Fourier Transform (IFFT) into an MU-OFDM symbol. This is then transmitted through a slowly time-varying, frequency-selective Rayleigh channel with bandwidth B. The subcarrier allocation is known to all users through a control channel; hence each user needs only to decode the bits on his assigned subcarriers. It is assumed that each user experiences independent fading, and the channel gain of user k in subcarrier n is denoted as $g_{k,n}$, with Additive White Gaussian Noise (AWGN) with power $\sigma^2 = N_0 B/N$ where N_0 is the noise power spectral density. The corresponding subcarrier Signal-to-Noise Ratio (SNR) is thus denoted as $h_{k,n} = g_{k,n}^2/\sigma^2$ and the kth user's received SNR on subcarrier n is $\gamma_{k,n} = p_{k,n} h_{k,n}$. The slowly time-varying channel assumption is crucial, since it is also assumed that each user is able to estimate the channel perfectly, and these estimates are known to the transmitter via a dedicated feedback channel. These channel estimates are then used as input to the resource allocation algorithms. In order that the BER constraints are met, the effective SNR has to be adjusted, accordingly. The BER of a square M-level QAM with Gray bit mapping as a function of the received SNR $\gamma_{k,n}$ and the number of bits $r_{k,n}$ can be approximated to within 1 dB for $r_{k,n} \geq 4$ and BER $\leq 10^{-3}$ [20].

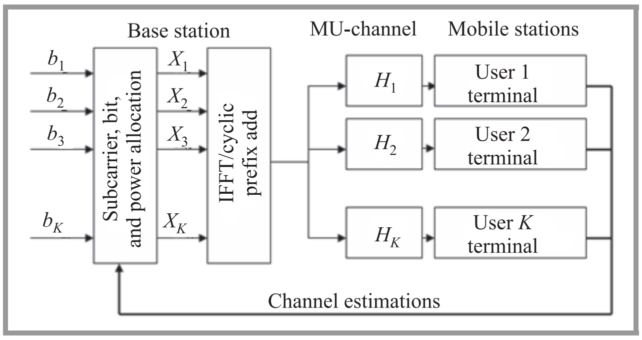

Fig. 1. System model of the downlink MU-OFDM.

$$BER_{MQAM}(\gamma_{k,n}) \cong 0.2 \exp\left(\frac{-1.6\gamma_{k,n}}{2^{r_{k,n}}-1}\right) \tag{1}$$

Solving for $r_{k,n}$

$$r_{k,n} = \log_2\left(1 + \frac{\gamma_{k,n}}{\Gamma}\right) = \log_2\left(1 + p_{k,n} H_{k,n}\right) \tag{2}$$

where $\Gamma = -\ln(5BER)/1.6$ is a constant SNR gap, and $H_{k,n} = h_{k,n}/\Gamma$ is the effective subcarrier SNR.

The problem of the MU-OFDM resource allocation with proportional rate constraints is formulated as follows.

Objective:

$$\max_{c_{k,n},\, p_{k,n}} \frac{B}{N} \sum_{k=1}^{K} \sum_{n=1}^{N} c_{k,n} \log_2\left(1 + p_{k,n} H_{k,n}\right).$$

Subject to

$$\begin{cases} C_1: & c_{k,n} \in \{0,1\},\ \forall\, k,n \\ C_2: & p_{k,n} \geq 0,\ \forall\, k,n \\ C_3 & \sum_{k=1}^{K} c_{k,n} = 1,\ \forall\, n \\ C_4: & \sum_{k=1}^{K}\sum_{n=1}^{N} p_{k,n} \leq P_t \\ C_5: & R_i : R_j = \phi_i : \phi_j,\ \forall\, i,j \in \{1,2,\ldots,K\},\ i \neq j \end{cases} \tag{3}$$

where the objective is to maximize the total sum-rate capacity within the total power constraint of the system, while maintaining rate proportionality among the users indicated in C_5. Here, $c_{k,n}$ is the subcarrier allocation indicator such that $c_{k,n} = 1$ if and only if subcarrier n is assigned to user k, and P_t is the total transmit power constraint.
In C_5,

