Dynamic Time Slot Allocation for Multiuser OFDM/TDMA Networks using Effective Bandwidth and βMWM Network Traffic Modeling

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***Abstract*—In this paper, we propose an adaptive allocation scheme which determines the number of time slots for each user in an OFDM/TDMA system using the Effective Bandwidth theory. For that purpose, we developed an algorithm to adaptively estimate the parameters of the MWM (Multifractal Wavelet Model) traffic model that allow us to calculate the effective bandwidth for the incoming traffic flows. We evaluate the performance of the proposed adaptive allocation scheme through simulations using real traffic traces.**

I. Introduction

As the Internet access through wireless networks increases, high speed transmission technologies for multiuser demand become even more necessary. A successful technology used by several wireless networks technologies is the Orthogonal Frequency Division Multiplexing (OFDM) [1].

The OFDM multiplexing is a technology for high speed radio transmitting systems used in several wireless networks, such as Wi-Fi (IEEE 802.11 [2]), WiMAX (IEEE 802.16 standard [3]) and Long Term Evolution (LTE) [4]. The data transfer occurs simultaneously through multiple subcarriers [5]. In OFDM/TDMA, OFDM technology provides data transfer at high speed and TDMA (Time Division Multiple Access) technology provides multi-user access to the system [6]. TDMA provides multi-user access by time slot division.

In this paper, we show that proportionally allocating data rates of the user traffic flows can improve performance and reduce system losses. This paper presents a proposal for allocating time slots in OFDM/TDMA networks in order to improve performance of some system parameters such as system data loss and the average loss per user.

The paper is organized as follows: in section II we propose an adaptive algorithm to estimate the parameters of the βMWM multifractal model; in section III we present the theory of effective bandwidth; in section IV the OFDM/TDMA system is presented; in section V we propose a dynamic allocation scheme of user's time in an OFDM/TDMA system; in section VI we validate the proposed method and in section VII we conclude.

II. Adaptive βMWM Multifractal Modeling

The Multifractal Wavelet Model (MWM) is an important multifractal model in the area of network traffic modeling [7]. It is based on a multiplicative cascade in the wavelet domain. The Discrete Wavelet Transform (DWT) [8], [9] is used in this model due to its capacity of signal multiscale representation. There are MWM modeling variations in the literature based on the wavelet and scaling coefficients that are achieved from the wavelet transform. One of them is called βMWM [7].

The βMWM model process performs the discrete Haar wavelet transform for a fixed number of scales, J, of the binomial multiplicative cascade [10]. From the wavelet coefficients ($W_{j,i}$) and scaling coefficients ($U_{j,i}$) that were generated, per scale $j \ \forall \ 0 \leq j \leq J-1$, the MWM parameters are estimated.

Once the scaling coefficients $U_{j,i}$ are estimated, the βMWM assumes that the coarsest scaling coefficients ($j = 0$) are independent and identically distributed (i.i.d.). The mean μ_c and the variance σ_c^2 of the scaling coefficients of the first scale - herein called $U_{0,0}$ - are estimated for the model. Next, the others scaling coefficients can be estimated by the wavelet and scaling coefficients from the first scale [7].

The multipliers of the multiplicative cascade are modeled following a symmetric Beta distribution [11]. The Beta probability distribution has two parameters. When both parameters have the same value, we call this distribution a symmetric Beta, because it has the property to be symmetrically distributed in the interval $[-1, 1]$ and it has mean equal to 0.

The βMWM relates the energy decay of wavelets coefficients n_j at scale j to the p_j parameter values of the beta distributions, used to model the cascade multipliers. The wavelet energy decay for each coefficient is given by [7]:

$$n_j = \frac{E[W_{j-1,k}^2]}{E[W_{j,k}^2]} \tag{1}$$

and the parameters p_j are estimated, recursively, by:

$$p_j = \frac{n_j}{2}\left(p_{j-1} + 1\right) - \frac{1}{2} \tag{2}$$

We propose an algorithm for adaptively estimating the βMWM parameters. In this algorithm, the whole traffic trace is not processed at once. We propose an iterative processing method in windows of 2^J samples per time, where J is the number of cascade scales. Thus, only some variables are stored in the adaptive modeling process. Therefore, there is no need to store all the data about the traffic flow.

