On the Downlink Interference in Heterogeneous Wireless DS-CDMA Networks

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***Abstract*— In this paper, we show that the total downlink interference in heterogeneous wireless DS-CDMA networks follows an asymptotically self-similar (as-s) process. The as-s model is valid for the interference under certain conditions on channel variations and traffic characteristics that cover a range of practical situations. We derive these conditions and generalize earlier results, obtained for data-centric cellular networks, to heterogeneous cellular networks. Simulation results for actual cases confirm analytical results, and show that non-uniform spatial distribution of users and their soft-hand-off status do not affect the nature of this self-similar process. Furthermore, we discuss the impact of the analysis developed in this paper in designing appropriate mechanisms for controlling radio resources in such networks.**

***Index Terms*— Asymptotically self-similar process, downlink interference, heterogeneous cellular DS-CDMA networks, heavy-tail distribution.**

I. INTRODUCTION

IT is well known that *Direct Sequence Code Division Multiple Access* (DS-CDMA) systems have some desirable features such as dynamic channel sharing, wide range of operating environments, graceful degradation of the Quality-of-Service (QoS), and ease of cell planning. DS-CDMA systems can also support a heterogeneous mix of services with a broad range of bursty traffic characteristics and QoS requirements.

Since DS-CDMA systems have been shown to be interference-limited [1], multiple-access interference plays an important role in the performance analysis of such systems. Therefore, managing the total interference for all services is a major challenge in heterogeneous wireless networks [2]. Proper utilization of more accurate information on the temporal behavior of the downlink interference can lead to the development of effective resource control mechanisms. However, the conventional approaches for modeling interference in wireless DS-CDMA networks only use the marginal distribution of the total interference [2], [3], [4], and do not consider its temporal behavior. In contrast, here we consider such temporal behavior for heterogeneous services in wireless DS-CDMA networks, which can be utilized effectively in designing radio resource control mechanisms such as outer-loop power control, call admission control, and load balancing. These control mechanisms operate in substantially longer periods (i.e., from a few milliseconds to seconds) compared to other mechanisms in the lower layers including modulation, detection and fast power control. In this paper, we only focus on the downlink channel since it is more critical than the uplink channel [5].

Temporal behavior of interference in long time-scales for packet data services in a cellular network has been studied in [6], [7], [8], where interference is modeled as a continuous-time process, graceful degradation of the QoS for limited interferences is assumed, and the effects of call admission procedure are ignored. In [9], an ON-OFF process is assumed for user traffic, and the basic concept of heavy-tail processes is utilized to explain the self-similarity of the total interference. An ON-OFF process typically refers to the mutually independent, alternating ON-periods (during which packets are emitted at a constant rate) and OFF-periods (during which no packets are sent). Obviously, the above method is not applicable to heterogeneous DS-CDMA cellular networks that support both packet-based and connection-oriented services. Further to using an ON-OFF traffic model, [8] makes the following assumptions: the total bandwidth (and as a consequence the number of users) is infinity; the allocated power to each user is the inverse of the slow fading channel gain; and a specific wireless channel model is assumed in which the auto-correlation function of channel variations and the transmit power process are of the order of $O(k^{-\alpha+1})$ for $k \to \infty$ where α is the minimum decay exponent of the tail of the ON and OFF processes. Under these conditions, [8] shows that the total downlink (and also uplink) interference has asymptotic second-order self-similarity. We will show that, while the heavy-tail assumption of channel auto-correlation function and the infinite bandwidth are relaxed, the total interference yet depicts asymptotic second-order self-similarity in heterogeneous DS-CDMA networks.

In [10] and [11], the interference is shown to be an independent and identically distributed (i.i.d.) α-stable process. However, the independence assumption is often violated in practical systems. In [12], it is shown that under certain conditions, the interfering signal in a Poisson field of interferers becomes long-range dependent. This is useful for designing receivers that are optimum for small time-scales, but not suitable for long time-scales in heterogeneous cellular DS-CDMA networks.

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We propose a model for the downlink interference over long time scales, and show that it provides significant insight and considerable intuition for designing efficient radio resource control mechanisms. In these time scales, the QoS must be considered over the lifetime of a call/session. For this reason, and for better clarity, we will ignore many physical layer effects, as they are pertinent only to much shorter time scales. For example, we do not explicitly model the signature sequence of the DS-CDMA systems, nor the fast multi-path fading. Rather, we take a simplified model of the lower layers that capture enough of the physical layer characteristics for our purposes, and which has already been used successfully in [1], [2], [4], [13] and [14]. The network provides a heterogeneous mix of services, including data, multimedia and voice.

Several system parameters, such as the total number of active users (interferers), their call durations, the allocated power to each call in the corresponding base-station, channel variations and user mobility, cause temporal fluctuation of interferences. To model these effects we take a cross-layer approach as in [15] in which the traffic characteristics at the application layer and the information on the wireless channels are combined to model the downlink interference.

We begin by modeling the total transmit power of each base-station as a time-series representing the aggregate of the allocated power to each user in the coverage area of the corresponding base-station. We limit our consideration to the co-channel interference, and exclude the thermal noise. A mobile unit receives the superposition of all transmitted powers from adjacent base stations as well as the power allocated to other users in its serving cell affected by wireless channel gain that is manifested as path-loss and fading. This approach is similar to [9], [16], [17], except that we also consider temporal variations in the wireless channel. In cellular DS-CDMA networks, the status of a wireless channel depends on the individual wireless links as well as the network load conditions. We extend the results of [16] and [17] for modeling the temporal behavior of the downlink interference in heterogeneous DS-CDMA cellular networks to the case in which channel availability is uncertain. This is in contrast to [16] and [17], where only provisioning of a single service for a fixed channel condition is considered.

In cellular networks, different resource control mechanisms are performed in discrete time, but in different time scales ranging from a few milliseconds to seconds, minutes, and longer. In our treatment of the subject, only long time scale effects such as path-loss and shadowing are considered, since short time scale effects such as fading are cancelled partly by the fast power control and are also averaged out in long time scales. For simplicity, we also assume very low mobility or fixed mobile terminals.

