# Optimum Model-Based Non-Real-Time Downlink Data Transmission in Heterogeneous DS-CDMA Cellular Networks

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Abstract-Motivated by the results in [1] on the self-similarity of the downlink interference in heterogenous service DS-CDMA networks, in this paper, we propose a model-based linear adaptive-predictive method to estimate the level of interference for optimizing the system throughput and minimizing the delay for non-real-time data transmission. We use a fractional Gaussian noise (fGn) model in an appropriate time-scale to represent the self-similarity in the downlink interference. The estimated interference is utilized to allocate the available power to non-realtime services. In doing so, we use a utility-based optimization scheme and dynamic programming for time-domain optimal scheduling of non-real-time traffic. Simulation results validate the fGn model and show a substantial improvement in the delay fairness and a significant increase in the average cell throughput using our proposed scheme; and confirm that the interference model is valid for a broad range of arrival rates of non-real time traffic.

*Index Terms*—Downlink interference, DS-CDMA networks, dynamic programming, fractional Gaussian noise, packet scheduling, self-similar process.

#### I. INTRODUCTION

**PROMISING** air interface technology for wireless communications is the *direct sequence code division multiple access* (DS-CDMA), which has been shown to be interferencelimited [2]. Hence, exploiting the fluctuations of the total interference for improving system performance is a major challenge for the next generation heterogenous wireless networks. The time variation of the interference has been studied in [3], where it has been observed that the total interference in a data-centric DS-CDMA system is a self-similar process. It has been shown in [3] and [4] that the source of selfsimilarity of the total interference is user traffic characteristics.

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The predictive nature of the self-similar interference was used in [3] and [4] to adjust the transmission rate with the variation of the total downlink interference.

In [1], we have extended the results of [3], [4] and shown that, under certain conditions, the total downlink interference for a heterogenous cellular network is a self-similar process, and thus, has long-range dependence (LRD). In our heterogenous model, the network serves a mixed traffic of real-time and non-realtime services with non-Poisson traffic characteristics. User traffic characteristics are instrumental in creating selfsimilarity in the downlink interference. We have also shown in [1] that the conditions for the self-similarity in the downlink interference are more general than those proposed in [3] and [4]. The proposed model in [1] can be considered a cross-layer model since both physical characteristics of the wireless channel and user traffic parameters are utilized in the development of that model. The long-range dependence in the downlink interference is valid in time-scales of the order of that used in packet scheduling, rate-control, and admission control. Having established this fact, now the question is "how can we exploit the self similarity of the downlink interference to develop appropriate resource control mechanisms beyond those in [1], [3], and [4]?" The present paper is trying to answer this question.

The long-range dependence manifests itself in extended periods of time over which the downlink interference exceeds the performance threshold, and may lead to long outage periods. Therefore, the presence of self-similarity in downlink interference can be regarded as an opportunity for developing innovative new approaches for resource control mechanisms in heterogeneous DS-CDMA cellular networks. A very important idea that emerges from the existence of LRD in the downlink interference is the possibility of utilizing the predictive nature of the total downlink interference to develop novel adaptivepredictive resource control mechanisms in the appropriate time-scales. A simple application can be found in [3]. We have also proposed a method in [5] to exploit self-similarity of interference to increase throughput, however in that work the experienced delay of non-real time users is not considered.

The present paper utilizes the predictive nature of the selfsimilar interference to develop a novel cross-layer adaptivepredictive radio resource controller. In this paper, we model the self-similarity of the total downlink interference with the fractional Gaussian noise (fGn) [6] and then design an optimal linear adaptive predictor. Modelling interference with a Gaussian self-similar process is convenient since an infinite number of distributions can only be represented by three parameters over the entire scaling region. The three parameters are the mean, the variance, and the self-similarity index. The application of optimal linear predictor on the fGn model is simple and can easily be realized in either mobile terminal, base-station, or radio network controller.

In the proposed method, the mobile terminal measures the received downlink interference in each control window<sup>1</sup>. A linear predictor is then employed to estimate the interference level in the next control window based on this measured value and the stored interference levels in the past. The model parameters are also adaptively adjusted based on the stored interference values. The estimated interference is then used in the base-station or in the radio network controller to allocate power to users during the next control window. First, power is allocated to real-time traffic and then the remaining power is assigned to users with best-effort service.

This paper uses a multi-time-scale time domain scheduler in which each control window encompasses a number of transmission frames. In time domain scheduling, during each time interval, the total power is allocated to a single user with the rest of the users kept inactive. The temporal extent of the interval depends on the user data rate, the channel conditions, and the available power. An opportunistic scheduler allocates the total power only to the users with best channel conditions. Although this scheme maximizes the total throughput, it may introduce extensive delays for users far from the base station or with bad channel conditions. Proportional fairness schedulers have been proposed to reduce excessive delays of the opportunistic scheduler and to address fairness (see e.g. [7] and the references therein). In this paper, we propose a utility-based [8] scheme in which the packets are scheduled so as to maximize the total system utility. The proposed utility is a function of the corresponding channel condition and the relative experienced delay. We then use dynamic programming to find the optimal scheduling.

We use our adaptive-predictive algorithm to estimate the interference fluctuations and then exploit the multi-user diversity [9] through the utility-based optimal scheduling. The contributions of this paper are as follows: First, a model based adaptive predictor for the downlink interference is proposed based on our previous work in [1]. Second, resource allocation (i.e. traffic scheduling) for a given value of the basestation available transmit power is modeled in a multi-timescale, utility-based scheme. Third, a dynamic programming technique is proposed to solve the corresponding optimization problem.

We simulate a heterogenous DS-CDMA network based on the Universal Mobile Telecommunication System (UMTS) standard [10] to validate the model and observe self-similarity in total downlink interference when the call duration—of at least one service—has a heavy tail distribution. The selfsimilarity of downlink interference persists even after the timedomain scheduler is applied. Simulation results show that fGn

<sup>1</sup>The system is time-slotted and each time-slot is referred to as a control window.

is an appropriate model for the downlink interference and that our proposed method provides a better throughput/delay than the other existing schemes.