The proposed modeling process is designed as follows:

Algorithm 1: Algorithm for Adaptive Estimation of the βMWM Parameters

1) The model variables are initialized. We set: $E[W_{j,k}^2](0) = 0$, $\mu_c(0) = 0$, $\sigma_c^2(0) = 0$ and $n = 0$.
2) The Haar transform for the non-overlapping data window with 2^J samples. The Haar transform for each window of 2^J samples generates 2^j coefficients wavelets - named $\widetilde{W}_{j,k}$ - per scale j and a scaling coefficient - named $\widetilde{U}_{0,0}$ - in the scale $j = 0$;
3) Update the second order moment $E[W_{j,k}^2]$ of the wavelet coefficients using the following equation:

$$E[W_{j,k}^2](n+1) = E[W_{j,k}^2](n)\left(\frac{n}{n+1}\right) + \frac{\sum_{i=0}^{2^j-1}\widetilde{W}_{j,i}^2}{(n+1)2^j} \tag{3}$$

4) The energy rates n_j are recalculated using (1) and the parameters p_j are recalculated using equation (2).
5) The scaling coefficients statistics are updated using the following equations:

$$\mu_c(n+1) = \mu_c(n)\left(\frac{n}{n+1}\right) + \frac{\widetilde{U}_{0,0}}{n+1} \tag{4}$$

$$\sigma_c^2(n+1) = \left(\sigma_c^2(n) + (\mu_c(n))^2\right)\left(\frac{n}{n+1}\right)$$

$$-(\mu_c(n+1))^2 + \frac{(\widetilde{U}_{0,0})^2}{n+1} \tag{5}$$

The steps from step 2 until step 5 are repeated at each data window with 2^J samples, incrementing by one the variable n. Thus, using the proposed adaptive algorithm we obtain the βMWM parameters, which are: p_j, μ_c and σ_c^2.

The stochastic traffic process from βMWM model, in scale n, is given by [7]:

$$C^n[k] = 2^{-n}\mathrm{Norm}(\mu_c, \sigma_c^2)\prod_{j=0}^{n-1}(1 + \beta(p_j, p_j)) \tag{6}$$

where $\beta(\cdot,\cdot)$ is a beta random variable and $\mathrm{Norm}(\mu, \sigma^2)$ is a normal random variable with mean μ and variance σ^2.

III. Effective Bandwidth using Adaptive βMWM Modeling

The effective bandwidth of a considered traffic flow is defined by Kelly [12] as:

$$\alpha(s,t) = \frac{1}{st}\ln(E[e^{sX[0,t]}]) \quad s > 0, t < \infty \tag{7}$$

By this definition, the effective bandwidth of a process is dependent of a space parameter s and is also dependent of a time parameter t. The space parameter s represents the potential for statistical multiplexing of traffic flows and its value varies in the range from the average to the peak rate. $X[0,t]$ is the accumulated traffic during the time interval $[0,t]$.

The effective bandwidth has as lower bound, the average rate ($s \to 0$) and as upper bound, the peak rate ($s \to \infty$) of the traffic flow. When traffic flows have rates which are numerically equal to the effective bandwidth it is said that the QoS requirements have been achieved [13].

From equation (6) and (7), the effective bandwidth for the βMWM model can be written as:

$$\alpha(s,2^n) = \frac{1}{st}\ln\left(E\left[e^{\left[2^{-J+n}U_{0,0}\prod_{j=0}^{J-1-n}(1+\beta(p_j,p_j))\right]}\right]\right) \tag{8}$$

Once the MWM multiplicative cascade is dyadic, the value of t must be dyadic, that is, $t = 2^n,\ \ 0 \le n \le J-1$.