We assume that the call admission procedure is utilized in the actual DS-CDMA cellular networks to control the radio resources allocated to each user to satisfy the required QoS. In the literature, it is assumed that in the DS-CDMA cellular networks, no new call arrivals are blocked and no calls are terminated prematurely (see, e.g., [13], [14]). This can be justified to some extent by soft-blocking in DS-CDMA cellular networks where no hard limit is imposed on the number of simultaneous calls, and network load affects only the capacity of the respective cell. We focus on a network for which the actual arrival rates of new calls are less than the predetermined values assumed for designing that network. In such a case, concurrent calls in the systems may cause outage or service degradation if the resulting total interference exceeds the predetermined threshold. We further assume that the allocated power to a user is a concave function of its instantaneous rate, is continuously provided, and is utilized for the provision of the actual discrete bit-rate [18].

We focus on the asymptotic temporal behavior of downlink interference for long time-lags, which provides very critical information for predictive/adaptive radio resource control mechanisms. We use a cross-layer model to obtain the auto-covariance function of the downlink interference that is a function of channel auto-covariance, call/packet-duration distribution, call/packet arrivals, and the auto-correlation of the allocated power to each call/packets. We show that for long time-lags, the auto-covariance of the downlink interference in a constant channel, single cell DS-CDMA cellular network with a mix of Poisson and heavy-tail traffics, decays sub-exponentially. We then extend this result to show that the downlink interference has long-range dependence.

Traffic modeling for voice-only DS-CDMA cellular networks is based on a Poisson process [14], [19], which has its root in telephony, and may not be an adequate model for call/packet durations of multi-media and data traffics with heavy tail distributions [20]. Therefore, the impact of traffic characteristics on the downlink interference in a heterogeneous cellular network is different from that of voice-only networks. The effect of non-Poisson traffic on the performance of wireless network was first addressed in [21], [22], where the requirements for supporting a self-similar traffic were examined. It was shown in [23] that the capacity of a DS-CDMA cellular network, designed for Poisson traffic, is substantially reduced when the input traffic has long-range dependence.

We show that in a cellular network, for heavy-tail distribution of call[1] durations, the auto-covariance of the downlink interference decays sub-exponentially, and thus, the corresponding interference follows an asymptotic self-similar (a-s) process. The respective heavy-tail distribution depends on call durations, bit-rate variations, and channel characteristics. Asymptotic self-similar processes are used to characterize long-range dependence in local area networks [24], wide-area networks [25], and single-service traffic flows [26].

The main contributions of this paper are as follows. We extend the theoretical results in [9], [16], and [17], in which only provisioning of a single service for a fixed channel condition was considered, to heterogenous services wireless systems in which channel availability is uncertain. By considering a general channel model for a heterogenous services cellular network with a mixture of connection-oriented and connectionless services, we also extend the results on the self-similarity of the interference in [6], [7] and [8], where a packet cellular network with a particular channel model and infinite

[1]Throughout this paper, 'call' means either a packet of data or a connection-oriented service.

bandwidth was considered.

We simulate a heterogeneous wireless network using the Universal Mobile Telecommunication System (UMTS) standard [18]. We observe self-similarity in total downlink interference when the call duration of at least one service has a heavy-tail distribution. Simulation results show that non-uniformity in the spatial distribution of users and their Soft-Hand-Off (SHO) conditions do not affect self-similarity in the downlink interference.

II. Total Downlink Interference

We consider a cellular DS-CDMA network that provides heterogeneous services. In this network, the total downlink interference measured in the location of a given user is represented by a discrete time process $I(n)$, with $n \in \mathbb{Z} = \{\ldots, -1, 0, 1, \ldots\}$ where for convenience we set the origin of time to $-\infty$. For a user in the network coverage area, each sample of $I(n)$ is valid over a window of length T_w seconds that is the *time scale* of modeling. The measured value of $I(n)$ is the average of the received interference within T_w seconds, where $T_w \gg T_c$ and $1/T_c$ is the spreading bandwidth of the cellular DS-CDMA network. Therefore, $I(n)$ is the sum of the transmitted power by all base-stations, multiplied by the corresponding channel gain from each of those base-stations to the user under study, so

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

where N_C is the number of cells in the network, $P^c(n)$ is the total transmitted power by the base-station in cell c, $\xi^c(n)$ is the cross-correlation between the spreading sequences of other users and the user of interest, and $g^c(n)$ is the channel gain from the base-station in cell c to the user. Note that in (1), the power allocated to the user is not included in $P^1(n)$. For convenience, we assume that the user is located in cell $c = 1$ and that $\xi^c(n) = 1$.

In the time slot n, each base-station serves a set of active users (calls) in its cell coverage area. For simplicity we ignore the SHO users and thus each call is served by only one base-station. We assume that each call is started at the beginning of a time slot and its duration is an integer multiplication of the time scale of modeling (T_w). The transmitted power by the base-station is the sum of allocated powers to all calls in the corresponding cell c, therefore $P^c(n)$ is

$$P^c(n) = \sum_{j=1}^{J} \sum_{i=1}^{N_j^c(n)} p_{ji}^c(n - \upsilon_{ji}^c + 1) \tag{2}$$

where J is the number of services provided by the network, $N_j^c(n)$ is the number of calls of service j in cell c at time n, $p_{ji}^c(.)$ (Fig. 1)is the allocated power to call i of service j in cell c, and $\upsilon_{ji}^c \in \mathbb{Z}$ is the start time of the ith 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, $\upsilon_{ji}^c \leq \upsilon_{ji+1}^c$. For the ith call of service j in cell c with a call duration of $\tau_{ji}^c \in \mathbb{N}$ seconds, $\mathbb{N} = \{1, 2, \ldots\}$, $p_{ji}^c(.)$ has a real-value equal to the allocated power in its call duration, and is equal to zero otherwise. Fig. 2 illustrates a typical $P^c(n)$. In a broader view, υ_{ji}^c, $p_{ji}^c(.)$, and τ_{ji}^c are random processes. Equation (2), which specifies the total allocated power in each base-station, is an extension of a similar equation used in [17] to characterize the aggregated traffic in an Asynchronous Transfer Mode (ATM) switch, in which the channel gain is irrelevant, and the channel is available during the whole call duration. The uncertain wireless channel makes the analysis of the downlink interference more challenging and nontrivial. Note that in (1) and (2), there are no assumptions on the traffic characteristics and spatial distribution of users in the cell coverage area.