$$R_k = \frac{B}{N}\sum_{n=1}^{N} c_{k,n} r_{k,n} = \frac{B}{N}\sum_{n=1}^{N} c_{k,n}\log_2(1 + p_{k,n}H_{k,n}) \tag{4}$$

is the total data rate for user k and $\phi_1, \phi_2, \ldots,$ and ϕ_K are the normalized proportionality constants where $\sum_{k=1}^{K}\phi_k = 1$. Note that constraints C_1 and C_2 in Eq. (3) ensure the correct values for the subcarrier allocation indicator and the power, respectively. C_3 imposes the restriction that each subcarrier can only be assigned to a single user, C_4 and C_5 are the power and proportional rate constraints, respectively.

3. The Proposed Resource Allocation (PRA) Algorithm

The resource allocation problem of the MU-OFDM system is divided into two stages; subcarrier allocation and power allocation stage. In the first stage, the number of subcarriers to be allocated to each user is first determined before the actual subcarrier assignments are chosen, whereas the second one is concerned with subsequent power allocation. The proposed resource allocation algorithm depends on the first stage and uses the GPA algorithm to optimally allocate the total transmit power to subcarriers that were previously proportionally allocated by the greedy subcarrier allocation [19].
The subcarrier and power allocation algorithm proposed in [19], which is referred to in our simulations as Ian Resource Allocation (IRA) algorithm, is summarized in the following steps.

Step 1: Determine the number of subcarriers N_k to be initially assigned to each user;

Step 2: Assign the subcarriers to each user in a way that ensures rough proportionality;

Step 3: Assign the total power p_k for user k to maximize the capacity, while enforcing the proportionality;

Step 4: Assign the powers $p_{k,n}$ for each user's subcarriers subject to his total power constraint p_k.

The proposed algorithm considers the first two steps to optimally and proportionally allocate the subcarriers to the users, but uses GPA to avoid the mathematical complexity of the power allocation in [19].

3.1. Greedy Subcarrier Allocation

The subcarrier allocation stage is described as follows.

Step 1: Subcarriers Allocation

The subcarriers of each user in the MU-OFDM system are proportionally allocated to satisfy $N_1 : N_2 : \cdots : N_K = \phi_1 : \phi_2 : \cdots : \phi_K$ that relaxes the proportionality constraint C_5 in Eq. (3) to simplify the solution of the resource allocation problem of the MU-OFDM system. The proportion of subcarriers assigned to each user is approximately the same as their eventual rates after power allocation, and thus would roughly satisfy the proportionality constraints, i.e., $N_k = \lfloor \phi_k N \rfloor$. This may lead to $N^* = N - \sum_{k=1}^{K} N_k$ unallocated subcarriers.

Step 2: Subcarriers Assignment

This step allocates the per-user subcarriers N_k, and then the remaining N^* subcarriers in a way that maximizes the overall sum-rate capacity, while maintaining a rough proportionality with a greedy algorithm, which is a modification of the one used in [19], as described below:

```
(a) For $k = 1$ to $K$
        $R_k = 0$
        for $n = 1$ to $N$
            $c_{k,n} = 0$
        end
    end
    $p_{k,n} = P_t/N$
    $\mathbf{N} = \{1,2,\ldots,N\}$
```

In this step, all the variables are initialized. R_k is the capacity for each user, and **N** is the set of unallocated subcarriers.

```
(b) For $k = 1$ to $K$
        $\tilde{n} = \arg\max_{n\in\mathbf{N}} |H_{k,n}|$
        $c_{k,\tilde{n}} = 1$
        $N_k = N_k - 1$
        $\mathbf{N} = \mathbf{N}\backslash\{\tilde{n}\}$
        $R_k = R_k + \frac{B}{N}\log_2(1 + p_{k,\tilde{n}}H_{k,\tilde{n}})$
    end
```