Organization of this paper is as follows. In Section II, we present the interference model and review the results on the self-similarity of the interference. In Section III, we propose a model-based optimal downlink interference predictor. Then, in Section IV, we study the performance optimization of the proposed scheduling method. The simulation results are presented in Section V, followed by our conclusions in Section VI.

#### II. DOWNLINK INTERFERENCE MODEL

We first present several important definitions.

**Definition 1:** *Slowly Varying Function* [11]: A function  $f(x) > 0, x \in \mathbb{R}$  is called a *slowly varying function*, if for all  $u \in \mathbb{R}_+, \frac{f(ux)}{f(x)} \to 1$ , as  $x \to \infty$ .

**Definition 2:** *Heavy-tailed Random Variable*: A random variable X is said to be heavy-tailed with infinite variance, if for  $0 < \kappa < 2$ , there exist a slowly varying function L(x) such that as  $x \to \infty$ ,

$$P(|X| \ge x) \sim L(x)x^{-\kappa},$$

where the symbol '~' means behaves asymptotically as (e.g.  $\phi(k) \sim \varphi(k)$  means:  $\lim_{k\to\infty} \frac{\phi(k)}{\varphi(k)} = 1$ ).

An example of a heavy tailed distribution is *Pareto* distribution:

$$Pr\{\tau = l\} = \eta_0 l^{-\alpha - 1},$$
 (1)

where  $l \in \mathbb{N}$  and

$$\eta_0 \stackrel{\Delta}{=} \frac{1}{\sum_{l=1}^{\infty} l^{-\alpha - 1}}, \qquad 1 < \alpha < 2. \tag{2}$$

Pareto distribution has been used to model call duration of data traffic (see e.g. [12]).

**Definition 3:** Asymptotically Self-similar Process [13]: A real-valued second-order stationary random process  $I = \{\dots, I(-1), I(0), I(1), \dots\}$  is called an *asymptotically self-similar process* (as-s), with self-similarity index  $H = 1 - \beta/2$ ,  $0 < \beta < 1$ , if

$$\lim_{m \to \infty} C_{(m)}(k) = \frac{C_{(m)}(0)}{2} \Big( (k+1)^{2-\beta} - 2k^{2-\beta} + (k-1)^{2-\beta} \Big),$$
(3)

where  $k \in \mathbb{Z}_+$ ,  $C_m(k)$  is the auto-covariance function of  $I^m$  that is the average process of I over blocks of length m.

**Definition 4:** *Fractional Gaussian Noise* [6]: *Fractional Gaussian noise* (fGn) is a self-similar Gaussian process with the auto-covariance function

$$\gamma(k) = \frac{\sigma_0^2}{2} (|k+1|^{2H} - 2|k|^{2H} + |k-1|^{2H}), k \in \mathbb{Z}, \quad (4)$$

where  $\sigma_0^2$  is the variance and H is the self-similarity index.

If the variance and the self-similarity index, H, of a zeromean self-similar process are known—subject to assuming an idealized Gaussian setting—the process can be modelled by the fGn [6]. We consider a DS-CDMA cellular system. Time is assumed to be slotted, with each slot being a window of length  $T_w$ seconds. We further assume  $T_w \gg T_c$ , where  $1/T_c$  is the spreading bandwidth of the cellular CDMA network. The length of the control window  $T_w$  is chosen such that the channel variations are negligible within that time slot.

The total downlink interference<sup>2</sup>, I(n), is a weighted sum of the transmitted power of base-stations (BSs),  $P^{c}(n)$ , for  $n \in \mathbb{Z}, \mathbb{Z} = \{\dots, -1, 0, 1, \dots\}$  and  $c = 1, \dots, N_{C}$ , where  $N_{C}$  is the number of cells in the network [1],

$$I(n) = \sum_{c=1}^{N_C} \xi^c(n) P^c(n) g^c(n).$$
 (5)

The weight coefficients are the corresponding channel gains,  $g^c(n)$ , and the cross-correlation between the spreading sequences of other users and the user of interest. Each sample of the total downlink interference, I(n), is valid over a control window of length  $T_w$  seconds. We assume  $g^c(n)$  and  $\xi^c(n)$  are two stationary processes independent of  $P^c(n)$ .<sup>3</sup> Without loss of generality, let the user of interest be located in cell 1. We assume that the power allocated to that user is not included in  $P^1(n)$  in (5).

To study I(n), we assume that a *regular power transmission* regime is applied network-wide, in which the transmitted power by any BS is not substantially higher than the transmitted power by other BSs. This assumption is practically valid if a load balancing mechanism is applied in the cellular network.

In control window n, each BS serves a set of active users (calls) in its coverage area, therefore the transmitted power by the BS c,  $P^c(n)$ , is the sum of the allocated powers to all calls in the corresponding coverage area,

$$P^{c}(n) = \sum_{j=1}^{J} \sum_{i \in \mathbb{N}} p_{ji}^{c}(n - v_{ji}^{c} + 1),$$
(6)

where J is the number of services provided by the network,  $\mathbb{N} = \{1, 2, \ldots\}, p_{ji}^{c}(.)$  is the allocated power of call i of service j of cell c, and  $v_{ji}^{c} \in \mathbb{Z}$  is the start time of the *i*th call in cell c that receives service j. Calls are enumerated by i in the order of their arrival, such that in each cell c,  $v_{ji}^{c} \leq v_{ji+1}^{c}$ . For the *i*th call of service j in cell c with a call duration of  $\tau_{ji}^{c} \in \mathbb{N}$  seconds,  $p_{ji}^{c}(.)$  is the allocated power in its call duration, and is equal to zero otherwise.