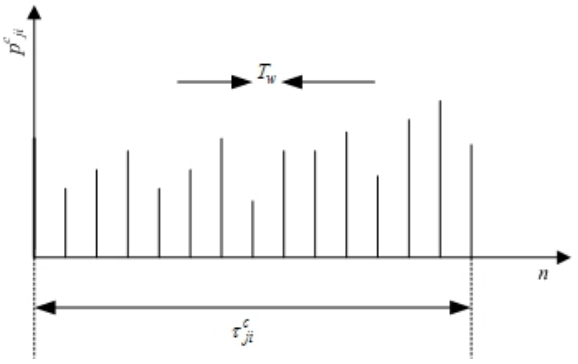

Fig. 1. The allocated power $p_{ji}^c(n)$ to a call i of service j in cell c during its call duration τ_{ji}^c versus time. T_w is the modeling time scale.

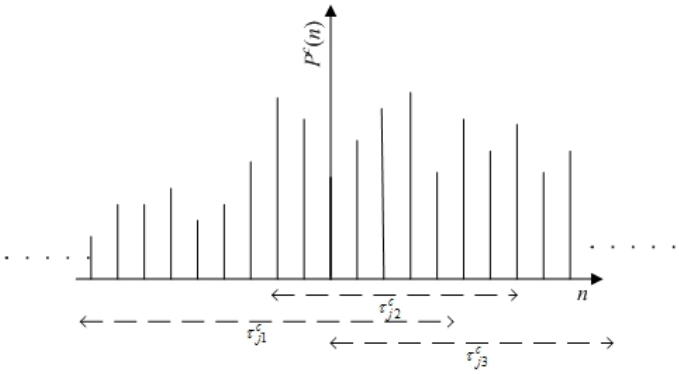

Fig. 2. Temporal behavior of $P^c(n)$ for the case that three users of service j are served in cell c, τ_{j1}^c, τ_{j2}^c, and τ_{j3}^c are the call durations of users 1, 2, and 3 respectively.

For all $n, m \in \mathbb{Z}$ and all c_0, c_1, we assume that $P^{c_0}(n)$ and $g^{c_1}(m)$ are second-order stationary processes and are independent from each other. To obtain the total interference in (1), in what follows, we obtain the characteristics of $P^c(n)$ and $g^c(n)$. We assume that for each given cell c and service j, the call duration sequence process $\{\tau_{ji}^c, i \in \mathbb{N}\}$, the 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 random processes with identically independent distribution (i.i.d.) variable. We denote τ_{ji}^c, $\mu_{ji}^c(n)$ and $p_{ji}^c(n)$ by the generic random variables τ_j^c, $\mu_j^c(n)$ and $p_j^c(n)$, respectively.

A. Base-station Transmit power

To obtain the characteristics of $P^c(n)$, we need to have the number of active calls for different service types and their

corresponding call durations in (2) as well as the allocated power in their respective call durations. In this model, the user traffic is specified by three processes, $\mu_j^c(n)$, τ_j^c and $p_j^c(n)$, where $p_j^c(n)$ is a function of the service type j, the bit-rate, and the power allocation strategy in the network. It is easy to show that the downlink interference can be completely specified by $p_j^c(n)$, $g^c(n)$, $\mu_j^c(n)$ and τ_j^c, for all j and c.

Let $\mu_j^c(n) \in \mathbb{Z}_+ = \{0, 1, 2, \ldots\}$ be the number of new call arrivals for service j in cell c at time n. Note that in (2) for a given $\mu_j^c(n)$, we can derive υ_{ji}^c. Mobile users are assumed to be uniformly distributed in the coverage area of each base station. In the following, we present the models for a new call arrival process $\mu_j^c(n)$, the call duration process τ_j^c, and the allocated power process $p_j^c(n)$. The channel process will be presented in the next subsection.

*1) **New Call Arrivals**:* In DS-CDMA cellular networks it has been assumed that no new call arrivals are blocked and no calls are terminated prematurely [13], [14]. This can be justified to some extent due to soft blocking of calls in DS-CDMA cellular networks, meaning that there is no hard limit on the number of available channels and all users suffer a gradual performance degradation as the load is increased. However, in reality such networks utilize call admission mechanisms to control the resources allocated to users while maintaining their required QoS. We assume that the arrival rates of new calls for each service type are less than the values for which the network was designed. This means that all requests for different service types whose arrival rates are less than the corresponding pre-determined values will be granted at the cost of other users' probable graceful QoS degradation.

It has been shown that the Poisson distribution is an appropriate model for call arrivals of voice and non-voice services [17], [23]. Here, we also assume that $\mu_j^c(n)$ has a Poisson distribution with parameter λ_j^c,

$$\Pr\{\mu_j^c(n) = \nu\} = \frac{(\lambda_j^c)^\nu e^{-\lambda_j^c}}{\nu!} \tag{3}$$

Consequently, the total downlink interference $I(n)$ in (1) can be fully specified by $\lambda_j^c = E[\mu_j^c(n)]$, the probability distribution of τ_j^c, as well as the processes $p_j^c(n)$ and $g^c(n)$. We further assume that $0 < \lambda_j^c < \infty$.

*2) **Call Durations**:* We denote both packet duration and call duration as 'call duration'. Assume that the call duration is a random variable with a known distribution. Call durations of different service types are assumed to be independent from each other. For voice-only wireless and wireline networks, it is invariably assumed [13], [27] that call durations are exponentially distributed. Distribution of call durations in future wireless systems are expected to be similar to the ones in current wireline networks, for which extensive statistical analysis and measurements have established that the distribution of call durations for data and multimedia services are heavy-tailed [20], [26], [28], [29]. For a heavy-tailed distribution, the rate of decay of its density function is much slower than that of the Poisson distribution. Pareto distribution has been used in [20], [28] to model call durations.

*3) **Allocated Power to Each Call**:* To obtain $p_j^c(n)$, we note that for a given channel, the allocated power to a given user at time slot n is generally a function of its bit-rate, that is $p_{ji}^c(n) = \chi_j(R_{ji}^c(n))$, where $R_{ji}^c(n)$ is the instantaneous bit-rate of the ith call of service j in cell c, and $\chi_j(x)$ is an increasing and concave function of x [2]. For simplicity, we assume $\chi_j(x)$ is a linear function of x for all j, but can also be any concave function of x. We also assume that the system can support any arbitrary bit-rate.