In this step, the unallocated subcarrier that has the maximum gain for each user is assigned for that user. Note that the probability of assignment of the same subcarrier for more than one user will be very low, when $N \gg K$.

```
(c) While size $(\mathbf{N}) > N^*$
        $\mathbf{K} = \{1, 2, \ldots, K\}$
        $\tilde{k} = \arg\min_{k \in K} \frac{R_k}{\phi_k}$
        if $N_{\tilde{k}} > 0$
            $\tilde{n} = \arg\max_{n \in N} |H_{\tilde{k},n}|$
            $c_{\tilde{k},n} = 1$
            $N_{\tilde{k}} = N_{\tilde{k}} - 1$
            $N = N \backslash \{\tilde{n}\}$
            $R_{\tilde{k}} = R_{\tilde{k}} + \frac{B}{N} \log_2(1 + p_{\tilde{k},\tilde{n}} H_{\tilde{k},\tilde{n}})$
        else
            $\mathbf{K} = \mathbf{K} \backslash \{\tilde{k}\}$
        end
    end
```

In this step, the subcarriers are assigned to each user according to the greedy policy that the user, who needs a subcarrier most in each iteration, chooses the best subcarrier. Since proportional rates are enforced, the need of a user is determined by the user who has the least capacity divided by its proportionality constant.

```
(d) $K = \{1, 2, \ldots, K\}$
    for $n = 1$ to $N^*$
        $k = \arg\max_{k \in \mathbf{K}} |H_{k,n}|$
        $c_{\tilde{k},n} = 1$
        $R_{\tilde{k}} = R_{\tilde{k}} + \frac{B}{N} \log_2(1 + p_{\tilde{k},n} H_{\tilde{k},n})$
        $\mathbf{K} = \mathbf{K} \backslash \{k\}$
    end
```

In this step, the remaining N^* subcarriers are assigned to the best users.

3.2. Greedy Power Allocation

After the available subcarriers are proportionally allocated to the users, a GPA algorithm is used to optimally allocate the transmit power between the allocated subcarriers to maximize the sum-rate capacity of the MU-OFDM under the proportional user rate constraint as in Eq. (3). The GPA algorithm of the MU-OFDM system can be described by the following steps.

Step 1: Calculate the power of each user in the MU-OFDM system as follows:

$$p_k = \sum_{n=1}^{N} c_{k,n} p_{k,n} \,. \tag{5}$$

Step 2: The problem of subcarriers and power allocation for the MU-OFDM system in Eq. (3) is simplified into the problem of power allocation for a single-user OFDM system as follows [21]:

$$\max_{p_{k,n}} \frac{B}{N} \sum_{n=1}^{N} c_{k,n} \log_2(1 + p_{k,n} H_{k,n}), \;\; \forall\, k \in \{1, 2, \ldots, K\} \tag{6}$$

with total user power budget p_k, target BER, and maximum permissible QAM modulation order. These constraints can be formulated as:

$$\sum_{n=1}^{N} c_{k,n} p_{k,n} \le p_k, \quad p_{b,n} = BER, \quad r_n \le r^{\max} \tag{7}$$

where $p_{k,n}$ is the amount of power allocated to the nth subcarrier of kth user to achieve a BER $p_{b,n}$, and $r^{\max}$ is the maximum number of permissible allocated bits per subcarrier. Note that the BERs are assumed equal, i.e., $p_{b,n} = BER$, $\forall\, n \in \{1, 2, \ldots, N\}$, and therefore the subscript n will be dropped from the BER notation to become p_b.

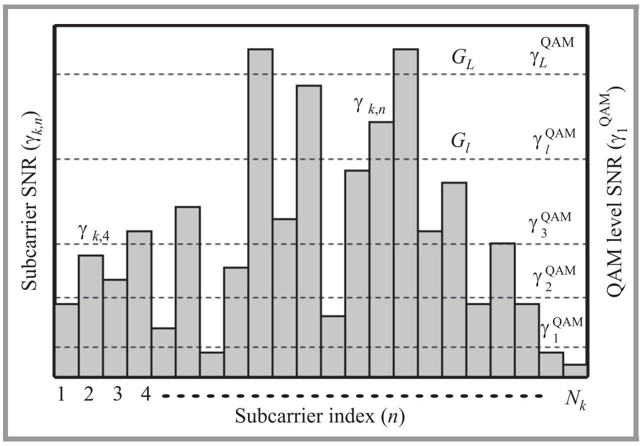

Fig. 2. An illustrative example for grouping of subcarriers.