To characterize I(n), we first need to obtain the characteristics of  $P^c(n)$  and  $g^c(n)$ . We assume that for each given cell cand service j, the call duration sequence process,  $\{\tau_{ji}^c, i \in \mathbb{N}\}$ , the new call arrival rates sequence process,  $\{\mu_{ji}^c(.), i \in \mathbb{N}\}$ , and the allocated power sequence process,  $\{p_{ji}^c(.), i \in \mathbb{N}\}$ , are independent and identically distributed (i.i.d.) random processes. We denote  $\tau_{ji}^c$ ,  $\mu_{ji}^c(n)$  and  $p_{ji}^c(n)$  by the generic random variables  $\tau_i^c$ ,  $\mu_i^c(n)$  and  $p_i^c(n)$ , respectively.

In this model, the *traffic characteristics* of a user of service j is specified by three processes,  $\mu_i^c(n)$ ,  $\tau_i^c$  and  $p_i^c(n)$ , where

 $p_j^c(n)$  is a function of the service type *j*, the bit-rate, and the power allocation strategy in the network.

In [1], we have shown that the downlink interference can be *completely specified* by *traffic characteristics* corresponding to different services provided by the network and *channel processes*,  $g^c(n)$ , for all c. Here, we briefly review the models we use in this paper for the new call arrival process, the call duration process, the allocated power process, and the wireless channel process.

- New Call Arrivals: Assuming that the arrival rate of new calls for each service type is less than the value for which the network was designed, we have shown in [1] that using a regular interface based call admission control, the Poisson distribution with parameter  $\lambda_j^c$  is an appropriate model for call arrival  $\mu_i^c(n)$ .
- **Call Duration**: Here, we denote both the packet duration (for packet-oriented transmission) and the call duration (for connection-oriented transmission) as "call duration". For voice service, an exponentially distributed call duration is assumed [14]. For non-voice traffic, a general heavy-tail distribution is considered (see e.g. [12]).
- Allocated Power to Each Call: For  $p_j^c(n)$ , we note that for a given channel, the allocated power to a given user at control window *n* is an increasing concave function of its bit-rate [14].
- Wireless Channel: We assume that the channel gain,  $g^c(n)$  is a second-order stationary process for  $c = 1, \ldots, N_C$ . To obtain the channel gain  $g^c(n)$ , we assume a deterministic distance-dependent path loss and two fading effects: fast fading and shadowing. Note that fast fading (e.g. Rayleigh or Rician) affects  $P^c(n)$  in (5) in smaller time-scales than the shadowing. Fast fading is also partly cancelled by the fast power control. Moreover, the short-range effect of fast fading is averaged out in longer time-scales such as  $T_w$ . We further assume that

$$C_q^c(k) \sim L_q^c(k) k^{-\beta_g^c}, \qquad k \to \infty,$$
 (7)

where  $C_g^c(k)$  is the auto-covariance function of  $g^c(n)$  and k denotes time with a temporal resolution  $T_w$ ,  $L_g^c(k)$  is a slow varying function, and  $\beta_g^c > 0$  is the channel auto-covariance decay exponent.

Here, we restate the results in [1] where we show that the total downlink interference in multi-service wireless CDMA networks is an asymptotically self-similar process where the self-similarity emanates from user traffic characteristics.

Suppose that the downlink interference process,  $I = \{\dots, I(-1), I(0), I(1), \dots\}$ , is a finite-mean, finite-variance, second-order stationary process. In the following proposition, we derive the necessary conditions for the self-similarity of downlink interference.

**Proposition 1** [1]: Consider the downlink interference process, I, and let  $\beta_P^c$ ,  $c = 1, \ldots, C$  satisfy

$$\sum_{j=1}^{J} \lambda_{j}^{c} \Pr\{\tau_{j}^{c} = k\} r_{j(k)}^{c}(k) \sim L_{P}^{c}(k) k^{-\beta_{P}^{c}-2}, \ k \to \infty, \quad (8)$$

where  $L_P^c(k)$  is a slowly varying function and  $0 < r_{j(l)}^c(k) < \infty$  is the auto-correlation function of  $p_{j(l)}^c$ . Now, I is an as-s

 $<sup>^{2}</sup>$ Interference is measured for a given user, therefore it should have a user index; however for brevity we have dropped the user index, but will use it again in the latter parts of this paper.

<sup>&</sup>lt;sup>3</sup>Here we assume that a fast power control mechanism is applied to deal with the undesirable effects of fast fading. Fast fading and shadowing processes are also assumed to be independent. Therefore,  $P^c(n)$  and  $g^c(m)$  are also independent from one another for all n and m.

process with self-similarity index  $H = 1 - \beta^*/2$  if there exists at least one c such that  $0 < \beta_P^c < 1$  or  $0 < \beta_q^c < 1$ , and

$$\beta^* = \min \min \{\beta_P^c, \beta_g^c\}.$$
 (9)

Proposition 1 gives the sufficient condition as a combination of the service call arrival rate,  $\lambda_j$ , the service call duration distribution,  $\Pr{\{\tau_j = k\}}$  for  $k \to \infty$ , and the asymptote of the correlation function of the allocated power,  $r_{j(k)}^c(k)$ , for  $k \to \infty$ .

The self-similarity in the downlink interference manifests itself in extended periods of time over which I(n) is smaller than the system performance threshold, meaning that the system resources are under-utilized. In the engineering sense, the presence of self-similarity in I can be regarded as "good news" as we can exploit these periods of low activity to transmit delay tolerant packet data. To do so, we first need to predict the interference fluctuation in an appropriate time-scale.

# III. MODEL-BASED OPTIMAL DOWNLINK INTERFERENCE PREDICTION

Since the self-similar processes have long-range dependence [6], the samples of data in such processes are correlated over long periods. Consequently, the accuracy of predictions can be improved by appropriately filtering the previous values. In this section, we model the total downlink interference with fGn and utilize this model to devise an optimal downlink interference predictor.

We assume a large number of users in the coverage area of the network. We also select an appropriate time-scale and assume that the resource control mechanism does not alter the total downlink interference model. The interference is then modeled using a fGn process as

$$I(n) = m_I(n) + z(n),$$
 (10)

where  $m_I(n)$  is the average interference of the process I(n) measured over a large window of size K (i.e. (n - K, n - 1]), and z(n) is fGn.