Given a service j call in cell c with call duration $\tau_{ji}^c = l$, the received power can be envisioned as a segment of a non-negative second-order stationary discrete-time process which depends on l and is denoted by $p_{j(l)}^c = (\ldots, p_j^c(-1), p_j^c(0), p_j^c(1), \ldots)$. The mean and auto-correlation function of $p_{j(l)}^c$ are $m_{j(l)}^c$ and $r_{j(l)}^c(k)$ respectively. We also assume that $0 < m_{j(l)}^c < \infty$ and $0 < r_{j(l)}^c(k) < \infty$.

B. Wireless Channel

In (1), the transmitted power by each base-station is multiplied by the corresponding channel gain. To obtain the channel gain $g^c(n)$, assume a deterministic distance-dependent path loss and two fading effects: fast fading and slow shadowing. Note that fast fading (e.g., Rayleigh or Rician) affects $P^c(n)$ in (1) in smaller time scales than the shadowing, which 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. Therefore, the channel gain $g^c(n)$ is

$$g^c(n) = L_c d_c^{-\gamma_c} \theta^c(n) \tag{4}$$

where d_c is the distance between the base-station c and the user for which the downlink interference is measured, γ_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 slow fading process. It has been shown that γ_c may vary from slightly less than 1 for hallways within buildings, to larger than 2.5 in dense urban environments and hard partitioned office buildings [30]. The slow fading process $\theta^c(n)$, has a log-normal distribution with standard deviation σ_c. The Gudmundson correlation model [30] is used for log-normal shadowing as

$$\Theta^c(n+1) = \rho^c \Theta^c(n) + (1 - \rho^c)\nu^c(n) \tag{5}$$

where the time scale is T_f (fading period), $T_f \geq T_w$, $\Theta^c(n) = \log \theta^c(n)$ is the log-normal fading in dB, $\nu^c(n)$ is a zero-mean white Gaussian noise with variance $\sigma_c^2(1 + \rho^c)/(1 - \rho^c)$, and $0 < \rho^c < 1$ is the channel correlation coefficient.

We assume that $g^c(n)$ is a second-order stationary process. The mean and auto-correlation function of process $g^c(n)$ are m_g^c and $r_g^c(k)$ respectively. We also assume that $0 < m_g^c < \infty$ and $0 < r_g^c(k) < \infty$. The auto-covariance function of $g^c(n)$ is denoted by $C_g^c(k)$. Consequently, the total downlink interference $I(n)$ in (1) can be obtained from $\lambda_j^c = E[\mu_j^c(n)]$, the probability distribution of τ_j^c, and the characteristics of the processes $p_j^c(n)$ and $g^c(n)$.

III. Temporal Behavior of Downlink Interference

In this Section, we derive the asymptotic temporal behavior (i.e., for $k \to \infty$) of the auto-covariance function of the downlink interference $C(k)$. Using the assumptions in Section

II on the independence of $P^{c_1}(n)$ and $g^{c_2}(m)$ for different values of c_1, c_2, n and m^2, it is easy to show that the auto-covariance function of $I(n)$ is

$$C(k) = \sum_{c=1}^{N_C} \Big[C_P^c(k) C_g^c(k) + C_g^c(k)(m_P^c)^2 + C_P^c(k)(m_g^c)^2 \Big]. \tag{6}$$

Using Theorem 4 in [17], it is straightforward to show that the mean and the auto-covariance function of $P^c(n)$ in (1) are

$$m_P^c = \sum_{j=1}^{J} \sum_{l=1}^{\infty} l \lambda_j^c \Pr\{\tau_j^c = l\} m_{j(l)}^c, \tag{7}$$

$$C_P^c(k) = \sum_{j=1}^{J} \sum_{l=k+1}^{\infty} \sum_{n=l}^{\infty} \lambda_j^c \Pr\{\tau_j^c = n\} r_{j(n)}^c(k), \quad k \in \mathbb{Z} \tag{8}$$

Before examining the effects of traffic characteristics on the auto-covariance of the downlink interference in (6), we define regular and slow varying functions.

***Definition** 1:* ([31]) A function $f(x) > 0$, $x \in \mathbb{R}$ is called a *regular varying function* (rvf) if there exist an $\alpha \in \mathbb{R}$ such that for all $u \in \mathbb{R}_+$, $\frac{f(ux)}{f(x)} \to u^\alpha$, as $x \to \infty$. The value of α is the *regularity index* of $f(x)$. If $\alpha = 0$, then f is called a *slow varying function* (svf). We denote $\mathcal{RV}_\alpha$ as the set of regular varying functions such that if $f(x) \in \mathcal{RV}_\alpha$ then $f(x) = L(x)x^\alpha$, where $L(x)$ is a svf.

A random variable X is said to be heavy-tailed with infinite variance if $P(|X| \geq x) \in \mathcal{RV}_\alpha$ for $0 < \alpha < 2$.

***Example 1: Downlink asymptotic temporal behavior (single-cell case)**:* Assume a single-cell system (i.e., $N_C = 1$) with constant channel gain $g^c(n) = g_0$. For brevity, we drop the cell index in the sequel. Suppose that there are two services (i.e., $J = 2$) both with Poisson distributions for call arrivals with rates of λ_1 and λ_2. Service $j = 1$ has an exponentially distributed call duration, and Service $j = 2$ has a heavy-tail distribution of call durations. Assume further that the call duration of service $j = 2$ has a discrete Pareto-type distribution,

$$\Pr\{\tau_2 = l\} = L_2(l) l^{-\alpha-1}, \qquad 1 < \alpha < 2 \tag{9}$$

where $L_2(l)$ is a slow varying function, and α is the 'shape parameter' of the distribution. A small value for parameter α results in a distribution with a heavier tail. Intuitively, (9) implies that there is no 'typical' distribution of call durations, i.e., call durations are highly variable, exhibit infinite variance, and fluctuate over a wide range of values.

In the simplest case, we assume that $E\tau_2$, $m_{j(l)}$ and $r_{j(l)}(n)$ are constants. Therefore, using (6) and (8), we get

$$C_P(k) \sim \sum_{l=k+1}^{\infty} \sum_{n=l}^{\infty} L(n) n^{-\alpha-1}, \qquad k \to \infty, \tag{10}$$

where $L(n)$ is a rvf and the symbol '$\sim$' means *behaves asymptotically as*[3]. Equation (10) does not include the terms corresponding to $j = 1$, since they diminish as $k \to \infty$.

[2]Note that here we assume a fast power control mechanism to deal with the undesirable effects of fast fading. Fast fading and shadowing processes are also assumed to be independent. Therefore we assume $P^c(n)$ and $g^c(m)$ are also independent for all n and m.