Step 3: The problem of power allocation for subcarriers in the single-user OFDM system is solved by the GPA algorithm that is summarized as follows:

(a) Calculate γ_l^{QAM} for all M_l, $1 \le l \le L$, and $P_b = BER$ using Eq. (1), where γ_l^{QAM} is the SNR of the QAM level that is permissible by the transmission system, i.e., $M_l = 2^{r_l^{\max}}$.

(b) Redistribute subcarriers according to their SNRs $\gamma_{k,n}$ into QAM groups G_l, $1 \le l \le L$ bounded by QAM levels γ_l^{QAM} and γ_{l+1}^{QAM} with $\gamma_0^{QAM} = 0$ and $\gamma_L^{QAM} = +\infty$ as shown in Fig. 2, i.e.,

$$\gamma_l^{QAM} \le \gamma_{k,n} < \gamma_{l+1}^{QAM} \,. \tag{8}$$

```
(c) For $n = 1$ to $N_K$
        Find $l_n$ that satisfies Eq. (8)
        if $l_n = 0$
            $r_{k,n} = 0 \; p_{k,n}^{up} = \frac{\gamma_{l_n}^{QAM}}{H_{k,n}}$
        else if $l_n < L$
            $r_{k,n} = \log_2 M_{l_n}, \; p_{k,n}^{up} = \frac{\gamma_{l_n+1}^{QAM} - \gamma_{l_n}^{QAM}}{H_{k,n}}$
        else
            $r_{k,n} = \log_2 M_{l_n}, \; p_{k,n}^{up} = +\infty$
        end
    end

(d) Collect power difference from total budget:
        $p_d = \sum_{n=1}^{N_k} \frac{\gamma_{k,n} - \gamma_{l_n}^{QAM}}{H_{k,n}}$
    Initiate greedy bit allocation to
        $r_{k,n}^{gpa} = r_{k,n}, \; \forall n \in \{1, 2, \ldots, N_k\},$
        $p_d^{gpa} = p_d$
    while $p_d^{pga} \geq \min(p_{k,n}^{up})$ and $\min(l_n) < L, 1 \leq n \leq N_k$
        $j = \arg \min_{1 \leq n \leq N_k} (p_{k,n}^{up})$
        $l_j = l_j + 1, \; p_d^{gpa} = p_d^{gpa} - p_{k,j}^{up}$
        if $l_j = 1$
            $r_{k,j}^{gpa} = r_{k,j}^{gpa} + \log_2 M_{l_j}, \; p_{k,j}^{up} = \frac{\gamma_{l_j+1}^{QAM} - \gamma_{l_j}^{QAM}}{H_{k,j}}$
        else if $l_j < L$
            $r_{k,j}^{gpa} = r_{k,j}^{gpa} + \log_2 \left( \frac{M_{l_j}}{M_{l_j-1}} \right), \; p_{k,j}^{up} = \frac{\gamma_{l_j+1}^{QAM} - \gamma_{l_j}^{QAM}}{H_{k,j}}$
        else
            $r_{k,j}^{gpa} = r_{k,j}^{gpa} + \log_2 \left( \frac{M_{l_j}}{M_{l_j-1}} \right), \; p_{k,j}^{up} = +\infty$
        end
    end
    $R_k^{gpa} = \sum_{n=1}^{N_k} r_{k,n}^{gpa}.$
```