We use the correlation structure of the total received interference and the auto-covariance of fGn, (4), to propose the following optimal linear predictor for the total interference [15]

$$\widehat{I}(k+1) = m_I(k) + (\mathbf{\Gamma}^{-1}\underline{\gamma})^T (\mathbf{I}(k) - m_I(k)\mathbf{1}_{M_L}), \quad (11)$$

where  $\widehat{I}(k+1)$  is the predictor of I(k+1),  $\mathbf{I}(k) \stackrel{\Delta}{=} [I(k), I(k-1), \ldots, I(k - M_L + 1)]^T$  is the  $M_L \times 1$  vector of stored interference measurements,  $M_L \leq K$  is the memory length of the predictor,  $\Gamma$  is the covariance matrix with entities  $\Gamma_{ij} \stackrel{\Delta}{=} \gamma(i-j), \gamma \stackrel{\Delta}{=} [\gamma(1), \ldots, \gamma(M_L)]^T$ , where  $\gamma(k)$  is given in (4) and  $\mathbf{1}_{M_L}$  is the  $M_L \times 1$  identity vector; the superscript T denotes vector transposition. In our proposed scheme, the parameters of the interference measurements.

The variance of the prediction error is

$$\varepsilon = \gamma(0) - \gamma_1^T \Gamma^{-1} \gamma_1.$$
(12)

In Fig. 1, we illustrate the variance of the prediction error versus self-similarity index H for a fGn process with  $\sigma_0 = 1$ 



Fig. 1. Variance of the prediction error versus self-similarity index, H, for different values of M, for a fGn model with  $\sigma_0 = 1$ .

with three values for  $M_L$ . It can be seen that the variance of error decreases with H. Also the variance of error is not sensitive to the value of  $M_L$  for  $M_L \ge 5$ , therefore the optimal linear predictor can be implemented using a small number of measured interference samples.

# A. Model Adjustment

To compensate for the effect of model parameter variations, we adaptively adjust the model parameters in appropriate time-scales. We assume that  $N_L$  samples of the measured interference in the past are available to the predictor. A simple weighted summation of measured values of total interference is used to estimate mean interference

$$m_I(n) = \frac{1}{N_L} \sum_{m=n-N_L}^{n-1} I(m).$$
(13)

The interference variance is also estimated by

$$\sigma_0(n) = \frac{1}{N_L - 1} \sum_{m=n-N_L}^{n-1} \left( I(m) - m_I(n) \right)^2.$$
(14)

To estimate the self-similarity index, H, we use an online version of the Abry-Veitch wavelet-based estimator [16]. This method uses a multi-resolution wavelet transformation for weighted least squares fitting of different octaves,  $j_1$ ,  $j_2$ ,  $j_2 > j_1$ . It is straightforward to show that the computational complexity of this method is  $O(N_L)$  [16]. The confidence interval of the estimated self-similarity index,  $\hat{H}$ , by the Abry-Veitch method is [16]

$$\widehat{H} - \sigma_{\widehat{H}} z_{\beta} \le H \le \widehat{H} + \sigma_{\widehat{H}} z_{\beta}, \tag{15}$$

where  $z_{\beta}$  is the  $(1 - \beta)$  quantile of the standard Gaussian distribution, (i.e.  $P(z \ge z_{\beta}) = \beta$ ) and

$$\sigma_{\widehat{H}} = \left(\frac{2}{(\ln 2)^2 2^{-j_1} N_L}\right) \left(\frac{1-2^J}{1-2^{-(J+1)} (J^2+4) + 2^{-2J}}\right),\tag{16}$$

where  $J = j_2 - j_1$ .

Note that in our proposed scheme, the interference predictor in Fig. 2 is implemented for all users including realtime



Fig. 2. Model-based adaptive-predictive throughput maximization of non-realtime data in the downlink: (a) user module, (b) BS module.

and non-realtime users. This interference predictor can be implemented in the mobile station, in the base-station or in the radio network controller. In each case, the measured interference level,  $I_i(n)$ , where *i* is the user index, should be provided to the predictor in appropriate time-scales. The basestation or the radio network controller then uses the predicted interference levels,  $\hat{I}_i(n + 1)$ , to allocate the transmit power in the next control window.

# IV. PERFORMANCE OPTIMIZATION FOR NON-REAL-TIME DATA TRANSMISSION

In the control window n, let  $\mathcal{G}(n)$  be the set of real-time users (such as voice and multimedia) served with a *guaranteed* delay requirement and  $\mathcal{B}(n)$  be the set of delay-tolerant users waiting in the queue to be served under the *best-effort* service category.

At a given instant n, the mobile terminal of each user measures the level of interference and uses the methods in Section III to adjust the values of parameters  $m_I(n)$ ,  $\sigma_0(n)$ and H. Then these values are used in (11) to estimate the level of interference in the subsequent control window.<sup>4</sup> The estimated interference is then communicated to the base-station. The base-station uses the predicted downlink interference to allocate the available power to non-realtime users.

In this section, we propose two techniques to allocate power to backlogged best-effort traffic. In the first technique, the available power is allocated to users with the best channel conditions. In such an approach, the users with bad channel conditions may experience excessive delay, hence the system may have poor delay performance. Next, to reduce the delay, we consider a utility-based approach [8] and propose an optimal utility-based scheduling algorithm to maximize the base-station utility for a given available transmit power.

Since in this section we consider the power allocation in a given cell, hereafter we drop the cell index for brevity.

# <sup>4</sup>In view of simplicity of mobile terminals, it would be possible to adjust the model parameters and predict the interference in the base-station.