IV. The OFDM/TDMA System

In the considered OFDM/TDMA system, we assume that the transmitter knows the Signal-to-Noise Ratio (SNR), which is an information of quality of the wireless communication channel. Using adaptive modulation and coding (AMC), the maximum number of bits per symbol sampled (per Hz) that the user n can transmit on subcarrier m during time slot t, detonated by $c_{m,n}$(t), can be written as a function of SNR and P_{ber} (the target bit error rate). There are several approaches to this equation, but they are all upper bounded by the following expression[5]:

$$c_{m,n}(t) = \left\lfloor \log 2\left(1 + \frac{-1,5}{\ln(5P_{ber})}\gamma_{m,n}(t)\right)\right\rfloor \tag{9}$$

where $\gamma_{m,n}(t)$ is the SNR value for subcarrier m, user n and time slot t.

V. Proposed Dynamic Time Slot Allocation Scheme

Let N be the number of users; M the number of OFDM subcarriers; Δt the minimum time allocated to a user, also called a time slot; $S_n(i)$ the number of time slots that user n has to transfer data in cycle i; $T_n(i) = S_n(i)\Delta t$ the time that user n has to transfer data in cycle i; $S_{ciclo}(i) = \sum_{n=1}^{N} S_n(i)$ the total number of allocated slots in cycle i; T_{inter} the time period among users when there is no transmission that aims to avoid intersymbol interference; $T_{ciclo}(i)$ the total time of cycle i, that is, $T_{ciclo}(i) = NT_{inter} + \sum_{n=1}^{n=N} T_n(i)$.

We propose an allocation scheme where the transmission time of a user is multiple of an infinitesimal time $\Delta t \to 0$. The transmission rate of a user n in cycle i, $C_n(i)$, is given by the following equation:

$$C_n(i) = \frac{S_n(i)H_n(i)}{T_{cycle}} = \frac{T_n(i)H_n(i)}{\Delta t T_{cycle}(i)} \tag{10}$$

where $H_n(i)$ is the amount of data that can be transferred by user n in the time interval Δt in cycle i.

The effective bandwidth is the minimum rate required to attain certain QoS requirements. Ideally, all users in a TDMA system should have a capacity equal to or greater than its effective bandwidth aiming to attain the QoS requirements. However, in a TDMA system with limited capacity, it is not always possible to attain the capacity required for all users. Taking this fact into account, we propose a scheduling scheme based on TDMA that allocates the time slots of users proportionally to their effective bandwidths.

Let P be a proportionality factor which is equal for all users and $B_n(i)$ be the effective bandwidth to attain a certain requirement of buffer overflow probability for user n in cycle i. For each user n, we propose that the system attains the following bandwidth value for each user:

$$pB_n(i) = C_n(i) \quad \forall\ \ 1 \le n \le N \tag{11}$$

Substituting equation (10) in equation (11), we obtain the following:

$$pB_n(i) = \frac{S_n(i)H_n(i)}{T_{cycle}(i)} \quad \forall\ 1 \leq n \leq N \tag{12}$$

Thus, the number of slots per user and per cycle is given by:

$$S_n(i) = pT_{ciclo}(i)\frac{B_n(i)}{H_n(i)} \quad \forall\ 1 \leq n \leq N \tag{13}$$

Once p and $S_n\ \forall\ 1 \leq n \leq N$ can assume arbitrary values, the slot allocation has multiple solutions. Fixing the cycle time T_{cycle} (equivalent to fix the number of slots per cycle S_{cycle}), the system will have a unique solution: the amount of time slots of each user is proportional to the ratio between its effective bandwidth and capacity, that is:

$$S_n(i) \propto \frac{B_n(i)}{H_n(i)} \quad \forall\ 1 \leq n \leq N \tag{14}$$

The number of slots for each user can be calculated by:

$$S_n(i) = \text{round}\left[S_{cycle}\frac{\frac{B_n(i)}{H_n(i)}}{\sum_{k=1}^{N}\frac{B_k(i)}{H_k(i)}}\right] \tag{15}$$

In a real environment, the proposed time slot allocation is carried out in an approximate way, since $\Delta t \to 0$ is not feasible, because the allocation is made, in practice, by packets and not by bits.