Step 4: Repeat the GPA algorithm for all users to calculate the sum-rate capacity of the MU-OFDM system:

$$R^{gpa} = \sum_{k=1}^{K} R_k^{gpa}. \tag{9}$$

4. Simulation Results

The frequency selective multipath channel was modeled as consisting of six independent Raleigh multipaths, with an exponentially decaying profile. A maximum delay spread of 5 μs and a maximum Doppler shift of 30 Hz were assumed. The channel information was sampled every 0.5 ms to update the subcarriers and power allocation. The total transmit power was assumed as 1 W, the total bandwidth as 1 MHz, and total subcarriers as 64. The average subcarrier SNR = 20 dB, and BER = 10^{-3}, giving an SNR gap $\Gamma = -ln(5 \times 10^{-3}/1.6 = 3.3$. This constant is used in the calculation of the rate $r_{k,n}$ of user k in subcarrier n given in Eq. (2).

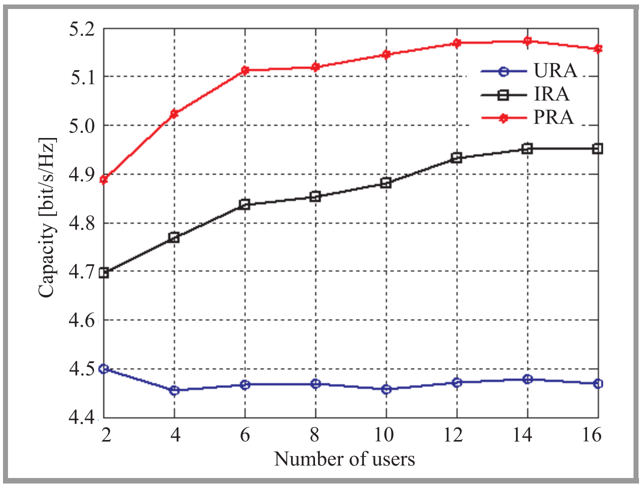

Fig. 3. Average sum-rate capacity versus number of users in an MU-OFDM system.

In Fig. 3, the average sum-rate capacity versus the number of users is depicted for the case of $N = 64$ and $\mathrm{SNR} = 20$ dB. This figure shows that the average sum-rate capacity for the two dynamic resource allocation algorithms; the IRA algorithm and the PRA algorithm is increased significantly with the number of users, while the average sum-rate capacity for the Uniform Resource Allocation (URA) algorithm remains approximately constant. In the URA algorithm, the resources (subcarriers and power) are allocated equally to the users of the MU-OFDM system regardless of their channel gains. So, the multi-user diversity is not exploited and the average sum-rate capacity of the URA algorithm is approximately constant at 4.48 bit/s/Hz. On the other hand, the capacities of the IRA and PRA algorithms are increased as the number of users is increased. This is the effect of multi-user diversity gain which is more prominent in systems with larger number of users.

Figure 4 depicts the total sum-rate capacity versus the average SNR for various radio resource allocation algorithms. This figure shows that the total sum-rate capacity for all the algorithms is increased with the increase in the average SNR and the two dynamic resource allocation algorithms; IRA and PRA outperform the URA algorithm. Both of the two dynamic resource allocation algorithms have approximately the same performance although the transmit power allocation strategies are different for them.

Figure 5 shows the normalized proportions of the capacities for each user for the case of 16 users averaged over 10000 channel realizations. The normalized user capacity is given by R_k divided by $\sum_{k=1}^{16} R_k$, and is observed for both IRA and PRA algorithms. This is compared to the normalized random generated proportionality constraints $\phi_1, \phi_2, \ldots, \phi_K$ that are referred to in Fig. 5 by Gamma. The IRA and PRA satisfy an acceptable proportionality among the users for MU-OFDM systems.