#### A. Power allocation to guaranteed service users

For a user *i* in  $\mathcal{G}(n)$ , with bit-rate  $R_i(n)$  and the required bit energy to the interference plus noise spectral density,  $\rho_i$ , the allocated power should be

$$p_i(n) = \frac{\rho_i R_i(n)}{W g_i(n)} (\widehat{I}_i(n) + P_N(n)), i \in \mathcal{G}$$
(17)

where  $g_i(n)$  is the channel gain between the base-station and user *i* and  $P_N(n)$  is the background noise power at the receiver of user *i*.

We assume that the total transmit power of the basestation at instant n is  $P_{max}(n)$ . This value may be set either permanently at the network dimensioning phase or adaptively by the radio network controller. Therefore, the available power for non-realtime users in the control window n,  $P_A(n)$ , is

$$P_A(n) = P_{max}(n) - \sum_{i \in \mathcal{G}(n)} p_i(n).$$
(18)

Next, we distribute  $P_A(n)$  among backlogged non-real-time traffics.

## B. Power allocation to delay-tolerant non-real-time users

Our objective is to find a set of users in  $\mathcal{B}(n)$ , namely  $\mathcal{S}(n)$ , to maximize the total throughput of non-real-time traffic for a given value of the available transmit power  $P_A(n)$  in the *n*th control window with length  $T_w$ . Let  $p_i(t)$  denote the allocated power to the *i*th non-real-time user at time *t*. The signal-tointerference ratio of non-real-time user *i* can be written as

$$\operatorname{SIR}_{i}(t) \stackrel{\Delta}{=} \frac{g_{i}(t)p_{i}(t)}{\sum_{j \in \mathcal{S}(t), j \neq i} \xi_{ij}p_{j}(t)g_{j}(t) + I_{i}(t) + P_{N}(t)}$$
(19)

where  $t \in [(n-1)T_w, nT_w]$ ,  $g_i(t)$  is the channel gain between the base-station and user *i* and  $I_i(t)$  is the total interference received from the adjacent stations and the transmission to other real-time users in the same cell. The coefficient  $0 < \xi_{ij} \le 1$  is the normalized cross correlation between  $p_i(t)$  and  $p_j(t)$  at the receiver of user *i*, that is the effective fraction of the received signal power from transmitter *j* that contributes to the interference experienced by user *i*.

Define the average rate of user i over control window n by

$$R_i(n) \stackrel{\Delta}{=} \frac{1}{T_w} \int_{nT_w}^{(n+1)T_w} r_i(t) dt \tag{20}$$

where  $r_i(t)$  is the instantaneous bit-rate defined as

$$r_i(t) = \frac{W}{\rho_i} \operatorname{SIR}_i(t), \qquad i \in \mathcal{S}(n)$$
(21)

where  $\rho_i$  is the required  $E_b/I_0$  for user *i*, and  $W = 1/T_c$  is the spreading bandwidth.

The maximum throughput of the non-real-time traffic for a given value of the available transmit power  $P_A(n)$  is found



Fig. 3. Multi-time-scale system: each control window contains M frames.

from

$$\max_{\mathcal{S}(n)} \max_{p_i(t)} T_w \sum_{i \in \mathcal{S}(n)} R_i(n)$$
(22)

s.t. 
$$\frac{1}{T_w} \int_{nT_w}^{(n+1)T_w} r_i(t) dt = R_i(n), \ i \in \mathcal{S}(n)$$
 (23)

$$r_{i}(t) = \frac{W}{\rho_{i}} \operatorname{SIR}_{i}(t), \quad i \in \mathcal{S}(n)$$

$$\sum_{i=1}^{n} p_{i}(t) \leq P_{i}(n) \quad t \in [nT - (n+1)T]$$
(24)

$$\sum_{i \in \mathcal{S}(n)} p_i(t) \le P_A(n), t \in [nT_w, (n+1)T_w]$$
(25)

We note that for maximizing the throughput, it is beneficial to allocate the maximum available power over the window  $[0, T_w]$ . Therefore, we consider that (25) holds with equality. It is straightforward to show that the solution of the optimization problem (22)-(25) belongs to the set of time domain schedulers [17], [9], [18]. Generally speaking, time domain scheduling is a scheme in which the total power is allocated to a single user over a fraction of  $T_w$ . During this period, the base-station transmits only to one user, and the rest of the users are kept inactive. Under the time-domainscheduling, in (22)-(25), a portion of  $T_w$  is allocated to a selected user and the base-station transmits to that user with transmission power  $P_A(n)$ . Therefore, in each control window,  $\mathcal{S}(n)$  includes those users with the best channel condition and backlogged traffic at the base station. Transmission to such users maximizes the total network throughput for a given value of  $P_A(n)$ . The order of transmission for the users in  $\mathcal{S}(n)$  during the control window n is not specified by the optimization problem in (22).

#### C. Delay Fair Resource Scheduling

We assume that each control window of length  $T_w$  seconds contains M frames of  $T_f$  seconds (see Fig. 3). Data traffic is packetized into fixed L-bit packets and transmitted in an integer number of frames. At control window n, a number of packets destined to the users in the coverage area are waiting in the base-station to be served. The available transmit power, to be allocated to the best effort service, is  $P_A(n)$ .

Let  $m_i(n)$  be the number of required frames for transmission of packet *i* in control window *n*,

$$m_i(n) = \left\lceil \frac{L}{R_i(n)T_f} \right\rceil,\tag{26}$$

where  $\lceil . \rceil$  gives the upper nearest integer and  $R_i(n)$  is the bit-rate of the channel to the corresponding destined user d(i). Note that  $R_i(n)$ , obtained from (20) depends on the predicted interference, and the channel gain. In practice variable bit-rates are implemented by using the orthogonal variable spreading factor technique (see e.g, [10]). Therefore, only a limited number of choices for  $R_i(n)$  would be available.