[3]$\phi(k)$ behaves asymptotically as $\varphi(k)$ means: $\lim_{k\to\infty} \frac{\phi(k)}{\varphi(k)} = 1$.

Using Lemma 1 in Appendix, the inner summation in (10) can be written as

$$\sum_{n=l}^{\infty} L(n) n^{-\alpha-1} \sim \int_l^{\infty} L(x) x^{-\alpha-1} dx, \qquad l \to \infty. \tag{11}$$

Using the Karamata theorem (Theorem 1.5.3 in [31]), (11) can be written as

$$\int_l^{\infty} L(x) x^{-\alpha-1} dx \sim \frac{L(l)}{\alpha} l^{-\alpha}, \qquad l \to \infty. \tag{12}$$

By the same argument for (12), the auto-covariance function of the transmit power $C_P(k)$ in (10) can be written as

$$C_P(k) \sim \int_k^{\infty} \frac{L(x)}{\alpha} x^{-\alpha} dx \tag{13}$$

$$\sim \frac{L(k)}{\alpha(\alpha-1)} k^{-\alpha+1}, \qquad k \to \infty. \tag{14}$$

Thus,

$$C_P(k) \sim \frac{L(k)}{\beta(\beta+1)} k^{-\beta}, \qquad k \to \infty \tag{15}$$

where $\beta = \alpha - 1$, $0 < \beta < 1$. Since $\beta < 1$, the auto-covariance function in (15) decays sub-exponentially (slower than $1/k$) and therefore

$$\sum_{k=-\infty}^{+\infty} |C_P(k)| = \infty \tag{16}$$

Eq. (16) indicates that in constant channels, the downlink interference exhibits extended temporal correlations. ■

A process whose auto-covariance function satisfies (16) is called a *long-range dependent* (LRD) process [32]. For an LRD process, the correlation between its two samples decreases very slowly with an increase in the temporal distance between those samples. In general, the auto covariance function of an LRD process for $k \to \infty$ is $C(k) \sim L(k)k^{-\beta}$, where $L(k)$ is a slow varying function, and $0 < \beta < 1$. In the above example, if the distributions of call durations are exponential for both services, their auto-covariance functions are absolutely summable, and therefore the resulting auto-correlation function decays exponentially, and creates a *short-range dependent* (SRD) process. The auto-correlation of a SRD process does not have a heavy tail. Note that for most standard time series, such as ARMA and Markovian models, the auto-covariance function decays exponentially [33], and thus $\sum_{k=-\infty}^{+\infty} |C(k)| < \infty$ [32].

A. Asymptotic Behavior of the Auto-covariance Function of the Downlink Interference

In Example 1, we showed that for a constant channel, the heavy-tailed distribution of call durations results in LRD downlink interference. We now extend this observation for more general channel conditions. Assume that the auto-covariance function of the channel process is

$$C_g^c(k) \sim L_g^c(k) k^{-\beta_g^c}, \qquad k \to \infty \tag{17}$$

where 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. For $\beta_g^c < 1$, the channel process

is LRD, and for $\beta_g^c > 1$, the channel process is SRD. For the corresponding time scales, this model is consistent with the Gudmundson correlation model for fading channels [34].

It is easy to show that $C_p^c(k)C_g^c(k) \in \mathcal{RV}_{-\beta_P^c-\beta_g^c}$. Using (6) and Lemma 2 in the Appendix, we conclude that $C^c(k) \in \mathcal{RV}_{-\beta^c}$, where $C^c(k) \triangleq C_P^c(k)C_g^c(k) + C_g^c(k)(m_P^c)^2 + C_P^c(k)(m_g^c)^2$ and $\beta^c = \min\{\beta_g^c, \beta_P^c\}$. If we employ Lemma 2 repeatedly, we get $C(k) \in \mathcal{RV}_{-\beta^*}$, where $\beta^* = min_c\beta^c$. Asymptotically, the regular varying function $C(k)$ is equal to a slow varying function $L^*(k)$ multiplied by an exponential part. Now, we present the following proposition.

***Proposition** 1:* For a finite-mean total transmit power process $P^c(n)$, a channel gain $g^c(n)$, and for $k \to \infty$, $C_P^c(k) \sim L_P^c(k)k^{-\beta_P^c}$ and $C_g^c(k) \sim L_g^c(k)k^{-\beta_g^c}$, the auto-covariance function of the total interference $C(k)$ satisfies

$$C(k) \sim L^*(k)k^{-\beta^*}, \qquad k \to \infty \tag{18}$$

where $L_P^c(k)$, $L_g^c(k)$ and $L^*(k)$ are svf, and $\beta^* = \min_c \min\{\beta_g^c, \beta_P^c\}$.

From Proposition 1 we conclude that for the above example whose channel auto-covariance is as (17), the downlink interference $I(n)$ is LRD.

IV. Self-similarity of Downlink Interference

We now propose an as-s model for the downlink interference which extracts the values of its LRD parameters. This model is valid under certain conditions on channel and traffic characteristics, which we derive in this Section.

For a given channel model, the arrival times and the durations of all calls in the downlink, we derive the time series $I = (I(n) : n = ..., -1, 0, 1, ...)$ that represents the interference in successive non-overlapping time intervals of unit lengths (T_w seconds). Assume that I is a second-order stationary process with a finite mean. We define the aggregate process $I^{(m)}$ of I at the aggregation level $m > 1$ by

$$I^m(n) = \frac{1}{m}\big(I(nm - m + 1) + \ldots + I(nm)\big). \tag{19}$$

The process $I^{(m)}$ is obtained from I by partitioning the observation interval into non-overlapping blocks of size m and averaging I in each block. For each $m > 1$, $I^{(m)}$ defines a new second-order finite-mean stationary process, and the family $(I^{(m)} : m \geq 1)$ of aggregate processes is useful for studying the temporal behavior of the total interference at different time scales corresponding to different resource control mechanisms. It is also useful for developing some mathematical concepts such as self-similarity that relate statistical properties of I to those of $I^{(m)}$ through a judicious scaling of time. To this end, the standard model for the total interference is a self-similar process in the asymptotic sense, or equivalently, an LRD process [32]. In what follows, we use the concepts presented in [16] and [17] to define an as-s process.