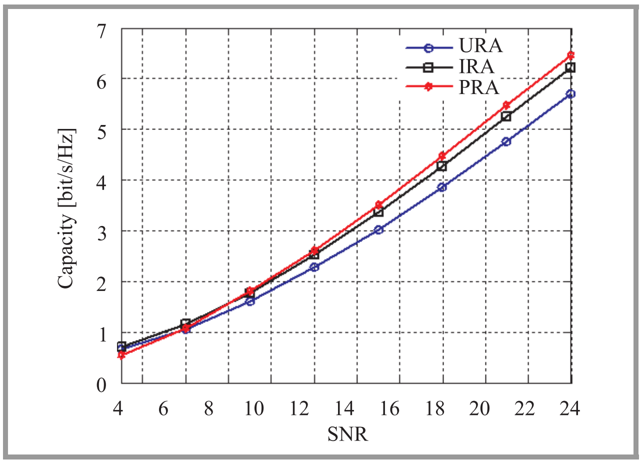

Fig. 4. Average sum-rate capacity versus SNR in an MU-OFDM system.

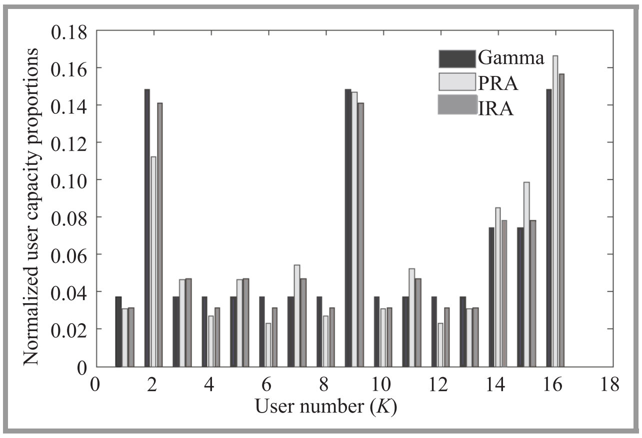

Fig. 5. Normalized user rate proportions versus user index in an MU-OFDM system.

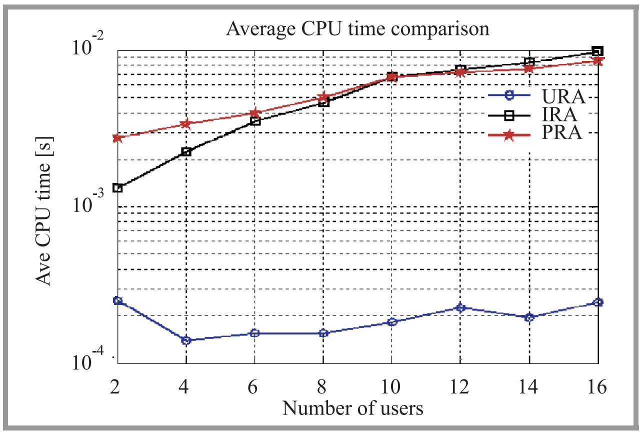

Fig. 6. Average CPU time for compiled Matlab code versus users' number in an MU-OFDM system.

Figure 6 shows a comparison of the computational complexity between the three resource allocation algorithms. These algorithms were run on a Pentium-4 3 GHz personal computer running Windows XP Professional. The simulation experiments used floating-point arithmetics. The simple URA algorithm exhibits less computational complexity with bad capacity performance, whereas the computational complexity of the two dynamic algorithms; IRA and PRA gets high with the number of users, and the PRA algorithm achieves less complexity at larger number of users.

5. Conclusion

This paper proposed an optimal solution for the rate-adaptive resource allocation problem with proportional rate constraints for MU-OFDM systems. It benefited from the greedy subcarriers allocation of [19] to proportionally allocate the available subcarriers to the users. After that, the resource allocation problem is dealt with as a single-user resource allocation problem which is solved by the GPA algorithm to maximize the sum-rate capacity of the system, while achieving approximate rate proportionality. This solution avoids the mathematical complexity of [19], while achieving a higher sum-rate capacity. It has been shown through simulations that the PRA algorithm achieves less complexity for higher numbers of users.

References

[1] "IEEE standard for local and metropolitan area networks part 16: Air interface for fixed and mobile broadband wireless access systems", IEEE, Tech. rep. 802.16, Oct. 2004.