For packet i, we associate the utility-function,  $u_i(n)$ , that shows the "benefit" that network earns if the packet is served in control window n. Utility function serves as an optimization objective for packet transmission. It can be used to optimize radio resource allocation to build a bridge among different service and network parameters in different layers. The earned benefit modelled by the utility function provides a priority metric for a packet served by a base-station, which means the larger the value of the utility function, the higher the priority of transmitting the corresponding packet. The utility function  $u_i(n)$ , is a function of allocated network resources to that packet as well as its experienced delay. For non-realtime traffic, it is a function of  $R_i(n)$  and  $\tau_i(n)$ , where  $\tau_i(n)$ denotes the amount of time that the packet has spent in the system. The benefit earned by the base-station is an increasing function of the wireless link quality. In addition, for two users with the same channel quality and backlogged packets at time n, it would be more beneficial—from the network point of view-to serve the packet with a larger experienced delay.

For a packet i, transmitted in control window n, we define the following utility function,

ι

$$u_i(n) \stackrel{\Delta}{=} \frac{1}{m_i(n)} \exp\left(\tau_i(n) - \overline{\tau}(n)\right),\tag{27}$$

where  $\overline{\tau}(n) = \frac{1}{N(n)} \sum_{i \in \mathcal{B}(n)} \tau_i(n)$  is the average delay and N(n) is the number of backlogged packets. Note that in (27), a packet is given a large utility either when the corresponding user experiences a "good" channel condition or when it experiences a relatively "bad" delay. The utility function in (27) is similar to that given in [19] that attempts to provide fairness in delay. Note that different utility functions can be designed to satisfy various design objectives. The formulation presented in this paper is independent from the definition of utility function. Generally, a utility function is defined by the service provider to quantify the trade-off between the performance (e.g. throughput) and fairness.

We define the total network utility at each control window n, as the network performance indicator

$$U(n) \stackrel{\Delta}{=} \sum_{i \in \mathcal{S}(n)} u_i(n).$$
(28)

The total system utility indicates the total system revenue. Our objective is to maximize the total system utility as

$$\max_{\mathcal{S}(n)|P_A(n)} U(n) \tag{29}$$

s.t. 
$$\sum_{i \in \mathcal{S}(n)} m_i(n) \le M \tag{30}$$

where in (29),  $S(n)|P_A(n)$  denotes finding S(n) subject to the available transmit power,  $P_A(n)$ , for non-real-time traffic in the *n*-th control window.

The inequality in (30) indicates the system downlink resource constraint. The output of the maximization problem, (29), is S(n). Maximization of (29) selects the packets that result in the highest total utility subject to constraint (30). Therefore, at each control window, the solution of (29) gives the packets that are scheduled for transmission. Since we solve this optimization problem for each control window, hereafter, we drop the time index n for brevity. 1) Scheduling Algorithm: Here, we show that the optimization problem in (29)-(30) is indeed a classical combinatorial problem; 0-1 Knapsack problem (0-1 KP). In the following, we first define the 0-1 KP.

**Definition 5:** 0-1 *Knapsack Problem* [20]: Given a set of items  $\mathcal{B}$ , each with a cost  $m_i$  and a value  $u_i$ , 0-1 Knapsack Problem determines the items to be included in a collection  $\mathcal{S}$ , so that the total cost  $\sum_{\mathcal{S}} m_i$  is less than some given cost M, and the total value  $\sum_{\mathcal{S}} u_i$  is as large as possible.

Consider the base-station as a knapsack with the resource constraint M. Resource constraints are the number of available frames in each base-station in each control window (i.e. M). For each packet i, the corresponding value is  $u_i$ . For each item, the required resource is  $m_i$ . Therefore, the downlink resource allocation in (29) is a 0–1 KP.

We note that 0–1 KP is NP-Hard [20], thus the brute force solution for KP would be to try all  $2^{N(n)}$  where N(n) is the number of packets in all possible subsets of  $\mathcal{B}(n)$ . Obviously, such algorithms are not suitable for practical purposes. Instead, we utilize a polynomial time dynamic programming approach.

We use dynamic programming to find an approximate solution for the knapsack problem in (29)-(30). Dynamic programming decomposes the optimization problem into smaller problems and then recursively obtains the value of the maximum utility in terms of the solutions to smaller problems [21].

Consider the array U(i : 1, ..., N, m : 0, ..., M), where N is the number of packets in the base-station in the corresponding control window. The entry U(i, m) contains the maximum achieved utility of any subset of packets  $\{1, ..., i\}$  of the total allocated frames m

$$U(i,m) \stackrel{\Delta}{=} \max_{S_i} \Big\{ \sum_{j \in S_i} u_j \Big| \sum_{j \in S_i} m_j \le m \Big\},\,$$

where  $S_i \in \{1, 2, ..., i\}$ . The maximum achieved utility is U(N, M). Now, U(i, m) can be defined in terms of the solution to the smaller problems,

$$U(i,m) = \max\left\{U(i-1,m), u_i + U(i-1,m-m_i)\right\}.$$
 (31)

The pseudo-code of the proposed algorithm is illustrated in Fig. 4. In the proposed algorithm, we compute the values of U(i,m) bottom up using (31) with the initial condition U(0,m) = 0.

To keep track of the selected packets for transmission, in Fig. 4, we have considered the auxiliary boolean array s(i, w), which is equal to 1 if the decision is to take the *i*-th file in U(i, m), and 0 otherwise. The set of the selected packets for transmission is then constructed using the array s(.,.) by the procedure in the second part of the algorithm in Fig. 4. Note that if s(N, W) is 1, then packet N is selected for transmission. We then repeat this argument for s(N - 1, M - m). If s(N, W) is 0, then packet N is not selected for transmission and we repeat this argument for s(N - 1, W). It is simple to show that the complexity of this algorithm is in the order of NM which makes it appropriate for real-time radio resource allocation in wireless communication networks.