The time allocation per user can be performed adaptively using the proposed adaptive βMWM modeling and by calculating its effective bandwidth which is adaptively obtained from the proposed model. The QoS requirements determined in the effective bandwidth calculus will not always be reached, since the capacity will not always be equal to the effective bandwidth. In such case, we have $p < 1$. However, if the system can attain all user's traffic, $p \geq 1$, the QoS requirements can be attained ($p = 1$) and possibly exceed ($p > 1$).

VI. Simulation and Results

In order to evaluate the proposed time slot allocation scheme, we simulated an OFDM/TDMA system with 4 users ($N = 4$). We consider the real TCP/IP traffic traces [15] – dec-pkt-1, dec-pkt-2, lbl-pkt-4 and dec-pkt-4 in order to represent respectively, traffic flows of users 1, 2, 3 and 4. We simulate the system with a fixed time slot for each user. The considered traffic traces represent the data to be transmitted by users. In simulations, the round-robin technique is the scheduling policy [5]. Users can transfer data via 256 OFDM subcarriers ($M = 256$) with bandwidth of 25 kHz per subcarrier. The bit error rate (BER) was set to be $P_{ber} = 10^{-6}$. The SNR per subcarrier and per user were defined as a normal random variable with the following mean and variance, 15 dB and 5, respectively [16].

Simulations were carried out using the proposed slot allocation scheme. In these simulations, the effective bandwidth was numerically calculated from the adaptive βMWM model by equation (8), in order to attain the buffer overflow probability requirement of 1% and buffer size of 60 kB. The βMWM model parameters were estimated using samples of aggregate traffic in an interval of 256 ms. In the proposed rate allocation scheme, the amount of slots was determined at each TDMA cycle.

Once the data traffic traces are in a time scale of milliseconds, the time per user was set to be 1 ms and the time between users was not considered ($T_{inter} = 0$). The cycle time was set to be 200 ms. In the simulation with fixed time, each user has 50 ms per cycle to send data.

Table I presents the overall system loss and the average loss per user, with and without the use of the proposed scheme. It can be observed that the proposed time slot allocation scheme reduces both the overall system loss and the average loss per user.

TABLE I. Overall system loss and average loss per user

	Without the Proposed Scheme	With the Proposed Scheme
Overall System Loss	21,55%	9,78%
Average Loss per User	14,77%	12,30%

Table II shows the average delay estimate. The delay estimation is obtained by dividing the queue size value in the buffer to the the user capacity per cycle. The average delay estimate increases for users with lower data rates – users 1 and 3 – and decreases for users with higher data rates – users 2 and 4 – when using the proposed time slot allocation scheme. This can be explained by the fact that the proposed scheme tends to increase the capacity of users with higher data rates and limit the capacity of users with lower data rates.

TABLE II. Average Delay Estimate

	Without the Proposed Scheme	With the Proposed Scheme
User 1	188.47 ms	326.09 ms
User 2	245.21 ms	98.97 ms
User 3	84.69 ms	413 ms
User 4	173.34 ms	69.64 ms

Table III shows the average system utilization. The system utilization was estimated by the following equation:

$$u(t) = \frac{V(t)}{C(t)} \tag{16}$$

where $V(t)$ is the output data rate at time t and $C(t)$ the capacity allocated to the user being served at time t. We can observe an increase in system utilization by applying the proposed allocation scheme.