[2] "IEEE standard for local and metropolitan area networks part 16 and amendment 2", IEEE, Tech. rep. 802.16e , Feb. 2006.

[3] H. Schulze and C. Lueders, *Theory and Applications of OFDM and CDMA Wideband Wireless Communications*. John Wiley, 2005.

[4] P. Chow, J. Cioffi, and J. Bingham, "A practical discrete multitone transceiver loading algorithms for data transmission over spectrally shaped channels", *IEEE Trans.Commun.*, vol. 43, pp. 773–775, 1995.

[5] R. Fischer and J. Huber, "A new loading algorithm for discrete multitone transmission", in *Proc. IEEE Global Telecom. Conf. Globecom 1996*, London, England, 1996, vol. 1, pp. 724–728.

[6] M. Sternad *et al.*, "Towards systems beyond 3G on adaptive OFDMA transmission", *Proc. IEEE Inst. Electr. Electron. Eng.*, vol. 95, iss. 12, pp. 2432–2455, 2007.

[7] S. Sadr, A. Anpalagan ,and K. Raahemifar, "Radio resource allocation algorithms for the downlink of multiuser OFDM communication systems", *IEEE Commun. Surveys & Tutorials*, vol. 11, no. 3, pp. 92–106, 2009.

[8] C. Wong, R. Cheng, K. Lataief, and R. Murch, "Multiuser OFDM with adaptive subcarrier, bit, and power allocation", *IEEE J. Select. Areas Commun.*, vol. 17, pp. 1747–1758, 1999.

[9] D. Kivanc, G. Li, and H. Liu, "Computationally efficient bandwidth allocation and power control for OFDMA", *IEEE Trans. Wireless Commun.*, vol. 2, pp. 1150–1158, 2003.

[10] L. Xiaowen and Z. Jinkang, "An adaptive subcarrier allocation algorithm for multiuser OFDM system", in *Proc. IEEE VTC 2003*, Orlando, Florida, USA, 2003, vol. 3, pp.1502–1506.

[11] G. Zhang, "Subcarrier and bit allocation for real-time services in multiuser OFDM systems", in *Proc. Int. Conf. Commun. IEEE ICC 2004*, Paris, France, vol. 5, pp. 2985–2989.

[12] H. Yin and H. Liu, "An efficient multiuser loading algorithm for OFDM based broadband wireless systems", in *Proc. IEEE Global Telecom. Conf. Globecom 2000*, San Francisco, USA, 2000, vol. 1, pp. 103–107.

[13] W. Rhee and J. M. Cioffi, "Increase in capacity of multiuser OFDM system using dynamic subchannel allocation", in *Proc. 51st IEEE Veh. Technol. Conf. IEEE VTC 2000*, Tokyo, Japan, 2000, vol. 2, pp. 1085–1089.

[14] G. Song and Y. G. Li, "Adaptive subcarrier and power allocation in OFDM based on maximizing utility", in *Proc. 57th IEEE Semian. Veh. Technol. Conf. IEEE VTC 2003-Spring*, Seoul, Korea, 2003, vol. 2, pp. 905–909.

[15] G. Song and Y. Li, "Cross-layer optimization for OFDM wireless networks-part ii: algorithm development", *IEEE Trans. Wireless Commun.*, vol. 4, pp. 625–634, 2005.

[16] J. Jang and K. Lee, "Transmit power adaptation for multiuser OFDM systems", *IEEE J. Select. Areas Commun.*, vol. 21, pp. 171–178, 2003.

[17] C. Mohanram and S. Bhashyam, "A sub-optimal joint subcarrier and power allocation algorithm for multiuser OFDM", *IEEE Commun. Lett.*, vol. 9, pp. 685–687, 2005.

[18] Z. Shen, J. G. Andrews, and B. L. Evans, "Optimal power allocation in multiuser OFDM systems", in *Proc. IEEE Global Telecom. Conf. Globecom 2003*, San Francisco, USA, 2003, vol. 1, pp. 337–341.