Calculating the maximum achieved utility  
for 
$$(m = 0 \text{ to } M)$$
  
 $U(0,m) \leftarrow 0$ ;  
for  $(i = 1 \text{ to } N)$  {  
for  $(m = 0 \text{ to } M)$  and  $(u_i + U(i - 1, m - m_i)) > U(i - 1, m))$  }  
 $U(i,m) \leftarrow u_i + U(i - 1, m - m_i)$ ;  
 $s(i,m) \leftarrow 1$ ;  
}  
else {  
 $U(i,m) \leftarrow U(i - 1, m)$ ;  
 $s(i,m) \leftarrow 0$ ;  
}  
}  
Constructing the answer set  
K=M;  
for  $(i = N \text{ to } 1)$  {  
if  $(s(i, K) == 1)$  {  
output i;  
 $K \leftarrow K - m_i$ ;  
}  
}

Fig. 4. A dynamic programming approach for optimal downlink resource allocation.

#### V. SIMULATION RESULTS

To study the system performance, we consider a two-tier hexagonal cell configuration with a wrap-around technique [22]. A UMTS [10] cellular network, with a fast power controller running at 1500 updates per second, is simulated. Cross-correlation between the codes is assumed to be 0.5. Three traffic types are used: 12.2 kbps voice (with the required  $E_b/I_0 = 5$  dB), 32 kbps data (with the required  $E_b/I_0 = 3$ dB) and 64 kbps data (with the required  $E_b/I_0 = 2$  dB). We assume a steady 5 Erlangs of voice traffic. For data traffic, we assume Pareto call duration (see Definition 2). The control window is  $T_w = 10$  ms.

We assume that the channel gain  $g^{c}(n)$  is given by

$$g^{c}(n) = L_{c} d_{c}^{-\gamma_{c}} \theta^{c}(n), \qquad (32)$$

where  $d_c$  is the distance between the base-station c and the user for which the downlink interference is measured,  $\gamma_c$  is the path loss exponent which is a function of the antenna height and the signal propagation environment,  $L_c$ is an environmental constant, and  $\theta^c(n)$  is the shadowing process, which has a log-normal distribution with the standard deviation  $\sigma_c$ . The Gudmundson correlation model [23] is used for log-normal shadowing as

$$\Theta^{c}(n+1) = \eta^{c}\Theta^{c}(n) + (1-\eta^{c})\nu^{c}(n), \qquad (33)$$

where the time-scale is  $T_f$  (fading period),  $T_f \ge T_w$ ,  $\Theta^c(n) = \log \theta^c(n)$  is the log-normal fading in dB,  $\nu^c(n)$  is a zero-mean white Gaussian noise with variance  $\sigma_c^2(1 + \eta^c)/(1 - \eta^c)$ , and  $0 < \eta^c < 1$  is the channel correlation coefficient. We assume  $\sigma_c = 8$  dB and  $T_f = 100$  ms. A distance-dependent channel loss with path exponent  $\gamma = -4$  is considered. Users are distributed uniformly with different service types. The details of the simulation setting are given in Table I.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Number of BSs	19
Cell Radius	100 m
BSs Transmit Power	10 W
Physical Layer	Based on UMTS
Power Control	Fast Power Control 1500/s
$T_w$	10 ms
Standard Deviation of Fading	8 dB
Loss Exponent	-4
Thermal noise density	-174.0 dBm/Hz
$T_{f}$	100 msec
$E\xi^1$	0.5
Services	12.2 kbps voice, 32 and 64 kbps data
12.2 kbps voice	$E_b/I_0 = 5$ dB, 5 Erlangs
32 kbps data	$E_b/I_0 = 3$ dB, Pareto Dist.
64 kbps data	$E_b/I_0 = 2$ dB, Pareto Dist.
Bit-rates (non-realtime traffic)	16, 32, 64, 144, 384 kb/s

Fig. 5. The Q-Q plot for the marginal distribution of total interference.

# A. Model Validation

We consider two data services in Table I with the Pareto type call duration with parameters  $\alpha_1 = 1.5, E\tau_1 = 2$  minutes and  $\alpha_2 = 1.8, E\tau_2 = 1.5$  minutes. Data call arrival in both cases is generated by a Poisson distribution with an average rate of 10 arrivals per second. The heavy-tail call durations of data traffic satisfy the conditions of Proposition 1, which gives the self-similarity index H = 0.75. We study the time trace of the received downlink interference measured at different arbitrary locations in cell c = 1. High variations are seen in traces with different time-scales. To estimate the self-similarity index H, the Whittle estimator [6] is used, which gives H = 0.65. The discrepancy between the estimated value of H by the simulations and that obtained from Proposition 1 is mainly due to the fact that in the simulations, the network will not accept all requests because of the interference threshold. Extensive simulations on the selfsimilarity in the total downlink interference are also presented in [1].

We now show that fGn is an appropriate model for I(n). We use the quantile-quantile (Q-Q) plot [6] to show that the total interference is a Gaussian process. The Q-Q plot is a graphical technique that determines whether two data sets have the same probability distribution. A Q-Q plot is a plot of the quantiles of the first data set against the quantiles of the second data set. A quantile is the fraction of points whose values are smaller than the given value; that is, the x% quantile is a point at which x% of the points in the data set have values smaller than the given value and (1 - x)% have values larger than that value. If the two sets come from a population with the same distribution, the points should fall approximately along the 45-degree reference line. The greater the difference from this reference line, the greater the evidence that the two data sets have different distributions. The received total interference values comprise the first data set, and the values generated by a Gaussian distribution with the same mean and variance are in the second data set. In Fig. 5, the Q-Q plot shows that the received total interference for the above configuration can be closely approximated by the Gaussian distribution.

#### B. Performance of the proposed adaptive-predictive method

To study the performance of the proposed method, we add a fourth non-real-time traffic. This traffic constitutes fixed-size packets with Poisson arrival with rate  $\lambda$ . We set  $N_L = 100$ and use a linear predictor with  $M_L = 5$  taps to predict the interference level; we have found that the predictor error is not sensitive to the value of  $M_L$  for  $M_L \ge 5$  (See Fig. 1). A confidence interval of 95% for the estimate of the selfsimilarity index, H, is considered. We also assume that the cross-correlation between DS-CDMA codes in cell c = 1, i.e.,  $\xi^1$ , is equal to 0.5.