A. Asymptotically Self-Similar Process

***Definition** 2:* ([17]) A real-valued second-order stationary random process $I = (\ldots, I(-1), I(0), I(1), \ldots)$ is called *asymptotically self-similar process* (as-s), with self-similarity index $H = 1 - \beta/2$, $0 < \beta < 1$, if

$$\lim_{m\to\infty} C_{(m)}(k) = \frac{C_{(m)}(0)}{2}\big((k+1)^{2-\beta} - 2k^{2-\beta} + (k-1)^{2-\beta}\big) \tag{20}$$

where $k \in \mathbb{Z}_+$, $C_m(k)$ is the auto-covariance function of $I^m = (\ldots, I^m(-1), I^m(0), I^m(1), \ldots)$ and $I^m(n)$, as defined in (19), is the average process over blocks of length m.

A process I is as-s if the correlation coefficients of the average process of block length m as $m \to \infty$ are identical to those of a self-similar process[4]. A sufficient condition for a second-order stationary process I to be asymptotically self-similar is that for $k \in \mathbb{Z}_+$, $k \to \infty$, the auto-covariance function of I, i.e., $C(k) \sim L(k)k^{-\beta}$, in which $0 < \beta < 1$, and $L(k)$ is a svf [17]. From (20) we conclude that an as-s process is LRD.

B. As-s Model for the Downlink Interference

We now develop an as-s model for the downlink interference. Suppose that the total interference, $I = (\ldots, I(-1), I(0), I(1), \ldots)$, is a finite-mean, finite-variance second-order stationary process. We assume that the auto-covariance function of the channel process $g^c(n)$ is as in (17) for $c = 1, \ldots, C$, $0 \leq \beta_g^c \leq 1$, in which for $\beta_g^c = 1$ the channel process is SRD. In the following proposition, we derive the necessary conditions on traffic and channel characteristics under which the downlink interference is an as-s process.

***Proposition** 2:* Consider the downlink interference process, I, and let β_P^c, $c = 1, \ldots, C$ satisfy

$$\sum_{j=1}^{J} \lambda_j^c \Pr\{\tau_j^c = k\} r_{j(k)}^c(k) \sim L_P^c(k)k^{-\beta_P^c-2}, \qquad k \to \infty. \tag{21}$$

where $L_P^c(k)$ is a svf. Now, I is an as-s process with self-similarity index $H = 1 - \beta^*/2$ if there exists at least one c such that $0 < \beta_P^c < 1$ or $0 < \beta_g^c < 1$, and where $\beta^* = \min_c \min\{\beta_P^c, \beta_g^c\}$.

***Proof*:** We define $f(n) \triangleq \sum_{j=1}^{J} \lambda_j^c \Pr\{\tau_j^c = n\}\, r_{j(n)}^c(n)$,$n \in \mathbb{N}$. From (21), $f(n) \in \mathcal{RV}_{-\beta_P^c-2}$. Since there exists at least one c such that $0 < \beta_P^c < 1$, from Lemma 1 in Appendix, we get

$$\sum_{n=l}^{\infty} f(n) \sim \int_l^{\infty} L_P^c(x)x^{-(\beta_P^c+2)}dx, \qquad l \to \infty. \tag{22}$$

Using (22) together with Karamata's Theorem (Theorem 1.5.3 in [31]), for $l \to \infty$, we get

$$\sum_{n=l}^{\infty}\sum_{j=1}^{J} \lambda_j^c \Pr\{\tau_j^c = n\}\, r_{j(n)}^c(n) \sim \frac{L_P^c(l)l^{-(\beta_P^c+1)}}{\beta_P^c + 1}. \tag{23}$$

[4]Equation (20) is the auto-covariance function of a fractional Gaussian noise (fGn) process, where fGn is the incremental process of a fractional Brownian motion (fBm) process. A fBm typically (but not always) is the limit in a fractional central limit theorem of properly scaled LRD processes [32].

Using the same argument for (23), we get

$$\sum_{l=k+1}^{\infty} \frac{L_P^c(l) l^{-\beta_P^c-1}}{\beta_P^c+1} \sim \frac{L_P^c(k) k^{-\beta_P^c}}{\beta_P^c(\beta_P^c+1)}, \qquad k \to \infty. \quad (24)$$

Thus,

$$\sum_{l=k+1}^{\infty} \sum_{n=l}^{\infty} \sum_{j=1}^{J} \lambda_j^c \Pr\{\tau_j^c = n\}\, r_{j(n)}^c(n) \sim \frac{L_P^c(k) k^{-\beta_P^c}}{\beta_P^c(\beta_P^c+1)},\ k \to \infty, \quad (25)$$

where from (8), the left-hand-side of (25) is $C_P(k)$. Thus,

$$C_P(k) \sim \frac{L_P^c(k) k^{-\beta_P^c}}{\beta_P^c(\beta_P^c+1)}, \qquad k \to \infty. \quad (26)$$

From (6), together with the channel auto-covariance function asymptote given in (17), as well as from (26) and Lemma 2 in Appendix, we conclude that $C(k) \sim L(k) k^{-\beta^*}$, where $\beta^* = \min_c \min\{\beta_P^c, \beta_g^c\}$. Theorem 2 in [17] gives an as-s I with the decay factor equal to β^*, therefore $H = 1 - \beta^*/2$. ■

Remarks on Proposition 2:

1) Consider the case that for a base-station c_q, $P^{c_q}(n) g^{c_q}(n) \gg P^c(n) g^c(n)$, $c = 1, \ldots, C, c \neq c_q$, thus $I(n) \approx P^{c_q}(n) g^{c_q}(n)$. Therefore, the LRD in the downlink interference is not a practical concern. In other words, even though there is a β^* obtained by a c that is 'dominant-in-correlations', that does not affect the downlink's temporal behavior for nominal values of k. For the results of Proposition 2 to be valid in actual cases, we assume that a *regular power transmission* regime is applied in the network in which the transmitted power by any base station is not substantially higher than the transmitted power by other base stations. This assumption is valid if users of different services are uniformly distributed in the coverage area of the network, or if a load balancing mechanism in the network layer is applied.
2) Proposition 2 shows that if $r_{j(k)}^c(k)$ is heavy-tailed, the condition (21) will be satisfied and this may (subject to other conditions in Proposition 2) result in an as-s total downlink interference. A heavy-tailed $r_{j(k)}^c(k)$ can be a consequence of self-similarity emanating from bit-rate variations during a call.
3) Proposition 2 gives the sufficient conditions for asymptotic self-similarity in the total downlink interference. It combines service call arrival rate, λ_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 $k \to \infty$, to give the sufficient conditions.
4) An important observation in Proposition 2 is that the asymptotic behavior of the auto-covariance function of the total downlink interference in a mixed voice and multimedia or packet data, with regular channel variations and regular power transmission is a result of providing the requested services to the respective users with heavy-tailed call durations.
5) A straightforward application of Proposition 2 is that the total interference in data-centric cellular packet networks with heavy-tailed packet length is self-similar. This was also reported in [6]–[8]. However, in Proposition 2, we have the channel gain condition (17), which is more general than those considered in [6]–[8].