TABLE III. System Utilization

Time Slot Allocation	Average Utilization
Fixed	68,89%
Dynamic (Proposed)	79,23%

Figure 1 shows the values of effective bandwidth adaptively estimated for each user in function of time. Figure 2 presents the time allocated to each user by the proposed scheme. Note that the higher the effective bandwidth of the flow, the greater the allocated time that is required by the user in the proposed scheme.

Figure 3 shows the system transmission rate as a function of time. The results were obtained by simulation using dynamic time allocation and fixed time allocation. From Figure 3, it can be observed that there is an increase in the system throughput.

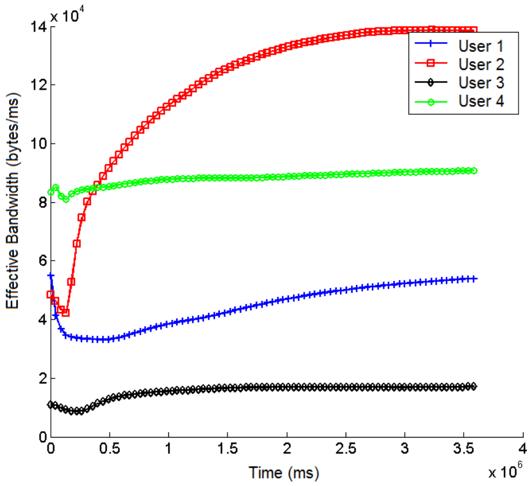

Fig. 1. Effective Bandwidth Adaptively Estimated for Each System User

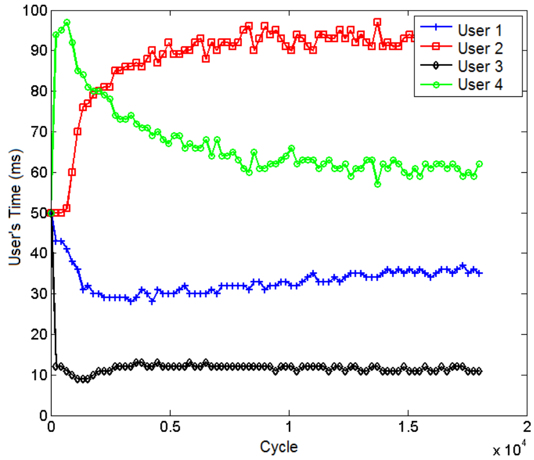

Fig. 2. Allocated Time for Each User Using the Proposed Scheme

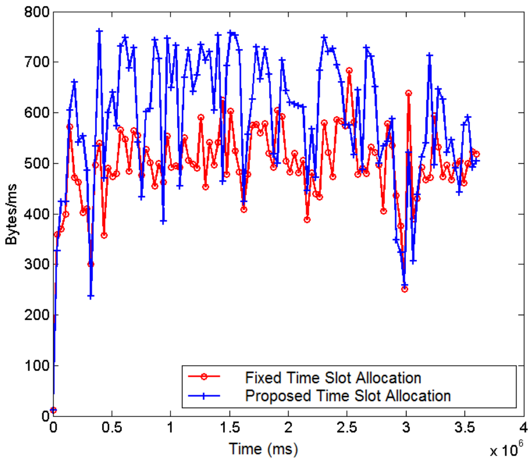

Fig. 3. System Transmission Rate

VII. Conclusion

In this paper, we proposed a dynamic time slot allocation in OFDM/TDMA networks that improves the performance of some system parameters such as the average loss per user, the overall system loss and link utilization. To this end, for real time applications, we proposed an adaptive multifractal model that can describe various traffic characteristics. The proposed scheme tends to increase the delay of the users with lower traffic rates and increase link utilization.

The proposed rate allocation scheme can be extended and applied to different systems that use OFDM/TDMA technology and other systems which apply resource sharing.

It is intended as future work, to evaluate the performance of the proposed allocation scheme in scenarios with different channel models and different traffic types. Furthermore, we aim to apply the proposed allocation scheme in systems based on specific characteristics of the OFDM technology, such as LTE (Long Term Evolution)[4].

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