To minimize the prediction error, the model parameters are adjusted based on the scheme presented in Subsection II. Using this adaptively adjusted linear predictor, together with 95% confidence interval for estimating the self-similarity index and a long window consisting of 100 samples (i.e.,  $N_L = 100$ ) for estimating the interference variance and mean, we expect very low prediction error.

We have run 50 independent simulation trials with users uniformly dispersed in the cell coverage area. In the sequel, we report the average values in these runs for two systems. The first system (System A) uses the proposed method in this paper for interference prediction. For non-real-time traffic, we first consider System A using the throughput-optimal time-domain-scheduling (System A-TDS-Th) in (22)-(25), and using the utility-maximized time-domain-scheduling in (29)-(30) (System A-TDS-U). The second system (System B) uses the average values of the 5 last samples of the measured interference as the predicted value. We consider System B using the throughput-optimal time-domain-scheduling (System B-TDS-Th) in (22)-(25), using the utility-maximized timedomain-scheduling in (29)-(30) (System B-TDS-U), and finally without it (System B-CDMA).

We compare the cell throughput for the non-real-time data service of the systems A and B for different values of the interference self-similarity index H. We consider System B-CDMA as the benchmark and normalize the cell throughput in each case to the corresponding value of the throughput in System B-CDMA. The results are illustrated in Fig. 6. A significant improvement in the average cell throughput

10

10

PDR

10



Fig. 6. The normalized average cell throughput versus H.

![](_page_8_Figure_3.jpeg)

Fig. 7. The standard deviation of the packet delay versus H.

is seen in Fig. 6 where our proposed adaptive-predictive method for interference prediction is used. As we expect, the cell throughput of System A-TDS-U is smaller than that of System A-TDS-Th since we trade the throughput for the delay fairness.

In Fig. 6, it is also interesting to note that even for greater values of H, the utility-based optimization results in larger throughput compared with that for System B-TDS-Th. This is because of the more accurate interference predication using our proposed predictive-adaptive method.

We have found the standard deviation of the actual packetdelay for systems A-TDS-U and A-TDS-Th. A lower value of the standard deviation indicates an improved fairness in delay. As can be seen in Fig. 7 using the utility based optimization, the fairness in delay is significantly improved.

A very important question is: "What is the impact of applying our proposed method on the self-similarity of interference?" Since the self-similarity of downlink interference emanates from user traffic characteristics, the application of the proposed scheme—and possibly other radio resource control mechanisms—would not alter the self-similarity of the

TABLE II ESTIMATED H FOR DIFFERENT SIMULATION RUNS.  $\hat{H}$  for different runs of simulation 0.6201 0.6357 0.6520 0.6431 0.6461  $\lambda = 5$  $\lambda =$ 10 0.6373 0.6480 0.6542 0.6516 0.639 0.6512 0.6439 0.6448 0.6484 0.6435  $\lambda = 15$  $\lambda = 20$ 0.6405 0.6534 0.6350 0.6282 0.6431 H=0.

![](_page_8_Figure_10.jpeg)

Averaging Prediction Averaging

Fig. 8. Packet drop ratio (PDR) for the best-effort data traffic versus the packet arrival rate  $\lambda$  using the proposed method. The PDRs for a system that in each time instance uses the average value of the 5 last samples of measured interference and pure CDMA are also shown.

downlink interference; but it may alter the model parameters. Table II illustrates the estimated values of H for the cellular network with the parameters given in Table I and with 95% confidence interval after our proposed method is applied. In this table,  $\hat{H}$  for five independent simulation runs for different non-real-time packet arrival rates for a given throughput R = 5000 bps are presented. The results in Table II confirm the following two points: first, the interference in the downlink is self-similar, as its self-similarity index is greater than 0.5; and second, the self-similarity index does not depend on the arrival rates of non-real-time traffic. This is due to the fact that the self-similarity in the downlink interference emanates from the traffic characteristics of the real-time calls, which have heavy tail call durations.

We also study the effect of utilizing the proposed method on the packet drop ratio (PDR) of non-real-time data traffic. Fig. 8 illustrates the PDR versus packet arrival rate of the besteffort (non-real-time) data traffic. In each case, we consider two traffic patterns: the first is the one we have used in Subsection V-A, and the second corresponds to a system with a higher self-similarity index (H = 0.7) in the downlink interference. As it is seen, the PDR of the system using the proposed method is smaller than that of the system using the average values of the measured interferences. Fig. 8 also shows the improvement in PDR with the higher value of self-similarity in the downlink interference. This demonstrates the ability of our proposed method to exploit temporal correlation in the downlink interference to improve the system performance.

## VI. CONCLUSIONS

In this paper, we use the predictive structure of the total downlink interference in [1] to maximize non-real-time data throughput in a heterogenous service DS-CDMA cellular network. We propose a model-based linear adaptive-predictive method to estimate the level of interference for optimizing the system throughput and minimizing the delay for non-realtime data transmission. We use a fractional Gaussian noise (fGn) model in an appropriate time-scale to represent the self-similarity of the downlink interference. The interference predictor can be implemented in the mobile station, in the base-station, or in the radio network controller.

The estimated interference is used to allocate power to nonreal-time services. We first utilize a throughput maximization approach. Although this scheme maximizes the total throughput, it introduces extensive delay for users far from the base station or with bad channel conditions. We then propose a utility-based scheme in which the packets are scheduled so as to maximize the total system utility. A utility function for each packet is considered which builds a bridge between the service and the network parameters including the channel status and the actual delay. We map the optimization problem for the downlink packet scheduling to a knap-sack problem, and propose a dynamic programming technique to solve the optimization problem. Simulation results validate the fGn model and show that our proposed scheme can substantially improve the delay fairness, and significantly increase the average cell throughput. The simulation studies also confirm that the interference model is valid for a broad range of arrival rates of non-real-time traffic.

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![](_page_9_Picture_28.jpeg)

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![](_page_9_Picture_33.jpeg)

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![](_page_10_Picture_1.jpeg)

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![](_page_10_Picture_4.jpeg)

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