V. Simulation Results

We consider a two-tier hexagonal cell configuration with a wrap-around technique [35]. A UMTS cellular wireless network [18], with a fast power controller running at 1500 updates per second, is simulated. The average cross-correlation between the codes ($E\xi^1$) is assumed to be 0.5. Three types of services are used: 12.2 kbps voice (with the required bit energy to the interference spectral density E_b/I_0 of 5dB), 32 kbps data (with E_b/I_0 of 3 dB) and 64 kbps data (with E_b/I_0 of 2 dB). We assume 5 Erlangs of voice traffic. For data services, we assume a Pareto call duration with $\alpha_1 = 1.5, E\tau_1 = 2$ sec and $\alpha_2 = 1.8, E\tau_2 = 1.5$ sec. The modeling time scale is $T_w = 10$ msec. The arrival rates of both data services have a Poisson distribution with an average rate of 10 arrivals per second. Channel fading is based on the Gudmundson model with $\sigma_c = 8$ dB and $T_f = 100$ msec. A distance-dependent channel loss with path exponent $\gamma_c = -4$ for $c = 1, \ldots, C$ is considered. Users of different services are distributed uniformly, and there are no users with soft-hand-off (SHO) condition. A power-based call admission control mechanism is also applied in the downlink, in which a new arrival is granted if serving that user does not cause the total base-station transmitted power to exceed its corresponding maximum value. Simulation settings are presented in Table I. The heavy-tail call durations of data services satisfy the conditions of Proposition 2 with $H = 0.75$.

In the above configuration, we study the time trace of the received downlink interference measured at different locations. To estimate the self-similarity index H, we use the variance plot method in [32], and divide $I(n)$ into non-overlapping blocks each with m samples. For an asymptotic self-similar process with self-similarity index H, the variance of the mean processes for $m \to \infty$ is $L(m) m^{2H-2}$, $0.5 < H < 1$ [17]. Therefore, in a logarithmic scale, the variance is a straight line. Using the slope of this line, we can estimate H. Fig. 3 shows the variance in the logarithmic scale. Using a linear curve fitting, we obtain $H = 0.63$. We also estimate the values of H using the Whittle estimator [36], which is more accurate than the variance plot. The Whittle estimator gives $H = 0.65$. The discrepancy between the estimated value of H and its value obtained from Proposition 2 is mainly due to the fact that the base-station transmit power exceeds its maximum predetermined value.

To study the effect of the channel fading process, we use the above network with a perfect power controller to completely eliminate the fast fading effect. A very large interference threshold is also assumed, and the call admission procedure is disabled. In Fig. 4, the variance is shown for two different values of $\frac{T_f}{T_w}$. Note that the self-similarity index H increases with $\frac{T_f}{T_w}$. As T_f decreases (moving toward fast fading), H becomes smaller and the self-similarity level decreases. Therefore, fast fading decreases the long-range dependence in the

TABLE I

SIMULATION SETTINGS.

Parameter	**Value**
Number of BSs	19
Cell Radius	100 m
BSs Transmit Power	10 W
Physical Layer	UMTS
Thermal noise spectral density	-174.0 dBm/Hz
Power Control	Fast Power Control 1500/s
T_w	10ms
Standard Deviation of Fading	8 dB
Loss Exponent	4
T_f	100ms
$E\xi$[1]	0.5
Services	12.2 kbps voice, 32 and 64 kbps data
For 12.2 kbps voice	$E_b/I_0 = 5$dB, 5 Erlangs
For 32 kbps data	$E_b/I_0 = 3$dB Pareto Dist., $\alpha_1 = 1.5, E\tau_1 = 2$
For 64 kbps data	$E_b/I_0 = 2$ dB Pareto Dist., $\alpha_2 = 1.8, E\tau_2 = 1.5$

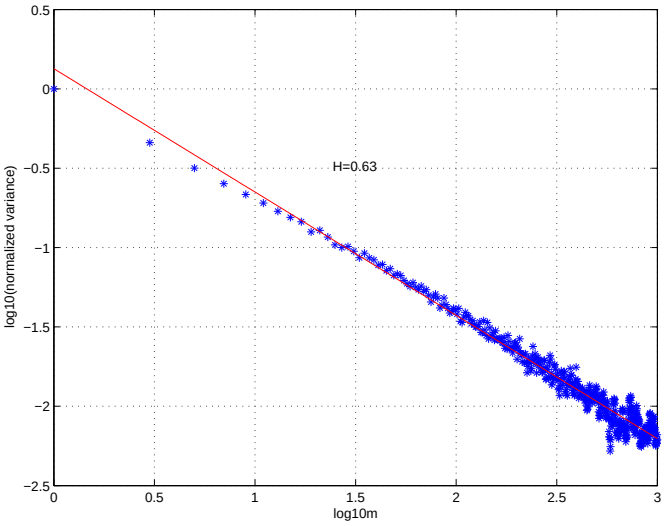

Fig. 3. Normalized variance plot for the total received downlink interference in the simulated network.

total interference. Similar results have been reported for data-centric wireless DS-CDMA networks in [6].

We also simulate different SHO conditions in the air interface and evaluate their effects on the self-similarity index of the downlink interference. We study three hand-off conditions, in which the averages of 0.2, 0.3 and 0.4 of users are in the SHO condition. The corresponding SHO gains [18] are assumed to be 1dB, 2dB and 2dB respectively. The values of H normalized with respect to H_0 (the Hurst parameter for no SHO) are presented in Table II. Self-similarity indexes in these cases are evaluated using the Whittle estimator.