[19] I. Wong, Z. Shen, B. Evans, and J. Andrews, "A low complexity algorithm for proportional resource allocation in OFDMA systems", in *Proc. IEEE Worksh. Sig. Proces. Syst. SIPS 2004*, Austin, Texas, USA, 2004, pp. 1–6.

[20] A. Goldsmith, *Wireless Communications*. Cambridge University Press, 2005.

[21] W. Al-Hanafy and S. Weiss, "Greedy power allocation for multicarrier systems with reduced complexity", in *Proc. 27th Nat. Radio Sci. Conf. NRSC 2010*, Menouf, Egypt, 2010, vol. 27, pp. 16–18.

Najib A. Odhah received the B.Sc. and M.Sc. from the Faculty of Electronic Engineering, Menoufia University, Menouf, Egypt, in 2002 and 2009, respectively. He is currently working towards the Ph.D. degree in Electrical Communications Engineering at Menoufia University, Egypt. From 2003 to 2006, he worked as a demonstrator in the Department of Electronics, Faculty of Engineering and architecture, Ibb University, Ibb, Yemen. His research areas of interest include Multicarrier Communication Systems, Multiple-Input Multiple-Output (MIMO) Systems, Digital Signal Processing, Digital Communications, Interference Cancelation, Channel Equalization and Channel Estimation.

E-mail: Najib_Odhah@yahoo.com
Faculty of Electronic Engineering
Menoufia University
Menouf, Egypt

Moawad I. Dessouky received the B.Sc. (Honors) and M.Sc. degrees from the Faculty of Electronic Engineering, Menoufia University, Menouf, Egypt, in 1976 and 1981, respectively, and the Ph.D. from McMaster University, Canada, in 1986. In 1986 he joined the teaching staff of the Department of Electronics and Electrical Communications, Faculty of Electronic Engineering, Menoufia University, Menouf, Egypt. He has published more than 180 scientific papers in national and international conference proceedings and journals. He is currently the head of the Dept. Electronics and Electrical Communications, Faculty of Electronic Engineering, Menoufia University. He has received the most cited paper award from Digital Signal Processing journal for 2008. His current research areas of interest include spectral estimation techniques, image enhancement, image restoration, super resolution reconstruction of images, satellite communications, and spread spectrum techniques.

E-mail: Dr_Moawad@yahoo.com
Faculty of Electronic Engineering
Menoufia University
Menouf, Egypt

Waleed E. Al-Hanafy received the B.Sc. (Honors) and M.Sc. degrees from the Faculty of Electronic Engineering, Menoufia University, Menouf, Egypt, in 1996 and 2002, respectively, and the Ph.D. from Strathclyde University, Glasgow, UK, in 2010. In 2010 he joined the teaching staff of the Department of Electronics and Electrical Communications, Faculty of Electronic Engineering, Menoufia University, Menouf, Egypt. He has published more than 20 scientific papers in national and international conference proceedings and journals. His current research areas of interest include the signal processing for communications in particular precoding and equalization methods of MIMO systems, adaptive power/bit loading approaches, Multi-User MIMO, OFDM systems, and resource allocation of wireless communication systems.

E-mail: Waleed_Alhanafy@yahoo.com
Faculty of Electronic Engineering
Menoufia University
Menouf, Egypt

Fathi E. Abd El-Samie received the B.Sc. (Honors), M.Sc., and PhD. from the Faculty of Electronic Engineering, Menoufia University, Menouf, Egypt, in 1998, 2001, and 2005, respectively. In 2005 he joined the teaching staff of the Department of Electronics and Electrical Communications, Faculty of Electronic Engineering, Menoufia University, Menouf, Egypt. He is a co-author of about 140 papers in national and international conference proceedings and journals. He has received the most cited paper award from Digital Signal Processing journal for 2008. His current research areas of interest include image enhancement, image restoration, image interpolation, super resolution reconstruction of images, data hiding, multimedia communications, medical image processing, optical signal processing, and digital communications.

E-mail: Fathi_Sayed@yahoo.com
Faculty of Electronic Engineering
Menoufia University
Menouf, Egypt