We also study the effects of non-uniform spatial distribution of users on the self-similarity of the downlink interference. Non-uniform spatial distribution of users in the network coverage area is expressed by an average non-uniformity factor ω_D which is the percentage of users that are non-uniformly distributed. The value of $(1-\omega_D)$ is the percentage of the total active users that are distributed uniformly. For non-uniform spatial distribution of users, we consider a number of hot

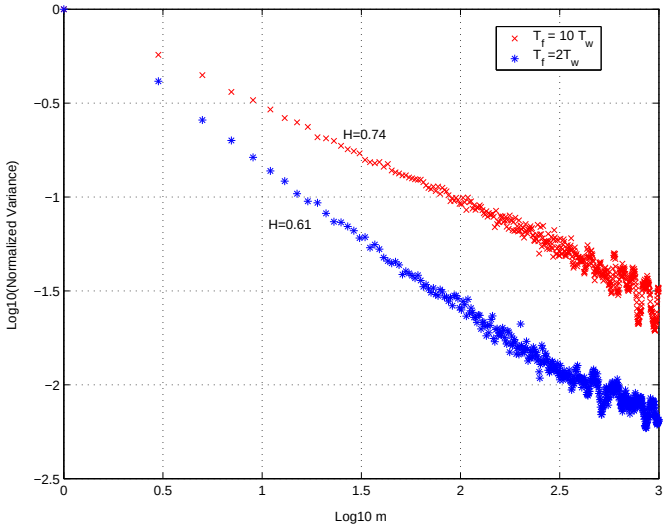

Fig. 4. The normalized variance of the total received downlink interference for two different fading conditions (T_f).

TABLE II

H/H_0 FOR DIFFERENT SHO CONDITIONS.

SHO condition	H/H_0
0.2 (1dB SHO gain)	0.995
0.3 (2dB SHO gain)	0.983
0.4 (2dB SHO gain)	0.977

spots, the average number of which in each cell is 2 and are randomly distributed in a uniform manner in the coverage area of the corresponding cell. Non-uniformly distributed users are then distributed uniformly in hot-spots. A load balancing mechanism as in [18] is used to satisfy the regular power transmission assumed in Proposition 2. The values of H normalized with respect to the same for a uniform distribution, namely H_0, is presented in Table III. Self-similarity indexes in these cases are also obtained using the Whittle estimator. It is evident now that non-uniform distribution of users and their SHO conditions do not affect the self-similarity of the downlink interference. This is because self-similarity emanates from the users' traffic characteristics.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we have formulated the total downlink interference in a heterogeneous cellular DS-CDMA network as a stochastic process that depends on the traffic characteristics of users, the transmit power, and the channel variations. We have shown that under certain conditions the auto correlation function of the total interference is a regularly varying function. We have showed that for heavy-tailed data and multimedia traffic, the auto-covariance function of the total interference decays sub-exponentially. We have further proposed an as-s model for the total interference and derived the conditions for the channel and traffic characteristics under which the as-s model for the total downlink interference is valid. The simulation results confirm the presence of self-similarity in the downlink interference. They also show that non-uniform distribution of

TABLE III
H/H_0 FOR DIFFERENT USERS' SPATIAL DISTRIBUTIONS.

Non-Uniformity Index ω_D	H/H_0
0.10	0.923
0.25	0.954
0.50	0.967

users and their SHO conditions do not affect the self-similarity in the downlink interference.

Having established this fact, now the question is 'what are the implications of self-similarity on the performance of cellular networks and their resource control mechanisms?' The long-range correlation manifest itself in extended periods of time over which the downlink interference exceeds the performance threshold, and may lead to long outage periods. In the engineering sense, the presence of self-similarity in the downlink interference can be regarded as 'good news'. This can lead to the development of 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 adaptive-predictive resource control mechanisms in the appropriate time scales. A very simple application can be found in [6]. Also, in theory (i.e., assuming an idealized Gaussian setting), it is now possible to represent an infinite family of distributions by only three parameters over the entire scaling region: the mean, the variability of the traffic process, and the self-similarity or Hurst parameter. This is a substantial simplification and can be quite useful in network resource management [37].

APPENDIX

***Lemma** 1:* If $f(x) \sim L(x)x^{\rho}$ in which $\rho < -1$, and $L(x)$ is a bounded svf in $[l, \infty)$, then

$$\sum_{n=l}^{\infty} f(n) \sim \int_{l}^{\infty} L(x)x^{\rho}dx, \qquad l \to \infty. \tag{27}$$

Proof: Let $a_i \stackrel{\Delta}{=} f(i)$ and $b_i \stackrel{\Delta}{=} \int_i^{i+1} f(x)dx$, and without loss of generality assume $i \in \mathbb{N}$. To show that for $l \to \infty$, $\sum_{i=l}^{\infty} a_i \sim \sum_{i=l}^{\infty} b_i$, we write

$$\Big|\sum_{i=l}^{\infty} a_i - \sum_{i=l}^{\infty} b_i\Big| \leq \sum_{i=l}^{\infty} b_i\Big|1 - (a_i/b_i)\Big|. \tag{28}$$

We use the inequality $m_i \leq b_i \leq M_i$, for $\rho < 0$

$$\begin{aligned} m_i &= \inf(f(x) : x \leq i+1), \\ M_i &= \sup(f(x) : x \geq i). \end{aligned}$$

Theorem 1.5.3 in [31] shows that for $i \to \infty$, $m_i \sim a_{i+1}$ and $M_i \sim a_i$. Lemma 1.9.6 in [31] states that $a_i \sim a_{i+1}$ for $i \to \infty$. Therefore, for $i \to \infty$ we have $a_i \sim b_i$. So, there exists an $\epsilon(l)$ such that

$$\Big|\sum_{i=l}^{\infty} a_i - \sum_{i=l}^{\infty} b_i\Big| < \epsilon(l)\sum_{i=l}^{\infty} b_i \to 0,\ l \to \infty. \tag{29}$$

Thus

$$\sum_{i=l}^{\infty} f(i) \sim \int_{l}^{\infty} f(x)dx, \qquad l \to \infty, \tag{30}$$

and $\int_l^{\infty} f(x)dx \sim \int_l^{\infty} L(x)x^{\rho}$. Thus Eq. 27 holds. ■

***Lemma** 2:* In [31] it is established that if $f_1 \in \mathcal{RV}_{\alpha_1}$, $f_2 \in \mathcal{RV}_{\alpha_2}$, then $f_1 + f_2 \in \mathcal{RV}_{\max(\alpha_1,\alpha_2)}$.

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